The Gender Data Foundations of Responsible and Equitable AI

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Who should read this report?

This report is intended for policymakers, governments, international organizations, donors, civil society organizations, the private sector, and academics. We invite these diverse stakeholders to understand:

- The importance of gender data in AI
- Why addressing gender data gaps is crucial, especially in an era where AI usage grows increasingly ubiquitous
- AI and gender data-related considerations in four key sectors: finance, health, agriculture, and climate and environment
- Actions and future areas of investment for various stakeholders, including best practices in AI design and gender data
- Research gaps in this topic, especially where additional analysis and insight are needed
- Specific recommendations and action pathways that these stakeholders can take to address gender data-related issues in AI

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Executive Summary

Artificial intelligence (AI) is increasingly becoming a part of how humans navigate our world. However, women and girls remain underrepresented across the AI lifecycle, leading to AI outputs that do not account for their needs and AI tools that are biased against women, girls, and marginalized communities. This happens because AI models learn from historical data, often reflecting entrenched gender biases. Existing gender inequalities may be embedded in the data that AI models process. These inequalities are then reflected in AI outputs, reinforcing the same systemic biases that shape the data in the first place.

Further, as Data2X and other gender data stakeholders have voiced, there are considerable gaps in the quality and availability of gender data globally. These gaps in gender data, while important in their own right, also have critical implications for AI. They limit the ability to detect and address bias in AI systems. Therefore, a continued focus on building and improving gender datasets, especially sex-disaggregated data, is important because it enables the measurement of disparities, informs governance, and ensures responsible AI development. Gender data is essential for ensuring that AI systems are fair, accountable, and do not reinforce gender inequalities.

Areas for investment and investigation

There are opportunities for investment that can help to address these issues, including incorporating emerging best practices in AI design. These best practices include auditing to uncover gender bias, standardized documentation for AI datasets, and building more inclusive AI training datasets. AI also has the potential to counteract existing gender inequalities, but nascent efforts require increased investment and scale. Bridging gender-related gaps in AI will also require a concerted investment in human capacity development across the AI value chain. There are also gaps in research -- especially around the appropriate use of gender data during AI model development and emerging capabilities like synthetic data – that warrant further investigation and analysis.

Stakeholder recommendations

Funders, the private sector, governments, civil society, and multilateral organizations all have unique and complementary roles to play in improving the production, quality, and use of gender data. In summary:

- **Funders:** Prioritize funding for the creation and use of gender datasets with standardized and complete documentation that supports sociotechnical AI research.
- **Private sector:** Commit to using AI to intentionally include the needs of women and girls and adopt standardized practices to promote fairness and transparency in AI products.
- **Civil society:** Advocate for open data and foster community participation in AI development.
- **Governments:** Mandate algorithmic audits and integrate gender data into policy.
- **Multilateral organizations:** Develop global standards and frameworks for the responsible use of high-quality gender data in AI tools.

Framing the Moment: Why gender data is critical in the age of AI

Artificial intelligence is reshaping societies, economies, and policymaking.[1] As the use of AI-driven products and services in private business and government has increased, so too have efforts by global stakeholders to ensure that these technologies are used responsibly and equitably. Such efforts include the Hiroshima AI Process (HAIP) Reporting Framework (a framework for businesses and other AI developers to self-report their efforts to increase transparency and accountability)[2], the UN Global Compact ("a comprehensive global framework for digital cooperation and governance of artificial intelligence")[3], the OECD's Principles for Trustworthy AI[4], as well as more country/jurisdiction-specific regulations such as the EU's AI Act.[5] Companies in the technology and AI industry have also made voluntary commitments to increase the trust and transparency of their AI tools.[6]

However, despite these efforts, women and gender-diverse individuals remain underrepresented across the AI lifecycle[7], leading to AI outputs that do not account for their needs and AI tools that are **biased against women, girls, and marginalized communities.** Why does this bias happen? The reason is that AI models learn from historical data, which often reflects entrenched gender biases.[8] Across various AI model types, existing data serves as the foundation for "learning." But existing data captures an unequal world across many facets, with gender inequality being an enduring phenomenon in most places around the world. For example, at the current rate of progress, it is estimated to take 134 years to close gender gaps.[9]

The ability of women, girls, and gender-diverse communities to be properly represented in data is essential to an AI revolution that benefits all. Without robust gender data, AI systems risk replicating and amplifying existing inequalities. Investing in high-quality, machine-readable gender datasets is essential to ensure that AI-driven advancements benefit all. From healthcare to finance, energy to agriculture, AI's potential for social good depends on its ability to incorporate diverse perspectives and more accurately reflect the people it seeks to serve.

Existing Gender Data Gaps

Data2X has long focused on filling gender data gaps and improving the quality and availability of gender data globally. Data2X's key initiatives in this area include a fund for research projects that apply big data innovations to better understand women's and girls' lives; collaboration with national statistical systems to strengthen the capacity of gender data experts across 15 countries; and advocacy for the use of gender data to drive financial inclusion and economic empowerment for women. While gender data stakeholders like Data2X and its partners play a pivotal role in shaping inclusive policies and driving equitable progress, their efforts have also uncovered critical gaps in the availability and quality of gender data for training and tuning AI products. Despite existing political will and commitment, the absence of robust and comprehensive gender data hampers their ability to develop targeted interventions and monitor progress effectively. Understanding the nature and causes of these gender data gaps is essential to knowing when and how to use gender data in AI systems.

Before we proceed, let us define two key concepts in this sector: 'gender data' and 'gender datasets'.

Gender data: Any data that captures the experiences of women, girls, and gender-diverse communities.[10] Gender data includes:

- Sex-disaggregated data: Data that can be broken-down and analyzed by sex.
- Data about women, girls, and gender-diverse communities: Data on topics that are unique to women and gender-diverse communities (i.e., access to reproductive and sexual health care, gender-based violence).
- Data about gender issues: Data that can be used to evaluate the impact of society on women and gender-diverse communities (i.e., gendering of professions, gendered roles).

