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Ethical use of artificial intelligence in food, land and water systems research: a guide for equity and inclusion

CGIAR Gender Equality and Inclusion

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About CGIAR Gender Equality and Inclusion (GENDER Accelerator)

CGIAR Gender Equality and Inclusion is CGIAR's Accelerator designed to put gender equality at the forefront of global agricultural research for development. The Accelerator will transform the way gender research is done, both within and beyond CGIAR, to kick-start a process of genuine change toward greater gender equality and better lives for smallholder farmers everywhere.
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1. Introduction

This document aims to support CGIAR researchers and their partners by providing guidance, recommendations and resources on ethical considerations in using artificial intelligence (AI) in food, land and water systems (FLWS) research and practice with attention to equity and inclusion dimensions. This toolkit complements the *GENDER Impact Platform Ethics and Standards Toolkit* and aligns with CGIAR's core ethical values outlined in the *CGIAR Ethics Framework* and the *CGIAR Research Ethics Code*.

In response to the rapid development and adoption of emerging AI technologies, the toolkit presents key issues and practical recommendations for researchers to consider across the research cycle, drawing on a comprehensive literature review and interviews with experts in AI ethics and social inclusion (see Appendix 2 for a detailed methodology).

AI systems, as used in this context, refer to technologies that mimic aspects of human cognition and behavior—interpreting real-world data, generating predictions, and adapting through continuous learning (Benefo et al. 2022; Fu 2022; Manning et al. 2022). (See also our glossary in Appendix 1.) These systems are increasingly central to a suite of AI and agricultural technologies poised to transform FLWS research: not only in how we conduct research and generate insights, but also in how we define best practice for gender-related research and understand the downstream impacts of our research outputs.

CGIAR and its partners steward some of the most valuable datasets available for training AI systems that respond to the needs of rural communities in the global South. This gives FLWS researchers a critical role in shaping how AI is used—and for whose benefit. Despite the growing promise of AI and an expanding body of ethics literature, however, practical guidance specific to FLWS research remains limited. Where ethical frameworks do exist, they are often too abstract, overgeneralized, or insufficiently responsive to the situated needs and constraints of researchers and communities working in FLWS contexts (Box 1).

Box 1. The limitations of AI ethics

Despite the development of over 50 ethics guidelines published by policy bodies, research institutes and private companies, and the identification of more than 80 general AI-related ethical principles (Munn 2023), several persistent challenges hinder meaningful implementation:

- **Lack of consensus on key terms and societal benefit:** Concepts like fairness, accountability, and societal good lack universal definitions, varying by cultural context and problem-framing (Cha et al. 2024; Fu 2022; Munn 2023). This ambiguity allows some companies to practice *ethics-washing*—appearing to follow ethics guidelines without making substantive changes to their practices (Munn 2023).

- **Limited research focus:** AI ethics often overlook guidelines that sectors like gender, agriculture, and the global South need, leaving these areas under-regulated (González and Rampino 2024). Agriculture, in particular, has largely escaped public scrutiny, limiting advocacy and accountability (Bronson and Sengers 2022).
- **Lack of measurable outcomes:** The proliferation of AI ethical principles without corresponding evaluation frameworks makes it difficult to assess the principles' real-world impact. Downstream harms are often unpredictable, and without standardized tools, it remains unclear whether these ethical challenges are unique to agriculture or indicative of broader cross-sectoral issues (González and Rampino 2024; Manasi 2024).
- **Ethics as an afterthought**: In AI tool development, ethical considerations are typically addressed late in the pipeline, after technologies are already built. For FLWS researchers relying on these tools, this means inheriting ethical blind spots and contending with reactive, patchwork solutions that emerge only when problems arise (Munn 2023; Ruttkamp-Bloem 2023).
- **Ethics fatigue in AI development:** As bespoke AI tools for FLWS research are developed, ethical considerations often fail to integrate seamlessly into the innovation pipeline, instead being treated as external requirements that interrupt core technical workflows. This misalignment can lead to frustration among engineers, who may view ethical evaluations as burdensome compliance tasks rather than integral to achieving impactful outcomes. Unlike the broader concerns of fairness or societal benefit, ethics fatigue stems from the perception that guidelines are disconnected from tangible results or the immediate goals of technological innovation. Experts in AI ethics and social inclusion observe that, without clearer integration into workflows or tools that demonstrate their value, ethical practices risk being reduced to a superficial exercise, limiting their effectiveness and undermining their credibility within development teams.
- **Theory–practice gap:** There is a disconnect between normative ethics—abstract principles derived from various philosophical frameworks—and applied ethics, which focuses on how research and development actors implement ethical practices. Overarching ethical principles often fail to translate effectively across different groups, stakeholders, or even within design teams, especially when it comes to the practical task of incorporating them into tangible features, interfaces and systems (Munn 2023; Sanderson et al. 2023).
- **Expectation–reality gap:** The hype surrounding AI creates unrealistic expectations about its capabilities, reinforcing a gap between technological promises and practical outcomes (Birhane et al. 2022; Kochupillai et al. 2022; Prabhakar and Prakash 2023). Narratives of radical innovation are often driven by developers seeking to avoid regulation and maintain control over technological

progress (Birhane et al. 2022; Munn 2023; Ruttkamp-Bloem 2023). Hype may encourage premature deployment of undertested tools, leading researchers to overpromise, or apply AI in contexts where it is inappropriate. Alternatively, fear of failure or reputational risk may lead to disengagement or inaction (Fu 2022; Okaibedi Eke et al. 2022; Wakunuma and Eke 2024). Both responses compromise responsible research practice and highlight the need for critical evaluation by FLWS researchers.

- **Environmental impact**: The energy-intensive nature of training and deploying AI models can have significant environmental consequences, contradicting sustainability goals common in FLWS (Li et al. 2023). For instance, AI-driven global supply-chain monitoring systems require substantial computational power, increasing the carbon footprint of interventions designed to reduce food loss and waste (Ryan et al. 2023). Moreover, the environmental costs extend beyond carbon emissions: the production and deployment of AI systems rely on resource extraction, energy consumption, and infrastructural expansion that disproportionately burden communities in the global South and perpetuate historical patterns of environmental injustice (Muldoon and Wu 2023). These impacts are rarely considered in assessments of relative benefits versus harms when research using AI is designed.

To guide our ethical approach, we draw from feminist perspectives on AI—approaches that do not view AI systems as neutral technical artefacts, but as sociotechnical constructs produced through intersecting systems of power, including gender, race, class and geography (Ricaurte 2024). This framing highlights two key commitments: first, that AI is grounded in human limitations—social, economic and environmental conditions that influence both the design and use of technology; and second, that AI systems are embedded within iterative cycles of FLWS research, development, deployment and evaluation, where researchers' ethical responsibilities emerge through engagement, reflexivity and care, rather than from static rules or abstract principles (D'Ignazio and Klein 2020).

Drawing on these commitments, we argue that for FLWS researchers, ethical responsibilities extend beyond traditional human-subjects research. Responsible AI in this context requires us to recognize that FLWS researchers are positioned within, and contribute to, decisions across the AI life cycle. We therefore define AI research to include how researchers:

- **Frame research problems and design studies** through the use of AI-driven diagnostic tools and predictive models.
- **Collect and curate data** via automated sensors, remote sensing, and behavioral monitoring, often producing training data that directly shapes AI systems.

- **Analyze and interpret findings** using machine learning and big data analytics, while also scrutinizing the accuracy, ethics and inclusiveness of these systems.
- **Deploy, test and scale AI-powered applications** such as advisory platforms and decision-support tools for farmers, policymakers and other end users, engaging with their efficacy, risks and distributional impacts (research about AI).

In this framing, "AI research" is not a bounded activity but a set of interconnected practices through which FLWS researchers both make use of AI and generate knowledge that feeds back into AI development, governance, and evaluation.

While many ethical responsibilities in research align with established research ethics frameworks, AI raises new and urgent questions that demand broader, more reflexive approaches. This toolkit is, therefore, designed not only to support general ethical research conduct, but also to help researchers engage more critically and proactively with AI-enabled tools as they intersect with research practice—ensuring that our work advances equity, inclusion and accountability across the research cycle. While the application of AI in FLWS research is still an emerging space, we draw on illustrative examples where possible to ground abstract principles in concrete practices and support their integration into real-world research contexts.

The inclusion of women, youth, and populations we seek to support through greater social inclusion is essential to ensuring that AI serves rather than harms the communities we work with (Chassin et al. 2022; UNESCO 2020; West and Kraut 2019). To be ethical in this space requires more than procedural compliance; it demands that researchers recognize their role in shaping AI's trajectory and take responsibility for its real-world implications. This toolkit offers a flexible, reflexive resource to support that effort.

Our collected recommendations are given in a checklist form in Appendix 3.

2. Research design

As in any FLWS research study, broadly defined, there must be a clear understanding of whether the use of technology such as AI is appropriate or necessary, particularly in contexts where populations such as women and ethnic minorities are at risk of being treated unfairly or subjected to bias (Fu 2022) during research processes or engaging with AI tools. While AI and data technologies hold immense potential to hold power to account, they can just as easily reinforce existing power structures. Data intended as a tool for equity can become a resource used by incumbent actors to sustain the unsustainable, advancing their positions at the expense of the vulnerable (Ghosh 2024).

Before turning to complex AI implementations, cost-effective and context-appropriate solutions should be considered when they can effectively address the challenges at hand. As Ryan (2024) emphasizes, the idea of technological progress is not inevitable or neutral, but socially and historically constructed, and we should be critical about when and how AI is used. Overreliance on AI risks overcomplicating problems that could be more effectively addressed through community-driven practices or low-tech innovations. Attempts to correct algorithmic inequities by introducing more technical solutions—such as increased surveillance or monitoring—may instead exacerbate the very issues they aim to resolve, deepening mistrust and perpetuating existing imbalances (Katell et al. 2020). Instead, ethical frameworks must shift the focus from what technology *can* do to what it *should* do, prioritizing values and societal needs over unchecked innovation (Hagerty and Rubinov 2019).

2.1 Recommendations for research design

- **Justify the use of AI.**
  Clearly articulate how AI contributes to your research objectives, and whether it adds significant value beyond the current expertise of a researcher. Avoid including AI merely for novelty, funding appeal or societal/peer expectation of its use, and be explicit about its value—especially for marginalized communities.
- **Evaluate necessity before complexity.**
  Consider whether simpler, context-appropriate, or community-driven methods could better meet your goals. Avoid defaulting to AI when low-tech or participatory solutions may be more effective.
- **Interrogate problem framing.**
  Ask who is defining the problem and who stands to benefit from the solution. Ensure your research design does not reinforce dominant narratives or sideline local knowledge systems.
- **Anticipate power dynamics.**
  Be aware that AI can entrench existing inequalities, even when intended to promote equity. Design research to challenge—not replicate—unjust structures of authority and access.

- **Apply ethical scrutiny to prototypes.**
  Avoid deploying untested or low-quality AI tools without adequate safeguards. Poorly governed AI (e.g., chatbots, AI decision-support systems) can erode trust, mislead participants, and compromise institutional credibility.
- **Shift from *can?* to *should?*.**
  Ground AI use in ethical reflection and societal relevance. Ask not just what AI is capable of, but what aligns with the values and long-term well-being of the communities involved.

2.2 Ethical principles and frameworks

A common pitfall in research that uses AI is the lack of attention to social inclusion and ethics considerations from the very beginning, which many private-sector actors view as economically unviable. Financial constraints in start-ups further hinder early engagement with target communities, creating inconsistencies between stated values and actual implementation (Ryan et al. 2023). Experts in AI ethics and social inclusion note that these concerns are typically only addressed after failed onboarding attempts or limited impact among certain users.

An intersectional lens to AI ethics recognizes how overlapping identities—such as gender, race, and socioeconomic status—shape experiences of privilege and oppression. Rooted in feminist theory and articulated by D'Ignazio and Klein (2020) in *Data Feminism*, this perspective emphasizes that data is never neutral; it reflects the biases and power structures present throughout all phases of development and use. For example, AI tools are often developed and framed within an ethnocentric paradigm that frames dominant Western norms and values as universal (Roche 2021). Similarly, ethical frameworks are predominantly shaped by Western ideals of what is constituted as legitimate, good and right. This orientation tends to marginalize alternative cultural perspectives on what may count as ethical within specific contexts, thereby constraining opportunities and excluding diverse ways of understanding ethics (Chassin et al. 2022; Manning et al. 2022).

This tension is illustrated in Fairbairn's (2023) critique of data aggregation in open science. In efforts to "set data free," Indigenous Peoples' knowledge is often decontextualized and abstracted to fit standardized formats. This erasure of cultural specificity diminishes the meaning embedded in relationships to land, kinship and community. For many Indigenous Peoples' communities, knowledge is not a static resource to be extracted, but a relational process rooted in place and obligation. When AI systems are trained with aggregated data stripped of this context, they risk reinforcing colonial logic and perpetuating epistemic harm.

Addressing these challenges requires a comprehensive intersectional feminist approach to AI ethics, which we suggest can be guided by four key principles derived from D'Ignazio and Klein (2020):

Conceptual principles for integrating social inclusion in research that uses AI

1. **Challenging power dynamics:** Structural and disciplinary limitations in studies involving AI often manifest in how research problems are framed, leading to the neglect of certain communities and their exclusion from the potential benefits of AI-supported research. Challenging power dynamics involves working with representatives of those communities and activists to ensure that marginalized perspectives are recognized and validated (Ruttkamp-Bloem 2023).
2. **Embracing pluralism:** An intersectional feminist approach must reject the imposition of dominant worldviews and instead focus on what it means to coexist equitably with others. This involves respecting diverse perspectives and ensuring that multiple voices with diverse perspectives, positions and goals may together inform the design and implementation of AI systems (Roche 2021). For example, integrating non-Western philosophies like Ubuntu— which emphasizes interconnectedness, solidarity and mutual respect—can enrich and broaden the ethical foundation for AI development (Gwagwa et al. 2022; Wakunuma and Eke 2024).
3. **Contextualizing biases:** What is often described as "missing" or "inaccurate" data is, in many cases, the result of systematic exclusion rooted in unequal social relations. Marginalized communities are frequently left out of data-collection not by oversight, but by design. Retroactively auditing or correcting these omissions through technical fixes is not enough. Ethical AI research must address the structural conditions that produce exclusion in the first place—requiring a normative and cultural shift in how research questions are framed, whose knowledge is valued, and how inclusivity is built into the design process from the outset (Suresh et al. 2022).
4. **Rethinking binaries and hierarchies:** Data feminism recognizes the interdependence of struggles and the need for solidarity across different identities and movements—freedom for one group is inextricably tied to freedom for all, requiring a radical reimagining of relationships, structures and priorities to achieve equitable outcomes; for example, challenging gender binary and other forms of oppressive classification (Suresh et al. 2022).