Gender datasets: In this report, our reference to "gender data" encompasses these three categories described above, and we use the term "gender datasets" to describe any machine-actionable dataset in which one or more of the above gender data categories are included. The most common gender dataset is a dataset about any topic that includes a column that disaggregates by sex. Gender datasets can also include data about women and girls, such as medical information about women's health concerns. Lastly, any machine-actionable dataset that includes data about gender issues, such as Demographic and Health Surveys (DHS), which can be used to assess women's differential access to mobile phones and more, is considered a gender dataset.

Globally, gender data is known to be lacking in both quantity and quality. At the current rate of data production, collection and reporting, it will take 22 years for all countries to make all SDG gender data *available*.[11] The various issues with gender datasets are well-documented and span from missing metadata to irregular and incomplete data production.[12] Below, we outline some of the priority gender data gaps. The following list does not cover all gender data gaps but rather offers a small window into the topic:

- Many datasets **lack the necessary metadata and documentation** to enable appropriate data analysis and use in AI systems. Metadata, including data formats and licensing details, provides key information for data analysts and statisticians. It gives users details to facilitate data discovery, use, and management. This key component supports data interoperability and enables easier searching and indexing.
- Many gender datasets are also **missing sufficient data on key non-gender variables** like geography, education, and income. Though gender is often the primary demographic factor in gender analyses, it would be erroneous for analysts and statisticians to exclude demographic and socioeconomic variables given the role that intersectionality plays in gender issues. Complete data on other descriptive categories allows for more detailed data disaggregation. Without disaggregated data, it is nearly impossible to conduct any type of effective gender analysis of a given population.
- Gender datasets **do not have sufficient data on multiple genders** to be able to perform cross-gender comparisons. To identify gender disparities (i.e., the effect of a health policy on men versus women), data users need to have access to enough data for each gender subgroup. This is particularly important for artificial intelligence applications to prevent over- or under-estimating effects on gender.

The Critical Role of Gender Data for Responsible AI

These gaps in gender data, while important in their own right, also have critical implications for AI. Gender data is essential for ensuring that AI systems are fair and accountable, and do not reinforce gender inequalities. Although all forms of gender data could contribute to responsible AI, as of 2023, only 30 percent of countries publish gender-relevant data, and nearly half of these datasets lack sex disaggregation.[13] This data gap limits the ability to detect and address bias in AI systems. Therefore, a continued focus on building and improving gender datasets, especially sex-disaggregated data, is essential because it enables the measurement of disparities, informs governance, and ensures responsible AI development.

In early 2024, the United Nations unanimously adopted its first resolution on AI, emphasizing the need for safe, secure, and trustworthy AI to advance sustainable development.[14] The resolution also warns that AI, if improperly governed, can reinforce inequalities, widen digital divides, and threaten human rights.[15] In this context, gender data serves as a foundational tool to:

- Ensure that AI systems do not perpetuate structural inequalities by identifying disparities in model predictions and outputs across genders.
- Test for discrimination and bias using fairness measures.
- Assess gender dimensions of digital divides and access to information.
- Document compliance with international law.
- Evaluate whether AI respects privacy, human rights, and fundamental freedoms.
- Mitigate risk through the identification of potential harms or exclusions by gender.

Without gender data, UN member states will not be able to achieve safe, secure, and trustworthy AI: a goal now normatively set by the international community. However, with the political willpower and commitment to machine-readable and actionable gender data, and the active use of such datasets, operationalizing responsible AI becomes possible.

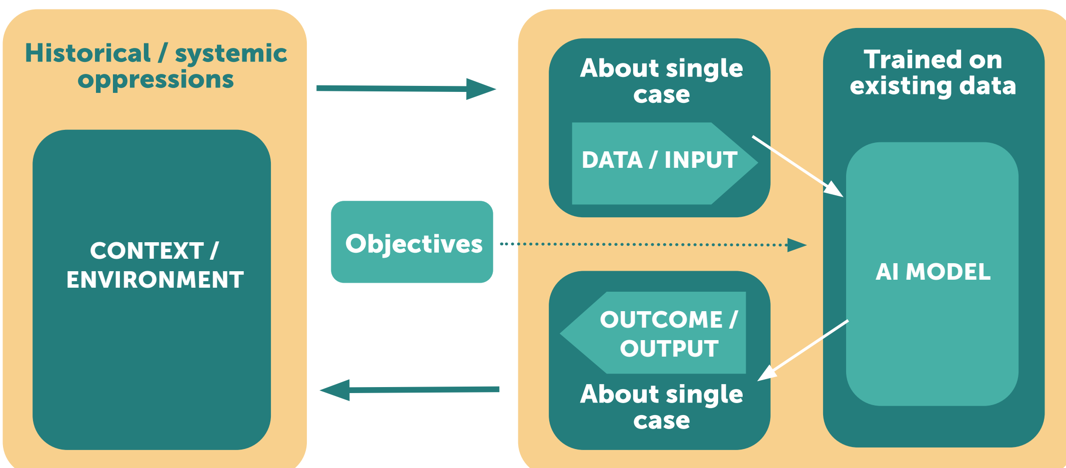
How Data Shapes AI: A cycle of perception, influence, and real-world harms

Traditional definitions of AI[16] focus on its ability to simulate human reasoning, problem-solving, and creativity,[17,18] but these definitions often overlook AI's *sociotechnical* nature. As defined, a sociotechnical approach "recognizes that a technology's real-world safety and performance is always a product of technical design and broader societal forces, including organizational bureaucracy, human labor, social conventions, and power."[19] Therefore, technology systems like AI cannot be fully understood without analyzing both their technical and social dimensions. Existing gender inequalities—such as pay gaps, disparities in political representation, and differences in agricultural productivity—may be embedded in the data that AI models process. These inequalities are then reflected in AI outputs, reinforcing the same systemic biases that shape the data in the first place.

Although data is the foundation of AI systems, human decision-making throughout the AI lifecycle also determines how well models perform and for whom. For example, when human designers of image generators do not account for gendered or stereotyped representations in image training datasets, the resulting systems have sexualized women[20] and reinforced cultural tropes.[21] This is because existing datasets, without intentional interventions, may reproduce existing biases. When we recognize the moments where human decision-making has played a role in AI development, we are better able to recognize how, where, and why bias has entered an AI model.

To visually represent AI systems, see Figure 1, where the OECD's "Definition of an AI System" was modified to highlight existing inequalities better. The blue boxes highlight moments in an AI system where existing social inequalities and how these are captured in data may enter into and influence AI system performance.

Figure 1. Sociotechnical definition of an AI system (adapted from OECD's AI System)[22]



Model designed by Emily Springer, PhD, founder and principal consultant of TechnoSoio Advisory. Modified from OECD's Definition of an AI System. Copyright: Springer, Emily, 2024. Sociotechnical Definition of an AI System.

To show how these inequalities enter the system, we use the hypothetical example of an AI model that helps to identify the best job candidates to hire at a company, thereby saving the company time and money by reducing the workload of their human resource team.

1. **Context/Environment: Influenced by historical and systemic oppressions**
   AI is built on existing datasets that reflect historical and systemic inequities. Gender disparities in employment, financial access, and healthcare outcomes, among others, exist and are captured in data.

   Example: Due to historical gender biases and systemic barriers, women—especially women of color, disabled women, and LGBTQI+ women—have faced lower employment rates, wage gaps, and underrepresentation in leadership roles.

2. **The Context/Environment is Perceived through Data**
   The way AI systems "see" the environment depends entirely on what is captured in available datasets, which may omit marginalized groups or underrepresent their experiences.

   Example: Only some employment-related data exists, while other data points typically remain undocumented. Existing data might include employee salaries, promotions, or workforce demographics, whereas some data might be excluded, such as salary negotiations, employment gaps due to caregiving, microaggressions and harassment in the workplace, and exit reasons.

3. **Data Inputs: A single case perspective**
   AI systems process input data as a single case (e.g., one person) and its many associated data points (e.g., date of birth, citizenship, highest education level achieved, etc.). Emphasizing the importance of a single case draws attention to how AI systems may work for individuals, especially those who are marginalized e.g., disabled individual, LGBTQI+ community members, Indigenous person, or multiple, overlapping identities.

   Example: When an individual candidate applies for a job, the AI system inputs their resume and profile as a collection of data points—such as their gender, education, years of experience, and prior employers and processes these data points using a mathematical equation determined through training.

4. **Data Is Processed by an AI Model: Trained on pre-existing data**
   Once input data is received, AI models analyze it based on pre-learned patterns. AI models have been trained on historical data to determine what factors are considered "important" in making predictions. The AI model's logic is shaped solely by the data it has been exposed to, meaning the choice of training data is critical.

   Example: If the AI model has been trained on hiring data where men were historically favored for leadership roles and women's career breaks were penalized, it may weigh these patterns heavily, making it less likely to recommend a highly qualified woman—especially a Black woman or a woman with a disability—for senior positions. This is not because others are more qualified but because the model has learned a biased correlation from historical trends.

5. **The AI Model Makes a Prediction: Output data influences opportunities**
   The AI model then generates an output—a decision, recommendation, or classification—based on its learned patterns. At this stage, data-driven predictions may directly affect individuals.

   Example: The AI system generates a ranked list of candidates for a management role, prioritizing men with continuous work histories over equally qualified women who took parental leave or transitioned from non-traditional career paths, reinforcing gendered employment patterns. As a result, women are not offered the position.

6. **The Output Becomes a New Data Point: Influencing context/environment**
   AI outputs feed back into the cycle, potentially becoming training data for a different AI system. Without attention, this cycle continues, with AI models continuously learning from decisions that they have already made, which may amplify disparities rather than correcting them.

   Example: As companies increasingly rely on AI for hiring, the model's biased decisions lead to fewer women being hired into leadership roles, which in turn creates new training data reflecting the same disparity, further entrenching gender inequalities in employment and leadership roles.

Types of Gender-related Harms in AI

As we show in the model above, at every stage, both human decision making and data shape AI's impact, potentially reinforcing biases unless proactively addressed. The example above focused on an AI hiring model; however, manifestations of gender bias occur across sectors: a bank's AI model may deny loans to women with fewer digital financial records due to training data including only individuals who use digital payments exclusively,[23] and a health chatbot may spread misinformation about contraception due to training datasets being culled from the internet.[24] Broadly, these harms fall into the following categories:

- **Allocative harms**: AI increasingly makes decisions on hiring, credit access, healthcare, and social benefits. If trained on biased datasets, AI could systematically exclude women and gender-diverse individuals from opportunities.
- **Representative harms**: AI-powered content creation influences public perception. If AI-generated narratives reinforce harmful stereotypes, gender biases may become further ingrained in media, workplaces, and policymaking.
- **Unequal distribution of harms:** Because AI models learn from historical data that reflects systemic biases, those experiencing multiple forms of oppression are more likely to face amplified allocative and representative harms. If trained on biased datasets, AI systems may compound the discrimination faced by individuals at the intersection of multiple marginalized identities (e.g., women of color, LGBTQ+ individuals, disabled women, women living in global majority countries). To assess this, intersectional data is needed.[25] Furthermore, AI training datasets are overwhelmingly biased toward the Global North, limiting the technology's accuracy and relevance in diverse global contexts.[26]

Without intentional intervention to address gender data gaps and careful decisions across the AI lifecycle, AI risks deepening these disparities rather than mitigating them.[27]

AI in the 'Real World': A sector-specific view of gender data gaps and AI

AI is cross-sectoral in nature: there are numerous use cases and possible applications that improve progress toward the SDGs. What are the 'real-world' implications of existing gender data gaps mean as AI increasingly enters the day-to-day toolkit of practitioners and programs in the sectors? We have chosen four sectors—agriculture, climate change, health, and finances—to understand these implications. *(Note: for readers interested in more sector-specific details, including questions to guide AI design, see Annex 1 on page 24*).