Depending on the research context and questions, applying each principle in isolation may lead to conflicting imperatives. For example, embracing pluralism suggests that amplifying local perspectives is critical—but not at the expense of tolerating practices that perpetuate oppression or harm. In high-stakes situations that demand immediate action, deliberative processes should not delay meeting urgent needs. In such cases, researchers must carefully balance the application of the four principles to ensure that action and ethical commitments are aligned.

When collecting data to inform research design, there need not be trade-offs between inclusion, responsiveness and scientific rigor—in fact, they can be mutually reinforcing. Participatory approaches such as living labs and farmer field trials allow researchers to co-define research priorities with farmers and gather data under real-world conditions. These methods help align AI innovation with the lived realities of end users by generating high-resolution, context-rich data that reflects diverse agricultural practices. In doing so, they meet farmers' immediate needs while also supporting the development of more adaptable, trustworthy, and relevant AI tools—grounding technological advancement in practical use (Gardezi et al. 2024).

To implement these principles, researchers can draw on a number of established frameworks that offer actionable approaches grounded in real-world applications. While many were originally developed to guide the design and development of AI tools—particularly in participatory and justice-oriented settings—their emphasis on engagement, reflexivity, care and contextual sensitivity also makes them valuable for researchers using AI in data-collection, analysis or evaluation. These frameworks help translate ethical principles into concrete research practices that shape outcomes, particularly when working with marginalized communities or in complex field settings.

Recognizing the power dynamics behind how problems are defined is critical for avoiding AI systems that reinforce the interests of dominant groups. Contextualizing historical, social and cultural inequities enables more-inclusive solutions that address the root causes of inequality rather than surface-level symptoms (Birhane et al. 2022; Fu 2022). In agricultural extension, for example, AI tools such as recommendation engines or diagnostic apps are often designed to support extension workers as trusted intermediaries. However, when these tools obscure how recommendations are generated or limit farmers' access to the underlying data, they can reinforce information asymmetries—centralizing the authority of extension staff and reducing farmers' agency to question or adapt the advice. Designing systems that support transparency, explainability and co-interpretation can help rebalance these dynamics and incorporate a broader range of perspectives (Leshed et al. 2018).

AI can strengthen agricultural decision-making by integrating localized knowledge, particularly the perspectives of women farmers. Women's perceptions of issues like pest impact or crop health are shaped by resource constraints that differ significantly from those of men farmers, who often have better access to inputs and technologies (Foster et al. 2023; Gwagwa et al. 2021).

Box 2. Inclusive ethical frameworks

These ethical frameworks offer methods for research design and assessment that can be, or were designed to, apply to AI research or development.

Ethical, Legal and Social Aspects (ELSA) framework	Algorithmic Equity Toolkit	Multidimensional Digital Inclusiveness Index (MDII) framework
Suited to upstream or exploratory research The ELSA framework was originally developed to support research into the development and deployment of emerging technologies, helping researchers assess the ethical, legal and social dimensions of innovation. While not specific to AI, it offers structured methods—such as scenario planning, stakeholder consultations, and normative deliberation—that can be applied to AI-supported research processes in FLWS contexts. ELSA is particularly useful for finding concerns related to sustainability, inclusion and accountability. Recent adaptations include question sets to help researchers navigate competing ethical considerations and anticipate downstream consequences (van Hilten et al. 2025). By embedding ethics throughout the development process, ELSA fosters transparency, promotes equitable outcomes, and helps researchers align AI tools with the values and priorities of local communities.	***Suited to auditing deployed tools*** The Algorithmic Equity Toolkit provides a structured and pragmatic method for auditing and interrogating existing AI tools. It is especially useful for researchers seeking to ensure that data practices, model interpretation, and evidence use do not reproduce existing power imbalances. The toolkit includes tools such as bias audits, equity-oriented checklists, and participatory consultations that can be applied throughout the research life cycle. The toolkit also emphasizes the importance of ensuring underserved communities benefit equitably from AI advancements, fostering trust and expanding adoption in those communities. This framework shows how ethics can be operationalized to directly address disparities and improve inclusivity in agricultural AI systems.	***Suited to participatory, field-based work with farmers*** Originally developed to support co-creation of digital tools, the MDII framework also offers a participatory approach to AI research. It emphasizes inclusive, iterative research design through structured engagement with farmers, researchers and other stakeholders. This enables ethical challenges—such as unequal access to digital tools or differing data-literacy levels—to be found early and addressed collaboratively. In research contexts, MDII offers a roadmap for adapting study design in response to stakeholder feedback and for promoting gender sensitivity and contextual relevance across project phases (Martins et al. 2024).

Recommendations about ethical principles and frameworks

- **Embed ethical principles from the start.**
  Apply the four principles of Data Feminism—*challenge power dynamics*, *embrace pluralism*, *contextualize biases*, and *rethink binaries and hierarchies*—throughout your research process. Where trade-offs arise, be transparent and assess whether the benefits justify the risks.
- **Choose context-appropriate ethical frameworks.**
  Match the framework to the use case (see Box 2)
  - use ELSA for upstream or exploratory research
  - apply the Algorithmic Equity Toolkit for auditing deployed tools
  - select MDII for participatory, field-based work with farmers
- **Use inclusive, participatory methods.**
  Implement principles through stakeholder workshops, bias audits, co-design processes, or community validation. These methods are effective even in low-resource environments and help democratize decision-making.
- **Engage trusted local partners.**
  Work with organizations embedded in the community to ground your engagement in local norms, values and needs. This encourages more relevant and respectful interactions with participants (see the section on Research partnerships, recruitment and training).
- **Define ethical exit strategies.**
  Establish ex ante decision rules for halting research or deployment if ethical standards are breached. These should apply to researchers, NGOs, and private-sector actors alike—and be made transparent to all stakeholders before research begins.

2.3 Research partnerships, recruitment and training

Ethical AI development requires interdisciplinary collaboration and partnerships across technical, social and policy domains to balance diverse perspectives and account for disciplinary nuances. However, AI development teams often lack diversity due to structural inequalities—such as gender biases in recruitment; unequal access to science, technology, engineering and mathematics education; and persistent workplace discrimination—which limit the inclusion of women and other marginalized groups (Manasi 2024). This lack of representation narrows the range of perspectives that inform critical decisions, such as which data sources are deemed valid, what use cases are prioritized and how outputs are communicated. For instance, if training data reflects only dominant farming models, smallholder practices or gender-specific agricultural roles may be overlooked entirely. Similarly, the design of decision-support tools without input from women farmers can result in features that fail to account for their specific labor constraints or information needs (Kronqvist and Rousi 2023). These omissions are not simply oversights—they are outcomes of structural barriers that exclude women from shaping AI systems. Prioritizing partners with diverse and transdisciplinary backgrounds is therefore essential, both to counter bias in technical design and to ensure that AI applications in FLWS are responsive to the realities of all users.

Given CGIAR's commitment to the production of global public goods, partnerships with private-sector and for-profit actors must be carefully considered to avoid conflicts of interest and minimize potential harms. Powerful actors often extract data from less powerful groups, modifying previously private spaces and times into monetized and privatized terrains of exchange (Mann and Iazzolino 2021). This process includes the privatization of Indigenous Peoples' knowledge, where valuable cultural insights and practices are appropriated and commercialized without fair compensation (Foster et al. 2023). By making these dynamics visible, markets can speculate on real-time data, enabling financial actors to trade and bet based on their informational advantage. This further entangles farmers' actions with market fluctuations, increasing their exposure to external economic forces (Bronson and Sengers 2022).

Proprietary AI tools also risk monopolizing sectors by limiting competition and restricting customization for specific or emerging use cases. Technical *lock-ins* for tools reinforce brand loyalty by restricting interoperability, forcing users into closed ecosystems that prioritize dominant narratives and marginalize alternative knowledge systems and innovations (Forney and Dwiartama 2022; Zheleva et al. 2017) For example, an AI-powered logistics system requiring proprietary data formats may exclude smaller, independent actors from adapting the technology to local needs. Researchers must ensure that all partnerships adhere to CGIAR ethical standards, and that interoperability is preserved consistent with the *CGIAR Open and FAIR Data Assets Policy*.

Recruiting diverse research teams can also be challenging because researchers in traditional institutions often lack technical expertise to design AI-driven interventions or collaborate effectively with engineers. This skills gap limits their ability to influence AI systems' design and critically engage with emerging technologies (Torero 2021). AI-literacy initiatives can equip both researchers and developers with the tools to engage critically with AI, communicate more effectively, build trust-based relationships, and promote collaboration by demystifying complex AI systems (Long and Magerko 2020). For instance, tailored training programs could focus on practical skills like understanding AI-driven recommendations, identifying biases and navigating consent frameworks, encouraging diverse user groups to meaningfully participate in the design and use of AI tools (D'Ignazio 2022). Providers such as SheAI and the Inclusive AI Lab offer both free and paid training courses on a range of AI topics.

While guiding principles, research ethics committees and institutional review boards play a crucial role in enforcing standards, researchers must also integrate critical and reflexive practices into their work, understanding integrity not just as individual conduct, but as a commitment to designing research that is accountable to those it affects. Tools like the

Ethics Pathways activity (Cha et al. 2024) allow researchers and developers to reflect on their own biases, making them more sensitive to value conflicts, and thus better able to measure and interpret where AI solutions do not align with participants' lived realities. Researchers should actively interrogate and address biases and inequities within their work, viewing themselves as actors within systems of power.

Research teams should model or "prefigure" the societal changes they aim to achieve, practicing inclusivity and equitable labor distribution within their own groups. These actions demonstrate the desired societal transformation in the present, rather than waiting for large-scale structural reform (D'Ignazio and Klein 2020; Suresh et al. 2022).

Recommendations about interdisciplinary collaboration and partnerships

- **Embed equity in partner selection.**
  Include diversity, inclusion and capacity-exchange criteria in calls for proposals. Prioritize collaborations with national agricultural research and extension systems and local actors, and ensure clearly defined roles for all team members, including early-career researchers.
- **Assess private-sector partnerships for conflicts of interest.**
  Review partnerships with for-profit actors to ensure data ownership, usage rights, and benefit-sharing align with CGIAR's Open and FAIR Data policy and broader ethical commitments.
- **Support mutual capacity building.**
  Ensure social scientists are equipped to engage with AI technologies, and that AI developers receive training in gender, ethics and inclusion. Cross-disciplinary literacy is essential for collaboration.
- **Invest in targeted training.**
  Use providers such as SheAI and the Inclusive AI Lab to offer technical or gender-focused training. Refer to curated training resources at CGIAR Gender Equality and Inclusion to build inclusive skill sets across teams.
- **Encourage critical self-reflection.**
  Use tools like the Ethics Pathways activity to examine how researcher positionality, assumptions and values influence design decisions. Make reflexivity a routine part of ethical engagement.
- **Model the values you aim to advance.**
  Structure research teams to reflect the equitable outcomes your project seeks. Practice inclusive labor distribution and shared decision-making within your team—prefiguring systemic change.

3. Data collection

3.1 Informed consent and explainability

Explainability remains a cornerstone of ethical research involving AI. However, the complexity and opacity of many AI models—especially deep-learning systems—pose significant challenges to transparent communication. While researchers may understand these systems mathematically, this knowledge often does not translate to participants, particularly farmers and other community members with limited access to technical education (Girmay and Felix 2025; Sanderson et al. 2023). This gap undermines the informed-consent process in research studies, particularly in two scenarios:

- **Intervention studies** that evaluate the effects of AI-driven tools—such as weather forecasts, market price alerts, or advisory platforms—on farmer behavior or decision-making. In such cases, participants may feel compelled to use the AI tool because it is framed as a beneficial service, even if they do not fully understand how it works or the risks involved.
- **Data-focused studies** that collect information—such as farm practices, yields or voice recordings—to train or fine-tune AI models. Here, the long-term implications of contributing data may be unclear to participants, especially when data is reused across contexts or incorporated into models that participants never directly interacted with.

In both cases, limited alternatives and the opaque nature of AI systems may pressure participants into agreeing without fully informed understanding—particularly in contexts where people have low digital literacy or receive few safeguards for their data rights. These conditions highlight the need for more context-sensitive, participatory consent processes.

Conventional methods of obtaining informed consent are also difficult to apply in large-scale or open-data projects. Challenges include explaining long-term risks of data reuse, addressing language barriers in disclosure forms, and clarifying how sensitive or locally specific knowledge might be used (Andreotta et al. 2022; Suresh et al. 2022). These challenges are especially pronounced in marginalized communities, where legal and technical support is limited.

In research contexts, it is important to distinguish between different types of AI studies. For projects that involve direct interaction between participants and AI systems—such as advisory platforms, digital surveys, or tools that request user input—consent procedures must go beyond traditional disclosure. Researchers must clearly communicate how personally identifiable or sensitive information will be stored, reused or removed, and ensure participants understand their rights to opt out. In contrast, studies using publicly available, de-identified datasets carry different risks, provided that re-identification is not possible and appropriate safeguards are in place.

Across these contexts, culturally appropriate consent frameworks—such as those co-developed through participatory workshops—can help align ethical research goals with local expectations and values.