AGRICULTURE	
Sector-specific AI use cases	▪ **Agricultural extension services via chatbot:** Providing expert information to supplement existing agricultural extension agent knowledge in the field.[28] ▪ **Forecasting models:** Forecasting models can use climate and ecological data to predict useful information, like future pest outbreaks, product prices, and crop yields.[29] ▪ **Crop disease identification:** Image recognition technology can detect diseases and pests from photos of crops.[30]
Overview of gender concerns	Although women's role in agriculture varies greatly by country and region, women smallholder farmers tend to face additional barriers to achieving the same productivity as their male counterparts, including relatively less access to productive land, agricultural inputs, time scarcity due to domestic and childcare tasks, skills and literacy gaps, as well as social networks.[31]
Existing gender data gaps	▪ Lack of data on women's role across the agricultural value chain, as women's labor tends to be more informal and thus not well captured. ▪ The division of agricultural labor within households is gendered with men often being considered the "farmer" while women are not, skewing data to represent men's interests in agriculture. ▪ Household survey data often only captures head of household perspectives, which skew toward men.
Threats from persistent gender data gaps	AI systems may reproduce and amplify these gendered patterns, resulting in agricultural AI tools that disproportionately serve men's agricultural roles and overlook women's involvement and contributions. Further, AI tools that serve the needs of women in agriculture are less likely to be built. This may exacerbate challenges for women who seek to support their own livelihoods and their families through agriculture, whether they are smallholder farmers or tech-enabled high-growth agripreneurs.

CLIMATE AND ENVIRONMENT	
Sector-specific AI use cases	▪ **Minimizing human-wildlife conflict**: AI-enabled drone surveillance makes it easier to monitor large areas and detect potential issues for human-wildlife contact. ▪ **Early warning systems**: Predicting and notifying people about extreme weather events before they occur can minimize the effects of disasters on vulnerable communities. ▪ **AI-driven energy**: Microgrids with AI can automatically allocate renewable energy as needed.[32] These systems can analyze current weather conditions and energy demand to ensure even the most rural communities have access to clean energy.
Overview of gender concerns	Though climate change has global impact, women are disproportionately negatively impacted by climate issues due to social and economic factors like limited access to information and control over key natural resources.[33] Climate change is a 'threat multiplier' and often escalates and advances other concerns, including health risks and gender-based violence.[34]
Existing gender data gaps	▪ Data is collected at the household level as opposed to the individual level ▪ Lack of data collection standards and common methodologies for many gender-relevant environment and climate change issues ▪ Gender data collection efforts are hampered in insecure environments ▪ Lack of data disaggregation by age, race, disability, sexual orientation, migration status, etc. ▪ Data needs depend on countries' own climate change impacts and priorities
Threats from persistent gender data gaps	AI systems may reproduce existing gender inequalities in access to environmental resources and valuable climate information. This may, in turn, reinforce women's reliance on their male counterparts and reduce women's agency in tackling climate-related challenges that affect them the most.

FINANCIAL SERVICES	
Sector-specific AI use cases	▪ **AI models used to assess creditworthiness**: AI models are commonly used by financial service providers (FSPs) to assess individual creditworthiness for business, educational, and/or personal loans. ▪ **AI support for loan applications**: AI personal assistants and financial advisors support applicants to fill out loan applications, improving quality and likelihood of acceptance/approval. ▪ **Non-traditional credit scoring**: Predictive tools can use a variety of alternate data sources in underwriting models to assess loan applicants.[35]
Overview of gender concerns	Globally, women have disproportionately limited access to and power over financial resources with nearly 800 million women still unbanked and, for those that are, additional barriers exist. Limited access to formal financial institutions and gender bias in lending systems are two factors that prevent women from managing and growing their finances and having more stability and autonomy.[36]
Existing gender data gaps	▪ Lack of data on financial assets and use of financial services outside of established financial institutions (i.e., savings at home, financial services accessed through men in the household).[37] ▪ Lack of data on barriers to accessing financial assets like credit and land for women. ▪ Lack of women-specific data on spending patterns and financial transactions. ▪ Lack of data on women's involvement in the informal sector. ▪ Lack of understanding on the opportunity cost of women's labor outside of the home and poor quantification of the unpaid labor women perform in the home.[38] ▪ Vast gender inequalities reflected in existing data about entrepreneurship and startup funding.
Threats from persistent gender data gaps	AI systems may amplify gender inequities in access to financing, further excluding women from financial services and assets.[39] If this trend continues when scaled to emerging markets, barriers to finances will increase. This threatens to worsen women's access to financial products and services, which are key tools in increasing women's integration with the formal economy, financial freedom, and access to entrepreneurship opportunities.

HEALTH	
Sector-specific AI use cases	▪ **Diagnostic testing:** Using the latest advances in image recognition technology to analyze the results of medical testing, including radiology scans and lab tests. AI for diagnostics can support medical technicians to interpret test results and screen for health issues. Tests specific to women's health include maternal/prenatal ultrasounds and mammograms. ▪ **Surgical education and training:** Surgery AI-powered simulation programs can help medical professionals practice high-risk skills in a low-risk environment. These technologies can teach students surgical techniques and procedures for all types of surgery. They can also support women entering the surgical field.[40,41] ▪ **Health supply chain:** Forecasting demand for healthcare resources to help government and healthcare institution managers plan and allocate resources (e.g., labor, medications, etc.) accordingly.
Overview of gender concerns	Globally, women encounter numerous barriers to healthcare that stem from various biological and social factors, including a lack of evidence on the biological differences between men and women, a fundamental misunderstanding of women's health[42], and a global healthcare system that undervalues women in the health workforce.[43]
Existing gender data gaps	▪ Lack of understanding of women's healthcare and how to define it, thinking beyond just reproductive health.[44] ▪ Existing data collection systems primarily collect healthcare information at health centers with data and digital infrastructure, failing to capture information from the smaller and more local health centers that provide most primary healthcare services to women and girls. ▪ Lack of sex-disaggregated healthcare data with granularity (geography, race, age, etc.). ▪ Unequal gender representation in datasets with downstream impacts, e.g., clinical trials (in the United States, including women participants was not mandated until 1993) and foundational health research (until today, most mice-based research is performed only on male mice).[45] ▪ Household survey data on healthcare use and access often only captures the perspectives of head of household, which tend to be men.
Threats from persistent gender data gaps	AI systems may reproduce and amplify sex and gender-related health issues, providing additional care, services, and R&D to and for men, while women's needs are overlooked. For example, recent research demonstrated that liver disease prediction models stated to have high accuracy, when disaggregated by gender, false negatives for women were nearly double that of men. Meaning that women's liver disease goes undiagnosed and untreated, creating increased morbidity and mortality for women.[46] This may worsen health outcomes for women, whose needs are already underserved by existing health systems, service providers, and institutions.