In downstream AI applications, such as advisory tools used in agricultural extension, trusted relationships also matter. Local advisors or extension officers can serve as intermediaries, helping users make informed decisions by translating risks and benefits into accessible, trusted terms (Chassin et al. 2022; D'Ignazio 2022; Rose et al. 2018). For example, when farmers hear success stories from peers or advisors they trust, they may feel more comfortable engaging with AI systems—provided that engagement is genuinely voluntary and well-informed, according to an expert in AI ethics and social inclusion.

Recommendations about informed consent and explainability

- **Clearly explain the research purpose and data use.**
  Describe what types of data will be collected—personal, behavioral or community-generated—and how they could be used, reused, or shared in AI development.
- **Emphasize voluntary participation and withdrawal rights.**
  Inform participants that their involvement is optional, can be withdrawn at any time, and that control over future data use may be limited once it is anonymized.
- **Disclose AI-specific risks and commit to data security.**
  Explain risks such as re-identification, unintended inferences and opaque algorithm behavior. Guarantee de-identification, secure storage and restricted access to sensitive data.
- **Renew consent in long-term or high-frequency studies.**
  When data are collected repeatedly or over extended periods, obtain updated consent at appropriate intervals to reflect new risks or uses.
- **Provide a trusted, local point of contact.**
  Ensure participants can ask questions or raise concerns through a designated individual or organization, especially in low-resource or multilingual contexts.
- **Co-develop consent protocols with communities.**
  Collaborate with community members to create consent formats that reflect local norms—such as oral, visual or narrative methods—while maintaining individual consent as a core requirement.
- **Openly document AI systems when feasible.**
  Share details about data sources, algorithmic processes and intended outputs to promote transparency and accountability in research.
- **Avoid black-box models in sensitive research settings.**
  Refrain from deploying opaque AI tools where outputs directly affect participants, or where transparency and reproducibility are essential.

- **Tailor consent to the AI use case.**
  In data collection for training AI models, explain long-term implications. In intervention studies, clarify how the AI system functions and interacts with participants.
- **Ethically justify the reuse of public datasets.**
  Even if data are publicly available, combining them with new analyses or contextual insights can expose sensitive information in ways that create risks of re-identification or stigmatization. Researchers should assess whether such reuse meets ethical standards.

3.2 Data privacy, safety and security

Applications of AI in FLWS rely on extensive data collection, raising concerns about privacy violations, misuse, potential cyberattacks, and unintended harms such as stigmatization (Kochupillai et al. 2022). For example, data on farmers' yields, land use, or soil characteristics—while not personally identifiable—can still be sensitive. If made public or shared without clear governance, such data could be exploited by corporations for competitive advantage or resource extraction, without the knowledge or consent of the communities involved. This risk is amplified when AI systems accelerate data aggregation and analysis, underscoring the need to evaluate not only how data is protected, but also who can access and benefit from it.

AI's expanded capabilities make it increasingly possible to re-identify individuals even from anonymized data (Sanderson et al. 2023). Safeguarding sensitive data is critical for building trust among stakeholders while protecting individual and community-level information. Without proper oversight, tools like remote-sensing technologies can inadvertently expose sensitive activities. Combined with contextual data, such exposure increases risks of corporate exploitation, data breaches and malicious hacking (Kochupillai et al. 2022; Prakash et al. 2021; Ryan et al. 2023).

A significant lack of public understanding about AI and information governance can grant disproportionate power to those who collect, store and use data (Carbonell 2016). According to experts in AI ethics and social inclusion, recognizing AI's inherent limitations in design and data-collection can foster more grounded expectations among practitioners and communities, leading to more realistic applications. Additionally, they observe that many challenges in AI research parallel well-recognized issues in FLWS research, suggesting that similar solutions—such as improved data handling and enhanced community involvement—could be applied effectively.

Recommendations about data privacy, safety and security

- **Publish a participant-friendly privacy and data-protection policy.**
  Clearly communicate how data will be collected, used, protected and deleted, using accessible language and formats.
- **Respect original consent agreements.**
  Use data only for the purposes agreed upon at the outset. Seek renewed consent before applying data in, or providing data for, any different context or use case.
- **Limit data collection to what is necessary.**
  Collect only data essential to the research purpose. Apply anonymization or 'pseudonymization' techniques to protect participant identities.
- **Follow best practices in information security.**
  Use secure channels for transmitting data and restrict access through PINs, passwords and unique invitations. Regularly audit access and ensure that only authorized, active personnel can view sensitive data.
- **Avoid storing identifiable data longer than needed.**
  Define clear retention periods that comply with legal, ethical and institutional guidelines. Delete or de-identify data once it is no longer required.
- **Anticipate risks through built-in safeguards.**
  In AI-related studies, embed safety mechanisms during research and testing to detect and mitigate potential harms before tools are deployed.
- **Include participant-feedback mechanisms.**
  Enable users to question, challenge or comment on AI-generated outputs during testing. Use their input to improve tools iteratively before deployment.
- **Use a human-in-the-loop approach.**
  Ensure researchers or trained staff review AI-generated recommendations before they are shared with participants—especially when outputs carry financial, health or livelihood implications.
- **Define when human judgment must override AI.**
  Establish clear thresholds and protocols for when AI suggestions should be paused, rejected or revised based on expert review or contextual concerns.
- **Refer to related standards and guidance.**
  Consult the sections on Informed consent and explainability and Deployment and onboarding, and the CGIAR GENDER research ethics and standards toolkit for additional guidance.

4. Using secondary data

CGIAR collects a lot of data, and it is our ethical responsibility as researchers to ensure that the data our research participants have shared lead to useful insights that generate benefits for these communities. Most CGIAR datasets are open access and therefore subject to further use by researchers as secondary data sources, especially when combined with other data.

There are both risks and opportunities from AI-powered data processing and analytics that use big data techniques and machine-learning models. In particular, the growing availability of mobile and satellite data can facilitate AI-driven analyses to identify needs, inform decisions, and address challenges specific to the global South. For instance, AI applications could leverage satellite imagery to monitor agricultural practices, predict harvests, or track food-waste trends, enabling informed decision-making in underserved areas (Braun 2021). Another example shows how integrating climate-risk data with gender-disaggregated labor statistics from the International Labor Organization was used to create a geospatial map highlighting gender-specific vulnerabilities to climate change (Koo et al. 2022). This analysis reveals where women’s labor sectors may face heightened climate risks, offering valuable insights for policymakers aiming to develop targeted climate adaptation strategies that address gender-specific economic and environmental challenges (Koo et al. 2022).

Existing datasets often reflect significant gaps and biases, which are mirrored and amplified in AI systems. Overrepresentation of large-scale farmers and underrepresentation of smallholders and Indigenous knowledge systems can skew AI recommendations toward practices that do not meet the needs of marginalized groups (Chassin et al. 2022; Friedman et al. 2024). Even efforts to fill data gaps using mobile technologies can reproduce inequalities, since mobile data underrepresents people without reliable access to digital services (Belsare et al. 2022; Kochupillai et al. 2022). Without deliberate intervention, AI systems trained on biased datasets risk reinforcing these kinds of structural exclusions rather than addressing them (Hagendorff 2024).

To mitigate these risks, researchers must ensure that secondary data are *findable*, *accessible*, *interoperable* and *reusable* (FAIR), particularly for under-represented populations. For example, ongoing efforts to develop a metadata schema for qualitative data led by the Gender Equality and Inclusion aim to increase the use of this rich contextual data in gender, youth and social inclusion FLWS research (Kruseman et al. 2024). Researchers are encouraged to review the *CGIAR Open and FAIR Data Assets Policy* and relevant institution-level data policies, such as the *International Food Policy Research Institute (IFPRI) research data management and open access policy*, for more information.

Platforms like DevelopMetrics use retrieval-augmented generation and fine-tuning techniques to synthesize large datasets against predefined frameworks, allowing researchers to interactively retrieve, curate and interpret data linked to domain-specific concepts such as agricultural practices or gender indicators.

While qualitative data are rarely publicly released given the risk of identifying research participants, AI tools such as natural language processing can be used to analyze previously collected data to supplement traditional qualitative analysis and uncover new insights. For example, Jones-Garcia et al. (2021) used affective computing methods—for example, automated emotion recognition and sentiment analysis—on interview transcripts with farmers, uncovering insights difficult to obtain through conventional approaches.

For quantitative data, harmonizing indicators across datasets enables more robust AI applications. Using standardized frameworks, such as the Women's Empowerment in Agriculture Index (WEAI), researchers can combine diverse datasets to generate new insights. For example, a study in Bangladesh applied WEAI metrics in a phone survey to capture the differential effects of COVID-19 on women during the early period of the coronavirus outbreak in Bangladesh, demonstrating how secondary-data interpretation can accelerate and deepen gender analysis (Ahmed et al. 2020).

Expanding the usefulness and real-world applicability of AI systems involves combining open datasets with contextual data collected through systematic, community-driven approaches (Fu 2022; Gerdes 2022). Involving target users—such as farmers—in annotating and contextualizing data strengthens model relevance and equity. Collaborative definition of socioeconomic variables enables more precise intersectional analysis: encoding multiple identity categories together (e.g., a farmer who is a woman, Indigenous, and from a remote area) teaches the model to recognize the complex realities that shape people's lives (Suresh et al. 2022).

4.1 Recommendations about secondary data

- **Verify that secondary data meet ethical collection standards.**
  Confirm that the original data were collected in compliance with ethical norms, especially regarding ongoing consent, confidentiality and community rights.
- **Assess alignment with original consent.**
  Ensure secondary data reuse respects the scope of consent given by participants. Where sensitivities exist—such as cultural knowledge or risk of re-identification—consult communities and seek ethics review before reuse.
- **Document data provenance and planned uses.**
  Clearly record where the data came from, how it will be used, and whether any updates or notices are needed for communities or institutions involved in the original study.
- **Evaluate and mitigate potential harms from reuse.**
  Consider how secondary data might inadvertently expose individuals or groups to harm. Mitigation strategies include limiting disaggregation, applying noise, or using generalization and suppression (see Sondeck and Laurent 2025 for a practical assessment framework).

- **Ensure transparency about the dataset's origin and characteristics.** Provide metadata such as the source institution, collection period, access rights, data structure, populations represented, and intellectual property status. Clear documentation prevents misuse and misinterpretation, while enabling researchers to judge appropriateness, limitations, and safeguards.

5. Deployment and onboarding

Deployment refers to the process of making an AI system operational, while *onboarding* involves integrating AI into the daily workflows and processes of the intended users and organizations. There are five broad ethical issues during these stages that researchers, developers and implementers should address:

- Ensuring **compliance** with ethical frameworks and regulatory guidelines to ensure responsible use.
- Considering **privacy and security** by ensuring ongoing protection of user data and compliance with informed consent obtained, and specific privacy laws applicable to the countries where the AI system is in use. This also includes safeguarding AI systems against malicious attacks and ensuring data protection.
- Implementing **bias mitigation** through regular checks to assess whether AI-generated results remain accurate and appropriate for the intended context. This includes identifying performance drift—where model accuracy or contextual relevance declines over time—which can lead to unintended consequences or harms, particularly for marginalized groups. Use transparent benchmarks and engage interdisciplinary reviewers to reduce the risk of researcher-induced bias.
- Increasing the **transparency, accountability and explainability** of AI systems such that users clearly understand how AI systems make decisions and produce results.
- **Building user capacity** to interact with AI systems responsibly for researchers, developers, implementers and farmers; and **ensuring inclusive access**—such as using tailored training and support to ensure inclusive and informed use of AI.

5.1 Compliance

Integrating AI ethics into workflows can be challenging due to limited resources and resistance to changing well-established but unjust design norms (Müller et al. 2024). When compliance is treated as a box-ticking exercise, there is a risk of shifting burdens onto users through technical mechanisms rather than implementing meaningful internal reforms (Chi et al. 2021). To avoid this, localized AI governance systems should be established, fostering inclusive, context-sensitive solutions through phased testing and collaboration with target communities. For example, co-creating governance protocols with smallholder farmer cooperatives aims to ensure that decision-making reflects community priorities rather than the agendas of global tech companies (Katell et al. 2020).

Participatory action research ethics—which acknowledges researchers' positionality, assumptions and convictions, and follows an iterative cycle of planning, action, observation and reflection—offers a more effective alternative to compliance-based models. Rather than treating ethics as an external checklist, this approach integrates regular evaluations and ethical assessments throughout the research process. Social-justice assessments should involve smallholders directly and be based on their own notions of success beyond yield or efficiency (Heldert 2021; Suresh et al. 2022). Flexible, adaptive research processes are critical for identifying and addressing ethical dilemmas and evolving needs (Ryan et al. 2021).

5.2 Privacy and security

Researchers must consider how AI systems can compromise participant privacy, safety and security—often in ways that become visible only after data is repurposed or integrated into downstream applications. For example, farmers participating in a study that evaluates an AI-powered advisory tool may unknowingly share sensitive data on yields or land use. While collected for a research purpose, such data could later be used to automate agricultural processes or devalue farmers' local knowledge and expertise (Hanrahan et al. 2021).

Although open data is often promoted as a public good—enhancing transparency, collaboration, and innovation (Bronson and Sengers 2022)—it also creates risks of exploitation when local knowledge is shared without proper protections or compensation (Fairbairn et al. 2023). Even when consent is obtained at the point of collection, data reused in training AI systems may be put to purposes not originally anticipated, complicating ethical oversight (Andreotta et al. 2022). Interoperability across systems can further heighten privacy risks if robust security measures and clear governance mechanisms are not in place (Dubey et al. 2023).

5.3 Bias mitigation

Beyond issues of data representation, AI technologies often encode cultural and gender biases into system design and outputs (Birhane et al. 2022). These biases are not simply technical flaws; they are reflections of deeper societal inequalities embedded into the data itself. For example, AI language models have been found to reinforce gender stereotypes through word associations, such as linking certain professions to specific genders (Jun 2024). Even efforts to address gender bias can inadvertently perpetuate traditional divisions. Large language models that ostensibly promote gender equality, for instance, sometimes reinforce portrayals of women as "planners" and men as "physically intensive workers"—stereotypes that often go unchallenged because they are seen as "natural" or "inevitable."