Addressing Gender Data-related Challenges in AI

As we show above, AI's role across development— including in high-priority sectors such as agriculture, climate change, financial services, and health—is profoundly shaped by gender data gaps, resulting in AI systems that can either reinforce inequalities or drive progress. In this section, we show how, with careful human decision-making and high-quality gender data, AI systems can advance gender equity across these critical sectors. Specifically, we outline:

- Areas for future investment, with a specific focus on existing best practices in AI design
- Areas for future investigation, especially where there are gaps in research and analysis
- Stakeholder-specific recommendations for funders, private sector organizations, civil society, country governments and policymakers, and UN and multilateral organizations

Areas for Investment

Best Practices in AI Design

Bridging gender data gaps requires innovative approaches, as traditional methods fall short. Considering that, as of 2023, only 42 percent of the data needed to measure the SDG gender indicators is available, AI presents a powerful tool—when used responsibly—to analyze data, uncover hidden patterns, and drive gender equity. However, ensuring AI advances rather than harms gender inclusion demands understanding and implementing the following best practices at scale: auditing, documenting, and building.

Auditing: AI tools to uncover gender bias

Auditing is a key stage in the AI development process to ensure that products are fair and equitable. Various tools, some of which use AI technologies, can be used to audit other existing AI products for discrimination and bias. Many companies, like Aequitas[47] and IBM[48], offer products powered by machine learning and statistics to identify and address bias throughout AI systems. IBM's AI Fairness 360 Toolkit, for example, is an open-source toolkit that offers various algorithms and fairness metrics like demographic parity[49], equalized odds[50] to address gender bias at all stages of AI development, from data preprocessing[51] to model output post processing[52]. These types of products, however, are only tools in a much larger toolkit.

Organizations must prioritize fairness and allocate appropriate financial and human resources to evaluating fairness in their AI products. Without active efforts to create truly equitable gender AI products by development organizations, these fairness tools remain purposeless.

Documenting: Standardized documentation for AI datasets

In addition to conducting detailed audits, gender data stakeholders should ensure that the gender datasets used to build AI products are well-documented and that documentation is available and accessible. Tools like datasheets for datasets and model cards address these needs—both spearheaded by women AI researchers—by providing critical information about machine learning models and datasets to promote responsible AI practices.

Datasheets for datasets[53] provide structured documentation for datasets used in machine learning. Inspired by product datasheets in hardware engineering, datasheets include information about a dataset's creation, composition, collection methods, and potential biases. A well-documented datasheet would answer questions such as:

- Who collected the data?
- What was the motivation for creating the dataset?
- Were any demographic groups underrepresented?

Model cards[54] are a form of documentation for machine learning models. Model cards describe various model details, including the model's intended uses and evaluation metrics across different and potential biases.

Datasheets and model cards help researchers and developers evaluate the appropriateness of datasets for specific tasks while encouraging more ethical and transparent data practices.

Building: AI training datasets

Inclusive, global, and intersectional datasets are needed. Several donors are leading the way by supporting the creation of new training datasets specifically for training AI systems. Building training datasets takes significant human resources and time. Depending on the topic and objective, teams may need to manually collect data (e.g., taking pictures for an image recognition dataset), though datasets can be built by collating existing data (e.g., scraping images online). Through investment into these dataset building efforts, these organizations contribute to upstream, foundational inputs for responsible AI.

- The Lacuna Fund[55] directs its investments exclusively to developing datasets for AI stakeholders in low and middle-income contexts. The Lacuna Fund has supported the creation of openly accessible labeled datasets in health, agriculture, and language. Available datasets developed include image and spectrometry datasets for six main food security crops grown in sub-Saharan Africa,[56] a benchmarking dataset for languages in the Horn of Africa,[57] and an image dataset of blood samples for malaria diagnosis.[59]
- GIZ's Fair Forward program has created Open for Good, which builds localized, representative training datasets for Africa, Asia, and beyond with a focus on global majority representation.[59] This includes African language data, satellite and crop data, and other complementary programs.

Other inclusive efforts for training data include Mozilla's Common Voice initiative and CLEAR Global's 4 Billion Conversations.

Existing training datasets: Robust datasets, inclusive of gender, already exist that can be used to train and tune AI tools.

- Gender Data Portal: The Gender Data Portal[60], maintained and owned by the World Bank, is a centralized database for national gender statistics. The site displays data on various World Bank indicators but also provides an analysis on the availability of gender statistics by country, supplemented by ILOSTAT model estimates.
- The Demographic and Health Surveys (DHS) Program[61] supports the collection and dissemination of household data in over 90 countries and has published data from over 300 surveys since its inception in 1984. The DHS collects statistically representative samples on key population and health topics, including gender-based and domestic violence, HIV/AIDS, nutrition, family planning, and malaria. *(Note:* At the time of publication, the future of the DHS program is unclear given the cancellation of the program by the U.S. government.)

Invest in Thoughtful Applications of AI for Gender Equity

AI has the potential to counteract existing gender inequalities, but these nascent efforts require increased investment and scale. Some examples of AI applications that are helping to close gaps and promote fairness across sectors include:

- In a world where between 16 percent and 58 percent[62] of women experience online gender-based violence, Areto Labs[63] developed a tool to automatically detect and delete social media spam and harassment. The team uses text classification models[64,65,66] trained to identify hate speech and abuse to combat online harassment at scale without risking the negative impact on human content moderators. Content moderators often experience post-traumatic stress disorder and burnout because of constant exposure to review extreme content, including hate speech and violent images and videos.[67]

Another company, HiredScore[68], is addressing bias, including gender and racial bias, in hiring.[69] HiredScore offers explainable algorithms, automated bias testing, and AI-driven diversity analytics to support human resources teams discover, recruit, and hire staff.

Chatbots like Aunt Zuzi (co-designed by Gender Rights in Tech (GRIT) and the communities they serve[70]), Sophia.chat[71] (developed by Swiss non-profit Spring ACT[72]), and rAInbow (created by AI for Good[73]) harness the power of generative AI and specialized content to provide localized information and support to people experiencing domestic violence globally. AI enables users to interact with these platforms 24/7 in the language of their choice and receive tailored support, including how to identify and respond to abuse, as well as local resources for domestic abuse survivors.

Capacity Development across the AI Value Chain

Bridging gender-related gaps in AI will also require a concerted investment in human capacity development across the AI value chain. This includes increasing the role of women and girls as designers, contributors, investors, and innovators in AI data and tools. In addition to the ethical benefits, this kind of capacity development will provide tangible business benefits, including reduced costs and higher adoption.[74] Therefore, this will maximize not only create opportunities for women and girls, but it will also unlock the social and economic value of AI for all—not only women and girls, but men and boys too.

CASE STUDY:
Engendering agricultural extension with generative AI

Billions of people earn their livelihoods, and contribute to GDP, through farming, aquaculture, and forestry. Gaining access to accurate, trustworthy, and timely advice is often challenging for farmers, agricultural extension workers, and agripreneurs. Further, the stakes of quality information are high: inaccurate information could minimize the profit margin of families already struggling to maintain their livelihoods.[75] Women—compounded by age and education levels—disproportionately report that advisory services do not meet their needs.[76] Digital Green sought to address these concerns through a generative AI-powered advisory app, building for inclusion, ease of use, and ensuring gender equity throughout.

By combining their proprietary dataset of gender-inclusive agricultural videos with additional data sources (e.g., weather APIs, crop datasets) and using Retrieval Augmented Generation (RAG) techniques, Digital Green created a gender-inclusive chatbot that, to date, has not exhibited gender bias or toxicity.[77,78] By focusing on providing advisory through multiple channels (text, voice, video) across several platforms (WhatsApp, Telegram, etc.), Digital Green works to meet the needs of people of all genders and education levels. User research has shown that women users are extremely pleased with the accuracy and speed at which they can ask questions in a language and modality that works for them, saving them much-needed time and money.[79] However, users also note that increasing simplicity of language, minimizing math in answers, and clear UX menus designed for non-literate people would further improve the bot. Additionally, although voice capabilities are helpful, the bot currently struggles to understand both Swahili and Kenyan-accented English.[80] The iterative process of addressing these challenges from a technical perspective is acknowledged and the Digital Green team remains hard at work.[81]

What sets Digital Green apart in this space is that they are building iteratively, carefully, and considering gender dynamics throughout: between user groups, intersectional user groups (e.g., older/younger women with varying levels of digital literacy and by role in the agricultural system), and usage patterns.[82] By collecting gender-disaggregated data, the design team is better able to address the needs of women users and ensure equitable use of this valuable resource.

CASE STUDY:
Non-traditional credit scoring demonstrates improved access to business loans for Ethiopian women

In Ethiopia, many women are unable to access small business loans due to a lack of ownership and/or decision-making authority over assets that financial institutions will accept as loan collateral. To address this, World Bank Ethiopia's Women Entrepreneurship Development project piloted a non-traditional avenue for credit scoring: psychometric testing as a key input to loan decisions.[83] Applicants completed a 45-question exam, which was processed against 250,000 records, and the AI system predicted a three-digit score representative of the applicant's default risk. Lenders then approved loans for applicants who scored above a set threshold.

Women who were evaluated with psychometric testing were more than twice as likely as women who provided collateral to receive loans.[84] Meaning, this alternative method for credit scoring improved women's access to finance. The firms opened by women who were assessed via the non-traditional method were also less likely to fail during the COVID-19 pandemic, yet firm profitability data was not assessed.

This project is a strong "proof of concept"[85] for improving women's access to finances through non-traditional credit scoring.

Areas for Investigation

What is the appropriate use of gender data during AI model development?

AI adoption poses risks of disparate treatment (explicitly using gender in decision-making)[86] and disparate impact (unintended gender disparities even when gender is not a direct input).[87] While gender is a protected attribute[88] in many countries, AI models often infer gender through proxy variables, making bias difficult to eliminate. Even when gender is excluded from training data or from model processing, correlations across high-dimensional datasets allow AI to indirectly 'read' gender, leading to persistent inequalities. For example, despite removing gender as an attribute to prevent disparate treatment, Goldman Sachs' Apple Card exhibited algorithmic bias, granting husbands 10 times the credit limit of their wives, even when women had higher credit scores—resulting in disparate impact.[89] Similarly, despite removing race as an attribute, UnitedHealth's health risk algorithm prioritized white patients for medical assistance over equally sick Black patients.[90] Despite being well-resourced, Amazon was unable to build bias mitigation techniques to prevent a hiring algorithm to downrank women's applications even when removing gender as an attribute.[91] This bias arises because race and gender are highly correlated with other included attributes, allowing AI systems to infer and act on these characteristics through proxy variables.

This presents a key dilemma: gender data advocates push for sex-disaggregated data, yet some AI fairness strategies and legal protections require the removal of gender as an attribute, which still fails to eliminate bias. Addressing these tensions requires urgent interdisciplinary research, bringing social scientists and technical experts together to develop best practices for mitigating gender bias in AI. Key questions include: How should gender data be used in AI development? What techniques prevent disparate impact? What case studies demonstrate effective bias mitigation?

What are appropriate use cases and practices to safely incorporate synthetic data?

The lack of gender data on key issues makes it difficult to track disparities and measure progress. Without accurate data, identifying and addressing gaps remains a challenge. One way AI can help is by generating synthetic data, which mimics real data using generative AI and statistical tools.[92,93,94]

Synthetic data is especially valuable in privacy-sensitive sectors like healthcare[95] and finance. For example, UN Global Pulse used synthetic data to model COVID-19 interventions for Rohingya refugees in Bangladesh, experimenting while preserving privacy. The team generated synthetic data to simulate various policies, including mask wearing, home isolation, and physical distancing, and their respective impact on COVID-19 cases and spread. This enabled policies that minimized the spread of COVID-19, maximized freedom of movement, and retained privacy for refugees.[96]

However, the use of synthetic data carries both positives and negatives that must be properly weighed in context. Synthetic data can help address data deficits, protect privacy, reduce data bias, ensure compliance, and reduce data costs. At the same time, synthetic data generation and use introduces new risks: data quality, the potential for "reverse engineering" of security risks,[97] Further, experts from regions like Africa – where 90 percent of data remains.[98]

While synthetic data can help fill gender gaps, experts stress that it must be built on robust, representative datasets to avoid reinforcing biases. Given AI's rapid advancement, waiting for real-world gender data may not be feasible[99]—but without careful design, synthetic data could amplify existing inequalities instead of reducing them.[100] Currently, there are no standards or safeguards outlining appropriate use of synthetic data, making inadvertent harms more likely, especially in circumstances where synthetic data is used for allocative decisions in welfare, health, and education sectors.[101] Developing standards for synthetic data is an area in need of increased investigation and research.