Several technical approaches have been developed to mitigate bias within AI systems. For example, de-biasing methods applied to hiring algorithms have disentangled grammatical gender signals from job recommendations, resulting in fairer outputs (Sabbaghi and Caliskan 2022). Similar techniques could be adapted for agricultural AI systems to correct gendered disparities in advisory content (Singh et al. 2024). See Parraga et al. (2022) for a comprehensive review of de-biasing methods.

Two recent studies illustrate the persistence of deeper biases even when adversarial testing—deliberately probing a system with challenging or sensitive inputs to expose weaknesses—is used to detect and address them. Koo et al. (2025) evaluated five large language models by analyzing their responses to agricultural queries posed by women farmers in India. Although the models varied in depth, nuance and relevance to the local context, they consistently struggled to fully eliminate gender biases. Global nonprofit technology organization Digital Green applied a similar approach to stress-test its [FarmerChat]() AI chatbot, probing for gender-harmful, gender-responsive and gender-transformative outputs. While FarmerChat avoided overt stereotypes, it struggled with more nuanced issues such as gender-based violence, labor equity, and the specific challenges faced by women farmers such as time poverty and limited decision-making agency (Singh et al. 2024).

Both studies underscore that while technical interventions like de-biasing and adversarial testing are important, they cannot fully resolve the deeper structural inequalities embedded within data, system design and institutional priorities. Addressing these challenges requires fundamental shifts in how cultural and gendered assumptions are integrated into the design, evaluation and governance of AI systems.

5.4 Transparency, accountability and explainability

AI systems often operate as opaque *black boxes*, making it difficult for users to understand how data is prioritized, labeled or analyzed (Kochupillai et al. 2022). This lack of transparency undermines trust, as erroneous decisions remain inaccessible and unexplained (Fu 2022). Instead, AI models should strive to provide clear, accessible explanations for why certain people, places or variables were prioritized during development (Bi et al. 2023; Kochupillai et al. 2022).

Practical strategies include visualizing model performance through simple charts, dashboards or feature-attribution maps—such as illustrating how soil-quality metrics influence crop recommendations (Girmay and Felix 2025; Manning et al. 2022). Transparency reports that document model objectives, data sources, assumptions and known limitations can further increase accountability. Real-time monitoring systems can also support ongoing evaluation and traceability of transparency goals, alerting developers to potential drift, bias, or failures in explainability over time.

While technical mechanisms are essential, transparency must also be grounded in user-centered communication: explanations must be adapted to users' literacy levels, languages and contexts. Only then can explainability efforts truly support equitable and meaningful engagement with AI tools.

Integrated feedback mechanisms offer users a practical way to hold AI systems accountable. Features like feedback buttons, SMS reporting, or embedded community forums allow farmers to flag errors, suggest improvements and share experiences directly with developers (Eichler Inwood and Dale 2019). By giving users a voice in model refinement, these systems make transparency tangible, ensuring that AI tools remain responsive to farmers' real-world needs and concerns.

5.5 Inclusive access and capacity building

Generalized onboarding materials or training programs often fail to account for the diverse needs of users, particularly smallholder farmers and underrepresented groups with limited resources or technical skills (Pappa 2024). There are many hidden costs and barriers that can constrain specific groups from participating and benefiting from training programs.

Systemic challenges such as limited access to education, land and financial resources can restrict socially marginalized farmers' ability to adopt and benefit from AI technologies (Chassin et al. 2022; Dubey et al. 2023). These barriers are further exacerbated by limited digital literacy, lack of access to internet or mobile phone infrastructure, geographic distance or remoteness, and the absence of multilingual AI services—perpetuating inequitable resource allocation and limiting marginalized communities' access to agricultural innovation.

Enabling women in rural areas to access AI-driven agricultural services requires addressing practical challenges like those listed above, plus unreliable networks, limited charging options, and lack of internet or directories. Analog solutions, such as distributing printed posters showing service numbers or promoting solar chargers, can significantly improve access and usability (Schumann 2023). Offering short-term, low-cost rental options for software and hardware can broaden access for a wider network of farmers (Ryan et al. 2023). For instance, flexible financial models that allow farmers to trial AI-powered tools before committing to full adoption can build confidence and stimulate innovation (Fleming et al. 2021).

AI struggles to properly account for the onboarding needs of different languages and cultures during onboarding and ongoing use. Many farmers in rural areas struggle with AI systems that lack support for Indigenous Peoples' languages, which often do not have formal dictionaries or sufficient linguistic data to train AI tools (Dubey et al. 2023). In response to this gap, Farm Radio International, in collaboration with CGIAR, developed Longa—an automated speech-recognition tool that transcribes, translates and analyzes audio data in local languages such as Luganda and Swahili. Longa has been used to support the design of context-specific radio programs and agricultural advice tailored to the unique needs of underserved groups, including women and young farmers.

Where possible, software best practices such as open-source licensing can support dynamic, farmer-driven data-collection and real-time updates on conditions, crop selections, and practices (Sanderson et al. 2023). Systems that allow contextual customization through notes, images and personalized inputs can help AI-generated recommendations align with farmers' decision-making processes and practical realities (Bi et al. 2023; Friedman et al. 2024).

5.6 Recommendations for deployment and onboarding

- **Conduct regular ethical-compliance reviews.**
  Continually assess whether project activities align with ethical standards, legal frameworks and community expectations throughout deployment and use.
- **Stress-test models for robustness and fairness.**
  Incorporate adversarial testing to reveal hidden biases, ethical blind spots, and system weaknesses under real-world conditions.
- **Minimize data collection and protect identities.**
  Only collect data essential to the research scope. Apply anonymization or pseudonymization techniques to reduce privacy risks, especially in low-trust or high-risk contexts.
- **Ensure transparent data processing and informed consent.**
  Clearly explain what data is collected and how it will be used, and obtain explicit consent before collection—whether the tool is deployed for research purposes or as a product that collects user data during engagement.
- **Develop and maintain an incident-response plan.**
  Establish procedures to respond quickly to data breaches or security failures, including user notifications and institutional accountability.
- **Publish transparency reports and enable real-time monitoring.**
  Regularly document data sources, usage practices and system updates. Use monitoring systems to detect performance drift or privacy violations early.
- **Embed feedback loops into AI tools.**
  Create channels for users—such as farmers or advisors—to report errors, offer suggestions or raise concerns. Use this input to guide iterative improvements.
- **Tailor user training to diverse needs and constraints.**
  Design onboarding to account for differences in access, digital literacy, and language. Consider barriers such as connectivity, cost and literacy when planning delivery.
- **Design explainable and user-friendly AI outputs.**
  Ensure AI models generate clear, easily understandable recommendations. Support understanding through visualizations, plain-language summaries, or local-language interfaces.

6. Special topics

6.1 User research

User research is critical for tailoring AI tools to the everyday lives, values and knowledge networks of the specific people FLWS research targets, such as smallholders, women, young people, Indigenous Peoples and other under-represented groups.

Without insights from local people, researchers and developers of AI tools risk confirmation bias, sometimes leading them to design high-tech, innovation-driven solutions that fail to address users' real needs. This concern was raised by an expert in AI ethics and social inclusion, who emphasized the importance of adapting design to local needs. These tools may also fail to function reliably in harsh farming conditions (Rubambiza et al. 2022). For example, overly complex or poorly designed AI interfaces can overwhelm users, particularly those with limited digital literacy or experience (Friedman et al. 2024). In some regions, AI-driven agricultural advisory systems designed to empower women farmers have been underutilized because they require attending training sessions in public spaces where women's presence is culturally restricted—a challenge noted by an AI ethics and social inclusion expert.

Failure to involve users in the design process can create perceptions of surveillance or inadequate data protection, reducing user acceptance and leading to friction related to (or rejection of) AI technologies. For example, farmers may resist adopting AI-based crop-monitoring tools if they fear their data could be misused by corporations or government agencies (Kochupillai et al. 2022).

User research requires comprehensive needs assessments that capture users' lived experiences, values, and socioeconomic realities. These insights should inform decisions about system deployment, long-term maintenance, user onboarding, and resource requirements (Rose et al. 2018). Engaging users from the start helps lay the foundation for relationships that can evolve over time. Iterative engagement is often crucial for adapting to local realities and supporting more equitable and sustainable outcomes (Benefo et al. 2022; Fleming et al. 2021; Heldert 2021; Ruttkamp-Bloem 2023).

Participatory research methods are especially valuable not only for aligning AI research goals with the lived realities of target communities, but also for challenging the underlying structures that produce exclusion and inequality. For example, in Bangladesh, community members produced their own videos to represent themselves during the design process, amplifying local knowledge and contesting external assumptions about their needs (Bartindale et al. 2023). Similarly, participatory action research in mixed-gender settings has been shown to challenge traditional gender roles and foster more equitable decision-making partnerships (Chassin et al. 2022), contributing to broader cultural shift (González and Rampino 2024) and helping to prevent the reproduction of structural harms in technology deployment (Sloane et al. 2022).

Additionally, users who contribute to design processes or share their data should be formally acknowledged and fairly compensated (Sloane et al. 2022). Co-design initiatives could offer financial incentives, certificates of recognition, or profit-sharing models to reward farmer contributions—with careful consideration of ethical safeguards to avoid coercion, particularly among vulnerable populations, and oversight by institutional review boards.

CalcuCafé and NkhukuProbe illustrate the value of embedding user-centered design. CalcuCafé simplifies cost modeling for Peruvian coffee farmers, supporting collaboration within cooperatives and decision-making for production. NkhukuProbe helps Malawian poultry farmers monitor coop conditions in real time, enabling them to proactively manage environmental factors. Both tools integrate ongoing user feedback, ensuring cultural and technological relevance while strengthening farmers' decision-making agency (Hope Chidziwisano et al. 2021; Leshed et al. 2018). These examples demonstrate how participatory, user-centered AI design can foster trust, sustainability and empowerment in agricultural practices (see Doggett et al. 2023 for an extensive review of human–computer interactions research in FLWS).

Researchers are encouraged to refer to the Methods section of the CGIAR *User Research Toolkit*, which gives an overview on the most common user-research methods, how to plan for them, and hands-on implementation advice and support on how to adapt standard human-research methods to the context of agriculture in the global South.

Recommendations about user research

- **Refer to the Methods section of the *CGIAR User Research Toolkit*.**
  Use this resource to plan and adapt user-research methods to agricultural settings in the global South, with guidance on implementation and ethical practice.
- **Conduct comprehensive needs assessments.**
  Investigate users' daily realities, resource constraints, values and cultural norms to inform deployment, onboarding and long-term support strategies.
- **Use participatory-research methods.**
  Engage users in the design, testing and refinement of AI tools. Techniques like co-design workshops, community media, and participatory action research help align tools with local priorities and challenge structural inequalities.
- **Ensure users are fairly acknowledged and compensated.**
  Recognize user contributions to design and data-collection. Where appropriate, offer noncoercive incentives—such as financial compensation, certificates or shared benefits—in line with institutional review or ethics board approvals.

6.2 Monitoring and evaluating ethical AI systems

Ethical AI development requires clear goals, robust theories of change, and iterative processes—as emphasized by experts involved in AI ethics and inclusive innovation. However, the lack of measurable indicators for gender-focused outcomes complicates their monitoring and evaluation. Donors and funders often prefer results-driven narratives, but metrics are frequently reduced to surface-level data, such as 'number of app downloads', which has little to do with meaningful engagement (Steinke et al. 2021). This disconnect leads to underfunding and neglect of systemic gender-responsive interventions, experts noted.

Standardized performance metrics are essential for assessing AI systems and ensuring their alignment with ethical principles such as equity, inclusion and transparency (Munn 2023; Sanderson et al. 2023). However, benchmarking ethical AI remains a rapidly evolving and complex field—particularly in FLWS contexts, where inclusiveness, cultural appropriateness, and accountability may be as important as technical accuracy.

The MDII framework (Martins et al. 2024) and the accompanying MDII scorecard dashboard (Nisansa et al. 2024) offer one promising approach. Developed specifically to assess and promote inclusiveness in digital innovations within agricultural systems, the MDII framework supports both quantitative and qualitative evaluation across seven dimensions: *accessibility*, *beneficial impact*, *usage effectiveness*, *ethical and responsible innovation*, *co-creation and governance*, *risks and harms*, and *supportive ecosystem*. Each includes subdimensions, metadata and direct feedback from tool beneficiaries, providing a nuanced understanding of performance and enabling iterative improvements.

Importantly, the MDII dashboard has already been piloted in agricultural settings where it helped highlight disparities in access and engagement, particularly among women farmers, leading to concrete changes in platform design and outreach strategies (Singaraju et al. 2025). These kinds of tools show how ethics and inclusion can be systematically embedded into evaluation, not just assumed.

At the same time, ethical evaluation must remain adaptive. As AI applications diversify—from predictive models to participatory decision-support tools—additional tools and benchmarks may be needed to assess dimensions such as explainability, power asymmetries, or environmental impact. Future versions of this toolkit will aim to incorporate such emerging approaches, particularly those co-designed with stakeholders in the global South.

Maintaining ethical relevance, however, requires more than a one-time evaluation. Given the swift pace of innovation in fields such as climate adaptation, static or outdated models risk providing irrelevant or inaccurate advice, eroding trust and reducing the effectiveness of AI-enabled tools (Hagendorff 2024). Regular, context-specific data-collection and validation are essential for refining models, addressing weaknesses, and ensuring that AI systems continue to serve the evolving needs of farmers and other users (Suresh et al. 2022).

Recommendations about monitoring and evaluating AI systems

- **Apply the MDII framework from the outset.**
  Use the MDII to embed ethical and inclusion-focused goals—such as accessibility, co-creation and equity—throughout the research and development process.
- **Use the MDII scorecard dashboard to guide improvement.**
  Monitor a platform's performance across multiple dimensions using real-time feedback from users. Adapt the tools iteratively based on insights from marginalized groups, especially women and underserved communities.
- **Go beyond surface-level metrics.**
  Avoid overreliance on indicators like downloads or usage statistics. Instead, assess engagement, empowerment, and user satisfaction—especially among target populations in FLWS contexts.
- **Adapt evaluation strategies to evolving tools and contexts.**
  As AI use cases shift, develop new benchmarks that capture their explainability, power asymmetries, environmental impacts, and other emerging priorities.
- **Ensure ongoing validation and context-specific updates.**
  Continually update models using locally relevant data. Regularly test for relevance, accuracy and unintended impacts, to maintain users' trust and the tool's effectiveness over time.

6.3 Communicating research using generative AI

Many researchers are now using generative AI (GenAI) tools to summarize and communicate research findings.

In a randomized experiment Keenan et al. (2024) tested how readers across 10 countries (Bangladesh, Egypt, Ethiopia, Ghana, India, Kenya, Malawi, Nigeria, Rwanda, Sudan, Tajikistan and Uganda) evaluate the quality and trustworthiness of research blog posts written by humans versus by ChatGPT. They find that disclosing the use of AI signals transparency and maintains credibility, without undermining readers' trust in the content of the blog posts (see the IFPRI research write-up here).

However, broader ethical considerations must be considered when using GenAI in research communication. Studies highlight risks such as the introduction of factual inaccuracies ("hallucinations"), stylistic homogenization that can erode diversity of expression, and the potential for over-trusting AI-generated content. There are also concerns about the inadvertent leakage of sensitive information when unpublished data is used (Hagendorff 2024).

Recommendations about communicating research using AI

- **Disclose the use of AI tools clearly and consistently.**
  Signal transparency to readers by stating when and how AI was used. For example: "An initial draft of this post was generated using ChatGPT from author prompts, then revised and edited."
- **Use AI to increase accessibility, not erase expertise.**
  Simplify complex content to reach broader audiences, but tailor its tone and technical depth to your readers. Balance clarity with intellectual rigor.
- **Review and revise all AI-generated outputs.**
  Check for factual accuracy, contextual relevance and originality. Edit your drafts to retain the voice of the research team and avoid stylistic flattening.
- **Ensure fairness and inclusion in adapted content.**
  Carefully edit your work to avoid biased language, stereotypes or examples that may alienate or disadvantage certain groups, particularly in diverse cultural settings.
- **Protect sensitive and unpublished information.**
  Do not put confidential or unpublished data into AI tools unless explicit safeguards are in place to ensure privacy and prevent leakage.
- **Maintain human oversight at every stage.**
  Treat AI as a supportive tool—not a substitute—for ethical judgment, contextual interpretation and communicative intent.

6.4 Using generative AI assist with research processes

GenAI tools are extremely useful for increasing researchers' productivity by simplifying data analysis, and coding tasks.[1] These include:

- support for writing tasks such as editing, summarizing, proofreading and translating text
- rapidly synthesizing information from diverse sources, generating summaries and identifying key themes in research
- generating code snippets, offering suggestions, providing debugging assistance, and automating repetitive coding tasks

AI tools can also expand the opportunities for collaboration with researcher partners in low- and middle-income countries, reducing the need for prior coding knowledge and specialized training in analytical techniques.

[1] This section is aligned with IFPRI's AI approach and acknowledgment guidance.

For experimental research studies, Chang et al. (2024) recommend 12 best practices that researchers can do to accurately, credibly and ethically use GenAI to enhance experimental research.

Recommendations about using AI to help with research

- **Disclose GenAI use clearly and consistently.**
  Follow institutional guidance on how to acknowledge AI contributions. Before submitting papers, check journal-specific requirements regarding AI use, authorship and disclosures.
- **Review all AI-generated outputs for accuracy and quality.**
  Always verify the factual integrity, relevance and tone of AI-generated content before using it in research or communication.
- **Protect privacy and data security.**
  Do not put unpublished or sensitive data into GenAI tools without safeguards. Ensure models do not allow public training using your data.
- **Use GenAI to increase accessibility and reduce barriers.**
  Apply GenAI to support tasks such as summarizing text, editing, debugging code, translating or simplifying language—while retaining human oversight.
- For experimental research (adapted from Chang et al. 2024)
  - **Use GenAI to assist with pre-treatment procedures,** provided that researchers remain actively involved in reviewing and refining outputs to prevent any compromise in research quality.
  - **Prohibit public model training** on entered data and ensure the AI platform provides strong privacy protections.
  - **Elicit informed consent** when GenAI is used in a way that may affect participants, ensuring ethical transparency.
  - **Use GenAI to suggest possible mediators** (channels of impact) **and moderators** (factors shaping effect sizes)**, and to explore design variations** that test whether findings are likely to hold in other settings or at larger scale.
  - **Do not delegate experimental procedures** to GenAI without piloting, documenting and reviewing its roles and outputs.
  - **Check whether GenAI changes the fairness or consistency of the experiment—**for example, whether everyone gets the same treatment, follows instructions the same way, or stays unaffected by others' treatments—and adjust the design if it puts validity at risk.
  - **Re-initialize GenAI models consistently** and design prompts that capture the intended constructs.

- **Critically assess training data** and, when appropriate, manually train or fine-tune models to suit analytical tasks.
- **Document and stress-test GenAI results** to ensure replicability and transparency for the broader research community.
- **Reassess resource allocation** across research stages in light of GenAI's changing trade-offs.
- **Ensure AI-generated hypotheses are interpretable by humans**, even when aided by machine-learning techniques.
- **Remember that GenAI is not a replacement** for human creativity, innovation, quality or ethical reasoning.

6.5 Mitigating increased risks of gender-based violence

Researchers should pay attention to the increasing risk of gender-based violence (GBV) that women and girls may be exposed to because of the introduction of AI systems.[2] Generative AI, for example, can be weaponized through automated harassment campaigns, creation of non-consensual or manipulated images, and synthetic narratives aimed at defaming individuals—practices that already disproportionately harm women and girls online.

See Chowdhury's paper on *Technology-facilitated gender-based violence in an era of generative AI* for more information.

Recommendations about mitigating risks of GBV

- **Establish an anonymous reporting system for GBV.**
  Provide confidential mechanisms for participants or users to report harassment, abuse or other harms linked to AI use or research participation.
- **Follow local ethical protocols for support and referral.**
  Ensure your research complies with country-specific procedures regarding GBV response, including referral pathways and duty of care.
- **Refer to CGIAR's GBV Guidelines.**
  Consult the *CGIAR Guidelines for Ethical Engagement with Gender-based Violence in Food Systems Research* for detailed recommendations on safeguarding women and girls, and responsible engagement.

[2] This section is aligned with IFPRI's AI approach and acknowledgment guidance.

References

Ahmed, A., Bakhtiar, M. M., Abedin, N., & Ghostlaw, J. (2020). *Assessing COVID-19's effects on gender-related issues using a phone survey in the Feed the Future zone of influence in Bangladesh.* International Food Policy Research Institute (IFPRI). https://doi.org/10.2499/P15738COLL2.136536.

Andreotta, A. J., Kirkham, N., & Rizzi, M. (2022). AI, big data, and the future of consent. *OPEN FORUM*, *37*, 1715–1728. https://doi.org/10.1007/s00146-021-01262-5.

Bartindale, T., Lindsay, S., Richardson, D., & Olivier, P. (2023). Community Voice as Data: Affordances of Participatory Videos for International Program Development. *Human Factors in Computing Systems (CHI)*. https://doi.org/10.1145/3544548.3581458.

Belsare, H., Sohoni, M., Gokhale, R., Prasad, P., P., A. R., Marathe, C., Gupta, P., Sali, S., Patil, S., & Deshmukh, S. (2022). Computing for climate resilience in agriculture. *Communications of the ACM*, *65*(11), 74–79. https://doi.org/10.1145/3554928.

Benefo, E. O., Tingler, A., White, M., Cover, J., Torres, L., Broussard, C., Shirmohammadi, A., Pradhan, A. K., & Patra, D. (2022). Ethical, legal, social, and economic (ELSE) implications of artificial intelligence at a global level: a scientometrics approach. *AI and Ethics*, *2*(4), 667–682. https://doi.org/10.1007/s43681-021-00124-6.

Bi, N., Lu, A. P., & Yuan, C. W. T. (2023). Understanding Farmers' Expectations and Experiences in Using Sensor Technologies. *Human Factors in Computing Systems (CHI)*. https://doi.org/10.1145/3544549.3585902.

Birhane, A., Ruane, E., Laurent, T., S. Brown, M., Flowers, J., Ventresque, A., & L. Dancy, C. (2022, June 21). The Forgotten Margins of AI Ethics. *Fairness, Accountability, and Transparency*. https://doi.org/10.1145/3531146.3533157.

Braun. (2021). AI/Robotics and the poor. In M. von Braun, J., S. Archer, M., Reichberg, G.M., Sánchez Sorondo (Ed.), *Robotics, AI, and Humanity* (pp. 85–97). Springer. https://doi.org/10.1007/978-3-030-54173-6_7.

Bronson, K., & Sengers, P. (2022). Big Tech Meets Big Ag: Diversifying Epistemologies of Data and Power. *Science as Culture*, *0*(0), 1–14. https://doi.org/10.1080/09505431.2021.1986692.

Carbonell, I. M. (2016). The ethics of big data in big agriculture. *Internet Policy Review*, *5*(1), 1–13. https://doi.org/10.14763/2016.1.405.

Cha, I., Pillai, A. G., & Wong, R. Y. (2024). Ethics Pathways: A Design Activity for Reflecting on Ethics Engagement in HCI Research. *Designing Interactive Systems Conference*, 3515–3533. https://doi.org/10.1145/3643834.3660714.

Chang, S., Kennedy, A., Leonard, A., & List, J. A. (2024). *12 Best Practices for Leveraging Generative AI in Experimental Research* (33025). http://www.nber.org/papers/w33025.

Chassin, L., Olson Onyango, A., Tricarico, D., Lindsey, D., Gamble, E., Shanahan, M., & Jeffrie, N. (2022). Reaching and Empowering Women with Digital Solutions in the Agricultural Last Mile. *Digital Agri Hub*.

Chi, N., Lurie, E., & Mulligan, D. K. (2021). Reconfiguring Diversity and Inclusion for AI Ethics. *AIES '21, May 19–21, 2021, Virtual Event, USA.* https://doi.org/10.1145/11952.107.

D'Ignazio, C. (2022). Creative data literacy. *Information Design Journal*, 6–18. https://doi.org/10.1075/idj.23.1.03dig.

D'Ignazio, C., & Klein, L. F. (2020). Data Feminism. In *Data Feminism*. The MIT Press. https://doi.org/10.7551/MITPRESS/11805.001.0001.

Doggett, O., Bronson, K., & Soden, R. (2023). HCI Research on Agriculture: Competing Sociotechnical Imaginaries, Definitions, and Opportunities. *CHI '23, April 23–28, 2023, Hamburg, Germany*. https://doi.org/10.1145/3544548.3581081.

Dubey, N., Jayswal, H., Patel, A., & Goyal, D. (2023, November 23). State of the Art Review: Revolution in Farming with Assistance from Smart Internet of Things Based System. *ICIMMI 2023, November 23–25, 2023, Jaipur, India*. https://doi.org/10.1145/3647444.3647949.

Eichler Inwood, S. E., & Dale, V. H. (2019). State of apps targeting management for sustainability of agricultural landscapes. A review. In *Agronomy for Sustainable Development* (Vol. 39, Issue 1). Springer-Verlag France. https://doi.org/10.1007/s13593-018-0549-8.

Fairbairn, M., Cruz, S., & Kish, Z. (2023). Setting data free : The politics of open data for food and agriculture. *New Media and Society*, *March*.

Fleming, A., Jakku, E., Fielke, S., Taylor, B. M., Lacey, J., Terhorst, A., & Stitzlein, C. (2021). Foresighting Australian digital agricultural futures: Applying responsible innovation thinking to anticipate research and development impact under different scenarios. *Agricultural Systems*, *190*. https://doi.org/10.1016/j.agsy.2021.103120.

Forney, J., & Dwiartama, A. (2022). The project, the everyday, and reflexivity in sociotechnical agri-food assemblages: proposing a conceptual model of digitalisation. *Agriculture and Human Values*, *0123456789*. https://doi.org/10.1007/s10460-022-10385-4.

Foster, L., Szilagyi, K., Wairegi, A., Oguamanam, C., & de Beer, J. (2023). Smart farming and artificial intelligence in East Africa: Addressing indigeneity, plants, and gender. *Smart Agricultural Technology*, *3*. https://doi.org/10.1016/j.atech.2022.100132.

Friedman, N., Tan, Z., Haskins, M. N., Ju, W., Bailey, D., & Longchamps, L. (2024). Understanding Farmers' Data Collection Practices on Small-to-Medium Farms for the Design of Future Farm Management Information Systems. *Proceedings of the ACM on Human-Computer Interaction*, *8*(CSCW1). https://doi.org/10.1145/3637416.

Fu, G. (2022). *Toward Ethical Artificial Intelligence in International Development*. https://www.dai.com/uploads/ethical-ai.pdf.

Gerdes, A. (2022). A participatory data-centric approach to AI Ethics by Design. *Applied Artificial Intelligence*, *36*(1). https://doi.org/10.1080/08839514.2021.2009222.

Gardezi, M., Abuayyash, H., Adler, P. R., Alvez, J. P., Anjum, R., Badireddy, A. R., Brugler, S., Carcamo, P., Clay, D., Dadkhah, A., Emery, M., Faulkner, J. W., Joshi, B., Joshi, D. R., Khan, A. H., Koliba, C., Kumari, S., McMaine, J., Merrill, S., … Zia, A. (2024). The role of living labs in cultivating inclusive and responsible innovation in precision agriculture. *Agricultural Systems*, *216*. https://doi.org/10.1016/j.agsy.2024.103908.