Stakeholder-specific Recommendations and Action Pathways

Addressing gender data gaps requires a coordinated and multi-stakeholder approach, as no single entity can tackle this challenge alone. Funders, the private sector, governments, civil society, and multilateral organizations all have unique and complementary roles to play in improving the production, quality, and use of gender data. Though the actions that each take can differ significantly, all gender data stakeholders should operate moving forward with the following shared goals:

Funders

Funders play a critical role in shaping the future of gender-responsive AI by directing resources towards the collection, documentation, and research of comprehensive gender data, ensuring that AI systems are built on inclusive and representative foundations.

1. **Invest in inclusive, intersectional, and gender-diverse datasets:**
   Prioritize funding for the creation and use of datasets that capture the experiences of women and girls, with an emphasis on intersectionality across race, age, disability, gender diversity, and geography. Datasets should, at a minimum, include sex-disaggregated data. This will ensure AI models reflect diverse realities and address overlapping forms of discrimination.

2. **Enforce standardized documentation and metadata practices:**
   Require and codify the use of standard documentation practices like datasheets for datasets and model cards to enhance transparency, usability, and interoperability of gender data used in AI systems.

3. **Invest in sociotechnical AI research:**
   Fund interdisciplinary research that examines how systemic biases enter AI systems, connecting technical experts with gender and social science researchers to develop strategies for mitigating these biases.

4. **Promote research on gender bias mitigation in AI systems:**
   Support studies on best practices for addressing gender bias in AI, including the ethical use of synthetic data, techniques to prevent disparate impacts, and the development of global fairness standards.

Private Sector

Private sector actors—both companies that develop AI tools and those that apply AI tools in their business operations—hold the power to design, develop, and deploy AI systems that either perpetuate or mitigate gender biases. Their commitment to integrating gender data and fairness audits is essential for responsible AI innovation.

1. **Integrate gender-specific data throughout AI lifecycles:**
   Incorporate datasets about gender-diverse communities and gender-specific issues to ensure AI systems can detect and address complex biases.

2. **Implement rigorous fairness audits across sectors:**
   Develop in-house or adopt fairness auditing tools like IBM's AI Fairness 360 Toolkit and Aequitas in all stages of AI development. Demonstrate sector-specific audits for agriculture, health, finance, and climate-focused AI tools to build clear sector-specific best practices.

3. **Adopt standardized documentation practices:**
   Lead the industry in using datasheets for datasets and model cards to promote transparency, ethical AI practices, and accountability. Include specific mention of gender data and gender issues, risks, and appropriate downstream use of datasets.

4. **Develop AI tools addressing the needs and inequities faced by women and gender-diverse communities in key sectors:**
   Design AI applications that address the unique needs of women in agriculture, health, finance, climate resilience, and more. This could include diagnostic tools for women's

health or financial advisors that recognize informal savings and AI tools that actively counteract gender biases, like harassment detection tools or bias-aware hiring algorithms.

5. **Monitor and adjust AI systems through feedback loops:**
   Implement continuous monitoring systems to track how AI outputs influence future datasets, correcting any emergent gender biases over time.

6. **Invest in capacity development across the AI value chain, with a special focus on women and girls:**
   Increase the role of women and girls as designers, contributors, investors, and innovators in AI data and tools.

Civil Society

Civil society serves as a vital advocate and watchdog, pushing for transparency, accountability, and inclusivity in AI systems while ensuring that the lived experiences of marginalized communities are reflected in gender data and AI outcomes.

1. **Advocate for the inclusion of gender data in sectoral AI applications:**
   Campaign for comprehensive gender data integration in AI applications across sectors, including finance, health, and agriculture. Datasets should go beyond simple sex disaggregation and capture information about gender-diverse communities and systemic gender issues.

2. **Promote AI literacy and awareness of sociotechnical biases:**
   Develop public education campaigns highlighting how systemic biases enter AI systems through both data and human decision-making processes. Educate the public about how AI can perpetuate gender inequalities and empower communities to demand fair and accountable AI practices.

3. **Campaign for open and accessible gender data:**
   Advocate for governments and private entities to make gender datasets publicly available with comprehensive documentation for community-led monitoring and accountability.

4. **Engage in participatory data collection and validation:**
   Mobilize communities to collect grassroots gender data, particularly in underrepresented sectors like agriculture and climate resilience, ensuring that AI systems reflect diverse lived experiences.

Governments and Policymakers

Governments and policymakers—especially data governance authorities, AI safety institutes, national statistics offices, and their legislative counterparts—have the authority to institutionalize gender equity in AI by mandating the collection of gender data, setting regulatory standards, and ensuring that AI systems align with human rights and social justice principles.

1. **Mandate the collection and publication of comprehensive gender data:**
   Legislate the collection, reporting, and publication of sex-disaggregated and gender-specific data across sectors like health, agriculture, and finance to prevent AI from reinforcing structural inequalities. Require data to be published with complete and detailed data documentation.

2. **Incorporate gender data requirements in AI governance frameworks:**
   Develop national AI policies that establish standards for fairness audits and mandate the use of well-documented, gender-responsive datasets.

3. **Develop sector-specific AI fairness standards:**
   Create guidelines for evaluating AI fairness within specific sectors, ensuring continuous monitoring of gender bias in outputs, particularly in finance, healthcare, and public services.