Ghosh, R. (2024). Data-driven governance and performances of accountability: critical reflections from US agri-environmental policy. *Science as Culture*, *33*(1), 70–96. https://doi.org/10.1080/09505431.2023.2175654.

Girmay, M. B., & Felix, M. (2025). Perspectives on Explanation Formats From Two Stakeholder Groups in Germany : Software Providers and Dairy Farmers Perspectives on Explanation Formats From Two Stakeholder Groups in Germany : Software Providers and Dairy Farmers. *International Joint Conference on Artificial Intelligence*, *June 2024*.

González, A. S., & Rampino, L. (2024). A design perspective on how to tackle gender biases when developing AI-driven systems. *AI and Ethics*. https://doi.org/10.1007/s43681-023-00386-2.

Gwagwa, A., Kazim, E., & Hilliard, A. (2022). The role of the African value of Ubuntu in global AI inclusion discourse: A normative ethics perspective. In *Patterns* (Vol. 3, Issue 4). Cell Press. https://doi.org/10.1016/j.patter.2022.100462.

Gwagwa, A., Kazim, E., Kachidza, P., Hilliard, A., Siminyu, K., Smith, M., & Shawe-Taylor, J. (2021). Road map for research on responsible artificial intelligence for development (AI4D) in African countries: The case study of agriculture. In *Patterns* (Vol. 2, Issue 12). Cell Press. https://doi.org/10.1016/j.patter.2021.100381.

Hagendorff, T. (2024). Mapping the Ethics of Generative AI: A Comprehensive Scoping Review. *Minds and Machines*, *34*(4), 39. https://doi.org/10.1007/s11023-024-09694-w.

Hagerty, A., & Rubinov, I. (2019). Global AI Ethics: A Review of the Social Impacts and Ethical Implications of Artificial Intelligence. *Global AI Ethics*.

Han, D., & Rodriguez, M. (2023). Big Data Analytics, Data Science, ML&AI for Connected, Data-driven Precision Agriculture and Smart Farming Systems: Challenges and Future Directions. *ACM International Conference Proceeding Series*, 378–384. https://doi.org/10.1145/3576914.3588337.

Hanrahan, B. V., Maitland, C., Brown, T., Chen, A., Kagame, F., & Birir, B. (2021). Agency and Extraction in Emerging Industrial Drone Applications. *Proceedings of the ACM on Human-Computer Interaction*, *4*(CSCW3), 1–21. https://doi.org/10.1145/3432932.

Heldert, C. (2021). What Does AI mean for Smallholder farmers? A Proposal for Farmer-centred ai research. *Interactions*.

Hope Chidziwisano, G., Mariakakis, A., Wyche, S., Mafeni, V., & Gideon Banda, E. (2021). NkhukuProbe: Using a Sensor-Based Technology Probe to Support Poultry Farming Activities in Malawi. *Proceedings of 2021 4th ACM SIGCAS Conference on Computing and Sustainable Societies, COMPASS 2021*, 275–287. https://doi.org/10.1145/3460112.3471962.

Jones-Garcia, E., Kruseman, G., & Brown, B. (2021). *Emotion classification and sentiment analysis for sustainable agricultural development: exploring available tools for analyzing African farmer interviews*. https://repository.cimmyt.org/handle/10883/21789.

Jun, Y. (2024). *A Brief Overview of Gender Bias in AI*. The Gradient.

Katell, M., Young, M., Dailey, D., Herman, B., Guetler, V., Tam, A., Binz, C., Raz, D., & Krafft, P. M. (2020). Toward situated interventions for algorithmic equity: Lessons from the field. *FAT* '20, January 27–30, 2020, Barcelona, Spain*, 45–55. https://doi.org/10.1145/3351095.3372874.

Keenan, M., Koo, J., Mwangi, C. W., Karachiwalla, N., Breisinger, C., & Kim, M. (2024). *Man vs. machine: Experimental evidence on the quality and perceptions of AI-generated research content*. International Food Policy Research Institute. https://hdl.handle.net/10568/169363.

Kochupillai, M., Kahl, M., Schmitt, M., Taubenbock, H., & Zhu, X. X. (2022). Earth Observation and Artificial Intelligence: Understanding emerging ethical issues and opportunities. *IEEE Geoscience and Remote Sensing Magazine*, *10*(4), 90–124. https://doi.org/10.1109/MGRS.2022.3208357.

Koo, J., Azzarri, C., Mishra, A., Lecoutere, E., Ranjitha Puskur, Chanana, N., Singaraju, N., Nico, G., & Khatri-Chhetri, A. (2022). Effectively targeting climate investments: A methodology for mapping climate–agriculture– gender inequality hotspots. CGIAR GENDER Platform Working Paper #005. Nairobi, Kenya: CGIAR GENDER Platform. *Cgiar Gender …, May*. https://cgspace.cgiar.org/handle/10568/119602.

Koo, J., Castelo Magalhaes, M., & Singaraju, N. (2025). *Assessment of how well Large Language Models (LLMs) answer questions related to gender equality and women's empowerment*. Hugging Face. https://huggingface.co/blog/CGIAR/llm-gender-equality-womens-empowerment.

Kronqvist, A., & Rousi, R. A. (2023). A quick review of ethics, design thinking, gender, and AI development. *International Journal of Design Creativity and Innovation*, *11*(1), 62–79. https://doi.org/10.1080/21650349.2022.2136762.

Kruseman, G., Lopez, D. E., Muchiri, C., & Lecoutere, E. (2024). *Metadata schema for the GENNOVATE dataset and ways forward*. https://hdl.handle.net/10568/173341.

Leshed, G., Rosca, M., Huang, M., Mansbach, L., Zhu, Y., & Hernandez-Aguilera, J. N. (2018). Calcucafé: Designing for collaboration among coffee farmers to calculate costs of production. *Proceedings of the ACM on Human-Computer Interaction*, *2*(CSCW). https://doi.org/10.1145/3274418.

Li, P., Yang, J., Islam, M. A., & Ren, S. (2023). *Making AI Less 'Thirsty': Uncovering and Addressing the Secret Water Footprint of AI Models*. 1–10. http://arxiv.org/abs/2304.03271.

Long, D., & Magerko, B. (2020). What is AI Literacy? Competencies and Design Considerations. *Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3313831.3376727/SUPPL_FILE/A598-LONG-PRESENTATION.MP4.

Manasi, A. (2024). *Addressing Gender Bias to Achieve Ethical AI - IPI Global Observatory*. Global Observatory.

Mann, L., & Iazzolino, G. (2021). From Development State to Corporate Leviathan: Historicizing the Infrastructural Performativity of Digital Platforms within Kenyan Agriculture. *Development and Change*, *52*(4), 829–854. https://doi.org/10.1111/dech.12671.

Manning, L., Brewer, S., Craigon, P. J., Frey, J., Gutierrez, A., Jacobs, N., Kanza, S., Munday, S., Sacks, J., & Pearson, S. (2022). Artificial intelligence and ethics within the food sector: Developing a common language for technology adoption across the supply chain. In *Trends in Food Science and Technology* (Vol. 125, pp. 33–42). Elsevier Ltd. https://doi.org/10.1016/j.tifs.2022.04.025.

Martins, C. I., Opola, F., Andarcia, M. G., Joshi, D., Muller, A., & Christen, R. (2024). *Multidimensional Digital Inclusiveness Index: dimensionality reduction for improved applicability in Digital Agri-solutions*. International Water Management Institute (IWMI). CGIAR Initiative on Digital Innovation. https://hdl.handle.net/10568/163059.

Muldoon, J., & Wu, B. A. (2023). Artificial Intelligence in the Colonial Matrix of Power. *Philosophy and Technology*, *36*(4), 1–24. https://doi.org/10.1007/s13347-023-00687-8.

Müller, A., Steinke, J., Dorado, H., Keller, S., Jiménez, D., Ortiz-Crespo, B., & Schumann, C. (2024). Challenges and opportunities for human-centered design in CGIAR. *Agricultural Systems*, *219*. https://doi.org/10.1016/j.agsy.2024.104005.

Munn, L. (2023). The uselessness of AI ethics. *AI and Ethics*, *3*(3), 869–877. https://doi.org/10.1007/s43681-022-00209-w.

Nisansa, V., Martins, C. I., Opola, F., Roberto, C., & Andarcia, M. G. (2024). *MDII Scoring Dashboard (version 1.00): a tool for visualizing digital inclusiveness and innovation performance*. International Water Management Institute (IWMI). CGIAR Initiative on Digital Innovation. https://hdl.handle.net/10568/163047.

Okaibedi Eke, D., Wakunuma, K., & Akintoye, S. (2022). *Responsible AI in Africa Challenges and Opportunities*.

Pappa, F. (2024). Sounding the alarm for digital agriculture: Examining risks to the human rights to science and food. *Netherlands Quarterly of Human Rights*. https://doi.org/10.1177/09240519241270408.

Parraga, O., More, M. D., Oliveira, C. M., Gavenski, N. S., Kupssinskü, L. S., Medronha, A., Moura, L. V., Simões, G. S., & Barros, R. C. (2022). *Debiasing Methods for Fairer Neural Models in Vision and Language Research: A Survey*. https://doi.org/10.1145/363754.

Pizzi, M. (2023). *Governance of AI in Global Pulse's policy work: Zooming in on Human Rights and Ethical Frameworks*.

Prabhakar, S. V., & Prakash, A. (2023). ICT-Enabled Agriculture E-Markets: Reflecting on Local Level Resistance to a Large-Scale State-Sponsored Technology Intervention. *ACM International Conference Proceeding Series*, 135–142. https://doi.org/10.1145/3614321.3614338.

Prakash, J., Thorwe, P., & Quek, T. Q. S. (2021). AgriAuth: Sensor collaboration and corroboration for data confidence in smart farms. *WiSec 2021 - Proceedings of the 14th ACM Conference on Security and Privacy in Wireless and Mobile Networks*, 383–385. https://doi.org/10.1145/3448300.3468260.

Ricaurte, P. (2024, March 8). *How can feminism inform AI governance in practice?* UNESCO. https://www.unesco.org/en/articles/how-can-feminism-inform-ai-governance-practice.

Roche, C. (2021). Artificial Intelligence Ethics: An Inclusive Global Discourse? *Conference on Implications of Information and Digital Technologies for Development*.

Rose, D. C., Parker, C., Fodey, J., Park, C., Sutherland, W. J., & Dicks, L. V. (2018). Involving stakeholders in agricultural decision support systems: Improving user-centred design. *International Journal of Agricultural Management*, *6*(3–4), 80–89. https://doi.org/10.5836/ijam/2017-06-80.

Rubambiza, G., Sengers, P., & Weatherspoon, H. (2022). Seamless Visions, Seamful Realities: Anticipating Rural Infrastructural Fragility in Early Design of Digital Agriculture. *CHI Conference on Human Factors in Computing Systems (CHI '22), April 29-May 5, 2022, New Orleans, LA, USA*. https://doi.org/10.1145/3491102.3517579.

Ruttkamp-Bloem, E. (2023). Epistemic justice and Dynamic AI ethics in Africa. In *Responsible AI in Africa*.

Ryan, M. (2024). We're only human after all: a critique of human-centred AI. *AI and Society*. https://doi.org/10.1007/s00146-024-01976-2.

Ryan, M., Antoniou, J., Brooks, L., Jiya, T., Macnish, K., & Stahl, B. (2021). Research and Practice of AI Ethics: A Case Study Approach Juxtaposing Academic Discourse with Organisational Reality. *Science and Engineering Ethics*, *27*(2). https://doi.org/10.1007/s11948-021-00293-x.

Ryan, M., Isakhanyan, G., & Tekinerdogan, B. (2023). An interdisciplinary approach to artificial intelligence in agriculture. *NJAS: Impact in Agricultural and Life Sciences*, *95*(1). https://doi.org/10.1080/27685241.2023.2168568.

Sabbaghi, S. O., & Caliskan, A. (2022). Measuring Gender Bias in Word Embeddings of Gendered Languages Requires Disentangling Grammatical Gender Signals. *AIES 2022 - Proceedings of the 2022 AAAI/ACM Conference on AI, Ethics, and Society*, 518–531. https://doi.org/10.1145/3514094.3534176.

Sanderson, C., Douglas, D., Lu, Q., Schleiger, E., Whittle, J., Lacey, J., Newnham, G., Hajkowicz, S., Robinson, C., & Hansen, D. (2023). AI Ethics Principles in Practice: Perspectives of Designers and Developers. *IEEE Transactions on Technology and Society*, *4*(2), 171–187. https://doi.org/10.1109/tts.2023.3257303.

Schumann, C. (2023). *Technology for whom? Discovering how Human - Centered Design (HCD) and User Research can help switch perspectives in Ethiopia - CGIAR*. CGIAR. https://www.cgiar.org/news-events/news/technology-for-whom-discovering-how-human-centered-design-hcd-and-user-research-can-help-switch-perspectives-in-ethiopia/.

Singaraju, N., Gakhar, S., Jardinero, B., Pagianti, T. S., & … (2025). *Evaluating multidimensional digital inclusiveness of rice crop manager digital tool: Insights from Indonesia*. *February*. https://doi.org/10.13140/RG.2.2.25593.17761.

Singh, N., Wang'ombe, J., Okanga, N., Zelenska, T., Repishti, J., K, J. G., Mishra, S., Manokaran, R., Singh, V., Rafiq, M. I., Gandhi, R., & Nambi, A. (2024). *Farmer.Chat: Scaling AI-Powered Agricultural Services for Smallholder Farmers*. http://arxiv.org/abs/2409.08916.

Sloane, M., Moss, E., Awomolo, O., & Forlano, L. (2022, October 6). Participation Is not a Design Fix for Machine Learning. *EAAMO '22, October 06–09, 2022, Arlington, VA, USA*. https://doi.org/10.1145/3551624.3555285.

Sondeck, L.-P., & Laurent, M. (2025). *Practical and ready-to-use methodology to assess the re-identification risk in anonymized datasets. Scientific Reports, 15*, Article 23223. https://doi.org/10.1038/s41598-025-04907-3.

Steinke, J., van Etten, J., Müller, A., Ortiz-Crespo, B., van de Gevel, J., Silvestri, S., & Priebe, J. (2021). Tapping the full potential of the digital revolution for agricultural extension: an emerging innovation agenda. *International Journal of Agricultural Sustainability*, 549–565. https://doi.org/10.1080/14735903.2020.1738754.

Suresh, H., Movva, R., Dogan, A. L., Bhargava, R., Cruxen, I., Cuba, A. M., Taurino, G., So, W., & D'Ignazio, C. (2022). Towards Intersectional Feminist and Participatory ML: A Case Study in Supporting Feminicide Counterdata Collection. *ACM International Conference Proceeding Series*, 667–678. https://doi.org/10.1145/3531146.3533132.

Torero, M. (2021). Robotics and AI in food security and innovation: Why they matter and how to harness their power. In *Robotics, AI, and Humanity: Science, Ethics, and Policy* (pp. 90–107). Springer International Publishing. https://doi.org/10.1007/978-3-030-54173-6_8/FIGURES/8.

UNESCO. (2020). *ARTIFICIAL INTELLIGENCE and GENDER EQUALITY*. http://www.unesco.org/open-access/terms-use-ccbysa-en.

van Hilten, M., Ryan, M., Blok, V., & de Roo, N. (2025). Ethical, Legal and Social Aspects (ELSA) for AI: An assessment tool for Agri-food. *Smart Agricultural Technology*, *10*. https://doi.org/10.1016/j.atech.2024.100710.

Wakunuma, K., & Eke, D. (2024). Africa, ChatGPT, and Generative AI Systems: Ethical Benefits, Concerns, and the Need for Governance. *Philosophies*, *9*(3). https://doi.org/10.3390/philosophies9030080.

West, M., & Kraut, R. (2019). I'd blush if I could: closing gender divides in digital skills through education. *UNESCO*. https://doi.org/10.54675/RAPC9356.

Zheleva, M., Bogdanov, P., Zois, D. S., Xiong, W., Chandra, R., & Kimball, M. (2017). Smallholder agriculture in the information age: Limits and opportunities. *LIMITS 2017 - Proceedings of the 2017 Workshop on Computing Within Limits*, *12*, 59–70. https://doi.org/10.1145/3080556.3080563.

Appendixes

Appendix 1. Glossary

Accessibility
The usability and availability of information, tools or technology, ensuring that data can be obtained and used by both humans and machines. Accessibility includes appropriate authorization protocols and can be public or restricted (Manning et al. 2022).

Accountability
The mechanisms by which it is possible to track and explain how and why decisions are made, who makes those decisions, and the basis for those decisions. It includes answerability, liability and responsiveness (Manning et al. 2022).

Artificial intelligence
Computational technology that seeks to mimic, to differing extents, human abilities to perceive their environment, process information, make decisions and take steps to achieve predetermined goals (Manning et al. 2022).

Artificial intelligence research

In FLWS, AI research refers to how researchers engage with and shape decisions across the AI life cycle, including problem framing, data collection, analysis and deployment. It includes research *with* AI (using AI tools), *for* AI (producing data and knowledge that train or guide systems), and *about* AI (evaluating performance, ethics, and impacts).

Bias
A prejudice against, or inclination toward, certain individuals or groups that is often considered unfair or unbalanced. Bias can arise in the algorithm's development process, in the training of datasets, and in AI-generated decision-making (Kronqvist and Rousi 2023; Manasi 2024).

Black box
AI system architectures whose internal decision-making processes are opaque, making it difficult for humans to understand how outputs are generated from inputs.

Data feminism
An approach to data science and technology that exposes and challenges power imbalances, promoting fairness and inclusivity in how data is collected, interpreted and used (D'Ignazio and Klein 2020).

Deployment

The stage when an AI system is moved from development into real-world use. This is when it starts producing outputs or making decisions that affect people, organizations or environments (Muldoon and Wu 2023).

Ethics-washing
The practice by which technology developers—often private companies—self-regulate

through vague and unenforceable "codes of ethics" that create the appearance of responsible behavior without meaningful accountability (Pizzi 2023).

Exclusion
The inability to participate effectively in economic, social, political and cultural life, often resulting in alienation and distance from mainstream society (Gwagwa et al. 2022).

Fairness
A principle concerned with preventing the reproduction and reinforcement of existing biases in AI systems. Fairness aims to ensure equitable treatment and outcomes across different social groups, particularly those historically marginalized or under-represented (Hagendorff 2024).

Generative AI (GenAI)
AI systems designed to generate content or outputs—including text, audio, simulations, video and code. Unlike traditional AI, GenAI is typically unsupervised and trained to mimic patterns in data rather than being developed for a specific, predefined purpose (Wakunuma and Eke 2024).

Hallucinations
Errors in AI outputs that arise from reasoning mistakes within language models or from incorporating misinformation provided by humans. Hallucinations can also involve the unintended leakage of private or sensitive information by large language models (Hagendorff 2024).

Identifiable data
Information that can directly or indirectly link to an individual, such as names, addresses or unique identifiers (UNESCO 2020).

Inclusion
The process of improving the conditions under which individuals and groups can participate in society, enhancing the ability, opportunity and dignity of those disadvantaged due to their identity (Gwagwa et al. 2022).

Informed consent
An individual's voluntary and intentional authorization for the use of their personal data, given with substantial understanding of how the data will be used, repurposed and potentially affect them, despite challenges such as opaque algorithms and limited alternatives (Andreotta et al. 2022).

Intersectionality
A framework recognizing that systems of power—such as race, gender, class and others—are interdependent and mutually reinforcing. It highlights how overlapping social identities create unique experiences of disadvantage and privilege (Suresh et al. 2022).

Internet of Things (IoT)
A system of interconnected physical devices and sensors that collect, transmit and share data over the internet. In agriculture, IoT enables real-time monitoring and control of

factors such as soil conditions, crop growth, irrigation, and equipment performance—supporting data-driven decision-making and automation (Han and Rodriguez 2023).

Legitimacy
The perception that the actions of an individual or organization are desirable, proper or appropriate within a socially constructed system of norms, values, beliefs and definitions (Manning et al. 2022).

Machine learning
A method that enables computers to automatically improve their performance on a given set of tasks by learning from data, without being explicitly programmed (Fu 2022).

Onboarding

The initial process by which users are introduced to an AI system and begin to interact with it. This includes setting up the system, receiving instructions, adjusting preferences, and learning how to use the tool (Muldoon and Wu 2023).

Open data
Data that can be freely accessed, used, modified and shared by anyone for any purpose, subject only to requirements that preserve provenance and openness (Fairbairn et al. 2023).

Primary data
Data collected firsthand by researchers specifically for their current study, using methods such as surveys, interviews or experiments (UNESCO 2020).

Responsible AI
The design and development of AI systems that are ethical, lawful and socially accountable. Responsible AI denotes having clear accountability, control and authority over the system and its outcomes (Okaibedi Eke et al. 2022).

Responsibility
The obligation to ensure safety, trust and ethical behavior in technology design and use. Responsibility encompasses both proactive and reactive considerations of how AI systems affect users and society (Manning et al. 2022).

Safety
The prioritization of safe cultures and practices in AI development, rather than purely innovation-driven goals. Safety also addresses the risk of misuse by malicious actors and the unintended consequences of AI deployment (Hagendorff 2024).

Secondary data
Data originally gathered for a different purpose, but repurposed for new research or analysis (UNESCO 2020).

Sensitive data
Information that must be protected against unauthorized disclosure, including personal

identifiers, health records, financial details, or data whose release could cause harm (UNESCO 2020).

Traceability
The ability to follow the history, movement and location of an object (e.g., a product, ingredient or service) through specified stages of production, processing, and distribution. Traceability systems often use record keeping to improve consumer confidence and reduce information asymmetry across supply chains (Manning et al. 2022).

Transparency
The characteristic of being visible and open, enabling the disclosure of relevant, accurate and reliable information that facilitates trust and informed decision-making by stakeholders (Manning et al. 2022).

User-centered design (UCD)
An approach in which systems are adapted to align with existing user needs and workflows, often proving more effective than requiring users to change their behavior (Rose et al. 2018).

Appendix 2. Methodology: domain expert interview protocol

This study used a semistructured interview protocol to gather insights from domain experts in AI ethics, social inclusion and FLWS research. The approach aimed to explore ethical challenges, gender dynamics, and best practices in applying AI technologies to agricultural contexts.

Interview structure

Interviews followed a semistructured format, balancing guided discussion with flexibility for participants to introduce new insights. Questions covered themes such as:

- ethical challenges in AI design, including biases in data and algorithms
- gender dynamics and their influence on agricultural decision-making
- cultural and contextual factors in AI deployment
- policy, governance and frameworks for gender-sensitive AI development

Logistics

Interviews lasted 45–60 minutes and were conducted remotely via a secure, virtual meeting platform. Each session was recorded, transcribed and supplemented with interviewer notes to capture context and tone.

Post-interview

Transcripts were reviewed and coded using qualitative analysis software (NVivo) to identify key themes, ethical principles, challenges and actionable recommendations. Follow-up questions were addressed via email as needed.

Ethical considerations

The study was approved by the IFPRI Internal Review Board. Participants provided informed consent and chose whether to be acknowledged or remain anonymous.

Participants

Domain experts included academics and practitioners identified through literature reviews, professional networks and referrals. Further participants were added through ongoing searches and recommendations from initial interviewees. A total of 10 key informants were interviewed, of which six were women.

Appendix 3. Checklist of collected recommendations

AI ethics for inclusive and equitable FLWS research

- **Acknowledge that AI systems are not neutral.**
  Recognize AI as a sociotechnical system shaped by power relations—including gender, race, class, and geography—and reflect this understanding throughout your research design and implementation.
- **Align AI use with CGIAR's core ethical values.**
  Draw on feminist perspectives to move beyond abstract, externally developed ethics frameworks. Use grounded, situated approaches that reflect the lived realities of communities in the Global South.
- **Engage affected communities across the AI lifecycle.**
  Involve women, youth, and marginalized groups not just as users, but as co-creators and decision-makers in the design, testing, and deployment of AI systems.
- **Practice reflexivity and care, not just compliance.**
  Treat ethical responsibilities as dynamic and iterative—emerging through engagement and accountability, not fixed rules. Regularly question whose interests are served and whose knowledge is prioritized.
- **Design for inclusion at every stage of the research cycle.**
  Ensure equity is integrated into problem framing, data collection, model training, evaluation, and scaling. Avoid reinforcing structural exclusions by centering diverse, context-specific knowledge systems.
- **Hold yourself accountable for downstream impacts.**
  Recognize that research outputs may shape future AI applications. Anticipate potential harms, challenge extractive practices, and design for long-term benefit, not just innovation.
- **Support the ethical use of CGIAR datasets.**
  Steward data responsibly by ensuring that training datasets reflect the needs of underrepresented groups and that use cases prioritize equity over efficiency.

Conceptual principles for integrating social inclusion in research that uses AI

- **Challenging power dynamics:** Structural and disciplinary limitations in studies involving AI often manifest in how research problems are framed, leading to the neglect of certain communities and their exclusion from the potential benefits of AI-supported research. Challenging power dynamics involves working with representatives of those communities and activists to ensure that marginalized perspectives are recognized and validated (Ruttkamp-Bloem 2023).

- **Embracing pluralism:** An intersectional feminist approach must reject the imposition of dominant worldviews and instead focus on what it means to coexist equitably with others. This involves respecting diverse perspectives and ensuring that multiple voices with diverse perspectives, positions and goals may together inform the design and implementation of AI systems (Roche 2021). For example, integrating non-Western philosophies like Ubuntu— which emphasizes interconnectedness, solidarity and mutual respect—can enrich and broaden the ethical foundation for AI development (Gwagwa et al. 2022; Wakunuma and Eke 2024).
- **Contextualizing biases:** What is often described as “missing” or “inaccurate” data is, in many cases, the result of systematic exclusion rooted in unequal social relations. Marginalized communities are frequently left out of data-collection not by oversight, but by design. Retroactively auditing or correcting these omissions through technical fixes is not enough. Ethical AI research must address the structural conditions that produce exclusion in the first place—requiring a normative and cultural shift in how research questions are framed, whose knowledge is valued, and how inclusivity is built into the design process from the outset (Suresh et al. 2022).
- **Rethinking binaries and hierarchies:** Data feminism recognizes the interdependence of struggles and the need for solidarity across different identities and movements—freedom for one group is inextricably tied to freedom for all, requiring a radical reimagining of relationships, structures and priorities to achieve equitable outcomes; for example, challenging gender binary and other forms of oppressive classification (Suresh et al. 2022).

Recommendations for research design

- **Justify the use of AI.**
  Clearly articulate how AI contributes to your research objectives, and whether it adds significant value beyond the current expertise of a researcher. Avoid including AI merely for novelty, funding appeal or societal/peer expectation of its use, and be explicit about its value—especially for marginalized communities.
- **Evaluate necessity before complexity.**
  Consider whether simpler, context-appropriate, or community-driven methods could better meet your goals. Avoid defaulting to AI when low-tech or participatory solutions may be more effective.
- **Interrogate problem framing.**
  Ask who is defining the problem and who stands to benefit from the solution. Ensure your research design does not reinforce dominant narratives or sideline local knowledge systems.

- **Anticipate power dynamics.**
  Be aware that AI can entrench existing inequalities, even when intended to promote equity. Design research to challenge—not replicate—unjust structures of authority and access.
- **Apply ethical scrutiny to prototypes.**
  Avoid deploying untested or low-quality AI tools without adequate safeguards. Poorly governed AI (e.g., chatbots, AI decision-support systems) can erode trust, mislead participants, and compromise institutional credibility.
- **Shift from *can?* to *should?*.**
  Ground AI use in ethical reflection and societal relevance. Ask not just what AI is capable of, but what aligns with the values and long-term well-being of the communities involved.

Recommendations about ethical principles and frameworks

- **Embed ethical principles from the start.**
  Apply the four principles of Data Feminism—*challenge power dynamics*, *embrace pluralism*, *contextualize biases*, and *rethink binaries and hierarchies*—throughout your research process. Where trade-offs arise, be transparent and assess whether the benefits justify the risks.
- **Choose context-appropriate ethical frameworks.**
  Match the framework to the use case (see Box 2)
  - use ELSA for upstream or exploratory research
  - apply the Algorithmic Equity Toolkit for auditing deployed tools
  - select MDII for participatory, field-based work with farmers
- **Use inclusive, participatory methods.**
  Implement principles through stakeholder workshops, bias audits, co-design processes, or community validation. These methods are effective even in low-resource environments and help democratize decision-making.
- **Engage trusted local partners.**
  Work with organizations embedded in the community to ground your engagement in local norms, values and needs. This encourages more relevant and respectful interactions with participants (see the section on Research partnerships, recruitment and training).
- **Define ethical exit strategies.**
  Establish ex ante decision rules for halting research or deployment if ethical standards are breached. These should apply to researchers, NGOs, and private-sector actors alike—and be made transparent to all stakeholders before research begins.

Recommendations about interdisciplinary collaboration and partnerships

- **Embed equity in partner selection.**
  Include diversity, inclusion and capacity-exchange criteria in calls for proposals. Prioritize collaborations with national agricultural research and extension systems and local actors, and ensure clearly defined roles for all team members, including early-career researchers.
- **Assess private-sector partnerships for conflicts of interest.**
  Review partnerships with for-profit actors to ensure data ownership, usage rights, and benefit-sharing align with CGIAR's Open and FAIR Data policy and broader ethical commitments.
- **Support mutual capacity building.**
  Ensure social scientists are equipped to engage with AI technologies, and that AI developers receive training in gender, ethics and inclusion. Cross-disciplinary literacy is essential for collaboration.
- **Invest in targeted training.**
  Use providers such as SheAI and the Inclusive AI Lab to offer technical or gender-focused training. Refer to curated training resources at CGIAR Gender Equality and Inclusion to build inclusive skill sets across teams.
- **Encourage critical self-reflection.**
  Use tools like the Ethics Pathways activity to examine how researcher positionality, assumptions and values influence design decisions. Make reflexivity a routine part of ethical engagement.
- **Model the values you aim to advance.**
  Structure research teams to reflect the equitable outcomes your project seeks. Practice inclusive labor distribution and shared decision-making within your team—prefiguring systemic change.

Data collection

Recommendations about informed consent and explainability

- **Clearly explain the research purpose and data use.**
  Describe what types of data will be collected—personal, behavioral or community-generated—and how they could be used, reused, or shared in AI development.
- **Emphasize voluntary participation and withdrawal rights.**
  Inform participants that their involvement is optional, can be withdrawn at any time, and that control over future data use may be limited once it is anonymized.
- **Disclose AI-specific risks and commit to data security.**
  Explain risks such as re-identification, unintended inferences and opaque algorithm

behavior. Guarantee de-identification, secure storage and restricted access to sensitive data.

- **Renew consent in long-term or high-frequency studies.**
  When data are collected repeatedly or over extended periods, obtain updated consent at appropriate intervals to reflect new risks or uses.
- **Provide a trusted, local point of contact.**
  Ensure participants can ask questions or raise concerns through a designated individual or organization, especially in low-resource or multilingual contexts.
- **Co-develop consent protocols with communities.**
  Collaborate with community members to create consent formats that reflect local norms—such as oral, visual or narrative methods—while maintaining individual consent as a core requirement.
- **Openly document AI systems when feasible.**
  Share details about data sources, algorithmic processes and intended outputs to promote transparency and accountability in research.
- **Avoid black-box models in sensitive research settings.**
  Refrain from deploying opaque AI tools where outputs directly affect participants, or where transparency and reproducibility are essential.
- **Tailor consent to the AI use case.**
  In data collection for training AI models, explain long-term implications. In intervention studies, clarify how the AI system functions and interacts with participants.
- **Ethically justify the reuse of public datasets.**
  Even if data are publicly available, combining them with new analyses or contextual insights can expose sensitive information in ways that create risks of re-identification or stigmatization. Researchers should assess whether such reuse meets ethical standards.

Recommendations about data privacy, safety and security

- **Publish a participant-friendly privacy and data-protection policy.**
  Clearly communicate how data will be collected, used, protected and deleted, using accessible language and formats.
- **Respect original consent agreements.**
  Use data only for the purposes agreed upon at the outset. Seek renewed consent before applying data in, or providing data for, any different context or use case.
- **Limit data collection to what is necessary.**
  Collect only data essential to the research purpose. Apply anonymization or ‘pseudonymization’ techniques to protect participant identities.

- **Follow best practices in information security.**
  Use secure channels for transmitting data and restrict access through PINs, passwords and unique invitations. Regularly audit access and ensure that only authorized, active personnel can view sensitive data.
- **Avoid storing identifiable data longer than needed.**
  Define clear retention periods that comply with legal, ethical and institutional guidelines. Delete or de-identify data once it is no longer required.
- **Anticipate risks through built-in safeguards.**
  In AI-related studies, embed safety mechanisms during research and testing to detect and mitigate potential harms before tools are deployed.
- **Include participant-feedback mechanisms.**
  Enable users to question, challenge or comment on AI-generated outputs during testing. Use their input to improve tools iteratively before deployment.
- **Use a human-in-the-loop approach.**
  Ensure researchers or trained staff review AI-generated recommendations before they are shared with participants—especially when outputs carry financial, health or livelihood implications.
- **Define when human judgment must override AI.**
  Establish clear thresholds and protocols for when AI suggestions should be paused, rejected or revised based on expert review or contextual concerns.
- **Refer to related standards and guidance.**
  Consult the sections on Informed consent and explainability and Deployment and onboarding, and the CGIAR GENDER research ethics and standards toolkit for additional guidance.

Recommendations about secondary data

- **Verify that secondary data meet ethical collection standards.**
  Confirm that the original data were collected in compliance with ethical norms, especially regarding ongoing consent, confidentiality and community rights.
- **Assess alignment with original consent.**
  Ensure secondary data reuse respects the scope of consent given by participants. Where sensitivities exist—such as cultural knowledge or risk of re-identification—consult communities and seek ethics review before reuse.
- **Document data provenance and planned uses.**
  Clearly record where the data came from, how it will be used, and whether any updates or notices are needed for communities or institutions involved in the original study.

- **Evaluate and mitigate potential harms from reuse.**
  Consider how secondary data might inadvertently expose individuals or groups to harm. Mitigation strategies include limiting disaggregation, applying noise, or using generalization and suppression (see Sondeck and Laurent 2025 for a practical assessment framework).
- **Ensure transparency about the dataset's origin and characteristics.**
  Provide metadata such as the source institution, collection period, access rights, data structure, populations represented, and intellectual property status. Clear documentation prevents misuse and misinterpretation, while enabling researchers to judge appropriateness, limitations, and safeguards.

Recommendations for deployment and onboarding

- **Conduct regular ethical-compliance reviews.**
  Continually assess whether project activities align with ethical standards, legal frameworks and community expectations throughout deployment and use.
- **Stress-test models for robustness and fairness.**
  Incorporate adversarial testing to reveal hidden biases, ethical blind spots, and system weaknesses under real-world conditions.
- **Minimize data collection and protect identities.**
  Only collect data essential to the research scope. Apply anonymization or pseudonymization techniques to reduce privacy risks, especially in low-trust or high-risk contexts.
- **Ensure transparent data processing and informed consent.**
  Clearly explain what data is collected and how it will be used, and obtain explicit consent before collection—whether the tool is deployed for research purposes or as a product that collects user data during engagement.
- **Develop and maintain an incident-response plan.**
  Establish procedures to respond quickly to data breaches or security failures, including user notifications and institutional accountability.
- **Publish transparency reports and enable real-time monitoring.**
  Regularly document data sources, usage practices and system updates. Use monitoring systems to detect performance drift or privacy violations early.
- **Embed feedback loops into AI tools.**
  Create channels for users—such as farmers or advisors—to report errors, offer suggestions or raise concerns. Use this input to guide iterative improvements.
- **Tailor user training to diverse needs and constraints.**
  Design onboarding to account for differences in access, digital literacy, and

language. Consider barriers such as connectivity, cost and literacy when planning delivery.

- **Design explainable and user-friendly AI outputs.**
  Ensure AI models generate clear, easily understandable recommendations. Support understanding through visualizations, plain-language summaries, or local-language interfaces.

Special topics

Recommendations about user research

- **Refer to the Methods section of the *CGIAR User Research Toolkit*.**
  Use this resource to plan and adapt user-research methods to agricultural settings in the global South, with guidance on implementation and ethical practice.
- **Conduct comprehensive needs assessments.**
  Investigate users' daily realities, resource constraints, values and cultural norms to inform deployment, onboarding and long-term support strategies.
- **Use participatory-research methods.**
  Engage users in the design, testing and refinement of AI tools. Techniques like co-design workshops, community media, and participatory action research help align tools with local priorities and challenge structural inequalities.
- **Ensure users are fairly acknowledged and compensated.**
  Recognize user contributions to design and data-collection. Where appropriate, offer noncoercive incentives—such as financial compensation, certificates or shared benefits—in line with institutional review or ethics board approvals.

Recommendations about monitoring and evaluating AI systems

- **Apply the MDII framework from the outset.**
  Use the MDII to embed ethical and inclusion-focused goals—such as accessibility, co-creation and equity—throughout the research and development process.
- **Use the MDII scorecard dashboard to guide improvement.**
  Monitor a platform's performance across multiple dimensions using real-time feedback from users. Adapt the tools iteratively based on insights from marginalized groups, especially women and underserved communities.
- **Go beyond surface-level metrics.**
  Avoid overreliance on indicators like downloads or usage statistics. Instead, assess engagement, empowerment, and user satisfaction—especially among target populations in FLWS contexts.

- **Adapt evaluation strategies to evolving tools and contexts.**
  As AI use cases shift, develop new benchmarks that capture their explainability, power asymmetries, environmental impacts, and other emerging priorities.
- **Ensure ongoing validation and context-specific updates.**
  Continually update models using locally relevant data. Regularly test for relevance, accuracy and unintended impacts, to maintain users' trust and the tool's effectiveness over time.

Recommendations about communicating research using AI

- **Disclose the use of AI tools clearly and consistently.**
  Signal transparency to readers by stating when and how AI was used. For example: "An initial draft of this post was generated using ChatGPT from author prompts, then revised and edited."
- **Use AI to increase accessibility, not erase expertise.**
  Simplify complex content to reach broader audiences, but tailor its tone and technical depth to your readers. Balance clarity with intellectual rigor.
- **Review and revise all AI-generated outputs.**
  Check for factual accuracy, contextual relevance and originality. Edit your drafts to retain the voice of the research team and avoid stylistic flattening.
- **Ensure fairness and inclusion in adapted content.**
  Carefully edit your work to avoid biased language, stereotypes or examples that may alienate or disadvantage certain groups, particularly in diverse cultural settings.
- **Protect sensitive and unpublished information.**
  Do not put confidential or unpublished data into AI tools unless explicit safeguards are in place to ensure privacy and prevent leakage.
- **Maintain human oversight at every stage.**
  Treat AI as a supportive tool—not a substitute—for ethical judgment, contextual interpretation and communicative intent.

Recommendations about using AI to help with research

- **Disclose GenAI use clearly and consistently.**
  Follow institutional guidance on how to acknowledge AI contributions. Before submitting papers, check journal-specific requirements regarding AI use, authorship and disclosures.
- **Review all AI-generated outputs for accuracy and quality.**
  Always verify the factual integrity, relevance and tone of AI-generated content before using it in research or communication.

- **Protect privacy and data security.**
  Do not put unpublished or sensitive data into GenAI tools without safeguards. Ensure models do not allow public training using your data.
- **Use GenAI to increase accessibility and reduce barriers.**
  Apply GenAI to support tasks such as summarizing text, editing, debugging code, translating or simplifying language—while retaining human oversight.
- For experimental research (adapted from Chang et al. 2024)
  - **Use GenAI to assist with pre-treatment procedures,** provided that researchers remain actively involved in reviewing and refining outputs to prevent any compromise in research quality.
  - **Prohibit public model training** on entered data and ensure the AI platform provides strong privacy protections.
  - **Elicit informed consent** when GenAI is used in a way that may affect participants, ensuring ethical transparency.
  - **Use GenAI to suggest possible mediators** (channels of impact) **and moderators** (factors shaping effect sizes)**, and to explore design variations** that test whether findings are likely to hold in other settings or at larger scale.
  - **Do not delegate experimental procedures** to GenAI without piloting, documenting and reviewing its roles and outputs.
  - **Check whether GenAI changes the fairness or consistency of the experiment—**for example, whether everyone gets the same treatment, follows instructions the same way, or stays unaffected by others' treatments—and adjust the design if it puts validity at risk.
  - **Re-initialize GenAI models consistently** and design prompts that capture the intended constructs.
  - **Critically assess training data** and, when appropriate, manually train or fine-tune models to suit analytical tasks.
  - **Document and stress-test GenAI results** to ensure replicability and transparency for the broader research community.
  - **Reassess resource allocation** across research stages in light of GenAI's changing trade-offs.
  - **Ensure AI-generated hypotheses are interpretable by humans**, even when aided by machine-learning techniques.
  - **Remember that GenAI is not a replacement** for human creativity, innovation, quality or ethical reasoning.

Recommendations about mitigating risks of GBV

- **Establish an anonymous reporting system for GBV.**
  Provide confidential mechanisms for participants or users to report harassment, abuse or other harms linked to AI use or research participation.
- **Follow local ethical protocols for support and referral.**
  Ensure your research complies with country-specific procedures regarding GBV response, including referral pathways and duty of care.
- **Refer to CGIAR's GBV Guidelines.**
  Consult the *CGIAR Guidelines for Ethical Engagement with Gender-based Violence in Food Systems Research* for detailed recommendations on safeguarding women and girls, and responsible engagement.