4. **Support capacity strengthening for gender data collection:**
   Invest in training programs for statistical offices and data collection agencies to improve the quality, completeness, and intersectionality of gender data. Facilitate engagement between these offices/agencies and the private sector, especially data scientists.

5. **Address AI feedback loops through regulation:**
   Implement policies requiring AI systems to be monitored for how their outputs affect future datasets, with corrective measures enforced when AI perpetuates gender disparities.

Multilateral Organizations

UN entities and multilateral organizations are uniquely positioned to set global norms, facilitate cross-country collaboration, and monitor the international impact of AI on gender equality, ensuring that ethical standards and gender-responsive practices are upheld worldwide.

1. **Establish global standards and frameworks for gender data in AI systems in key sectors:**
   Define comprehensive standards for gender data in AI, including sex-disaggregated data and gender-specific issues, ensuring ethical and equitable AI development. Ensure that these gender-responsive datasets are incorporated into AI systems across agriculture, climate, health, and finance sectors.

2. **Facilitate global monitoring of AI's impact on gender equality:**
   Create an international monitoring body to track how AI systems affect gender equity globally, assessing both data inputs and AI outputs to promote continuous improvement.

3. **Promote cross-country collaboration on gender data initiatives:**
   Encourage member states to share best practices, tools, and resources for gender data collection and use in AI, integrating initiatives like the Gender Data Portal and DHS Program into global frameworks.

4. **Support research on the safe and ethical use of gender data in AI:**
   Lead efforts to establish guidelines for the ethical use of gender data in AI systems, especially synthetic data, ensuring that AI tools do not amplify existing inequalities.

Conclusion

Addressing gender data gaps is essential for ensuring that AI systems and data-driven solutions are inclusive, equitable, and effective. The persistent lack of high-quality, gender-disaggregated data has contributed to biased and harmful AI systems that overlook the unique experiences and needs of women and gender-diverse communities. Bridging these gaps is not merely a technical challenge but a critical step toward advancing gender equality in a world increasingly driven by AI technologies.

By closing gender data gaps, we can empower AI systems to produce more accurate insights, drive equitable policies, and create solutions that address systemic gender disparities. This requires collaborative action across development stakeholders. From developing standardized frameworks for collecting sex-disaggregated data to ensuring machine-actionable data for AI applications, stakeholders must prioritize ethical, transparent, and inclusive approaches. In doing so, we can harness AI's transformative potential to not only identify and address gender inequalities but also build a more just and equitable future for all.

Annex: Sector-Specific Overviews and Design Questions

The following pages detail sectoral applications of AI, focusing on agriculture, climate change, health, and finances, highlighting gendered dimensions with respect to data for AI and AI applications.

AGRICULTURE

Overview of gender concerns	Although women's role in agriculture varies greatly by country and region, women smallholder farmers tend to face additional barriers to achieving the same productivity as their men counterparts, including relatively less access to productive land, agricultural inputs, time scarcity due to domestic and childcare tasks, skills and literacy gaps, as well as social networks.[102]
Existing gender data gaps	▪ Lack of data on women's role across the agricultural value chain, as women's labor tends to be more informal and thus not well captured. ▪ The division of agricultural labor within households is gendered with men often being considered the "farmer" while women are not, skewing data to represent men's interests in agriculture. ▪ Household survey data often only captures head of household perspectives, which skew toward men.
Threats from persistent gender data gaps	AI systems may reproduce and amplify these gendered patterns, resulting in agricultural AI tools that disproportionately serve men's agricultural roles and overlook women's involvement and contributions. Further, AI tools that serve the needs of women in agriculture are less likely to be built. This may exacerbate challenges for women who seek to support their own livelihoods and their families through agriculture, whether they are smallholder farmers or tech-enabled high-growth agripreneurs.
Opportunities with high-quality gender data	With stronger gender data, agricultural productivity is likely to rise, leading to increased nutrition within farming households and increased livelihoods due to cash intake. Further, the specific needs and interests of women farmers are more likely to be included in AI builds.

Use case descriptions	▪ **Agricultural extension services via chatbot:** Providing expert information to supplement existing agricultural extension agent knowledge in the field.[103] ▪ **Forecasting models:** Forecasting models can use climate and ecological data to predict useful information, like future pest outbreaks, product prices, and crop yields.[103] ▪ **Crop disease identification:** Image recognition technology can detect diseases and pests from photos of crops.[105]
Illustrative questions to incorporate gendered dimensions	**Ag extension services via chatbot** a. Is there equal uptake between men and women agricultural extension workers? b. Does the chatbot provide the same quality of advice for domestic versus cash crops? c. Are quality datasets for training available for crops gendered "women"? **Forecasting models:** a. Do women have equal access to digital tools and the digital literacy to use forecasting models? b. Do women own devices that produce data that is utilized for forecasting at equal rates? **Crop disease identification:** a. Are these tools being equally built for crops that are often dominated by women at the same rate? b. Do women have equal access to digital tools and the digital literacy to use crop disease identification?

CLIMATE AND ENVIRONMENT

Overview of gender concerns	Though climate change has global impact, women are disproportionately negatively impacted by climate issues due to social and economic factors like limited access to information and control over key natural resources.[106] Climate change is a "threat multiplier" and often escalates and advances other concerns, including health risks and gender-based violence.[107]
Existing gender data gaps	▪ Data is collected at the household level as opposed to the individual level ▪ Lack of data collection standards and common methodologies for many gender-relevant environment and climate change issues ▪ Gender data collection efforts are hampered in insecure environments ▪ Lack of data disaggregation by age, race, disability, sexual orientation, migration status, etc. ▪ Data needs depend on countries' own climate change impacts and priorities
Threats from persistent gender data gaps	AI systems may reproduce existing gender inequalities in access to environmental resources and valuable climate information. This may, in turn, reinforce women's reliance on their male counterparts and reduce women's agency in tackling climate-related challenges that affect them the most.
Opportunities with high-quality gender data	With stronger gender data, more will be known about the negative impacts of climate change on women and how to mitigate those effects. As a result, women will be better prepared and resilient to the negative impacts of climate change, suffering less harm to and having greater autonomy over their lives and livelihoods.
Use case descriptions	▪ **Minimizing human-wildlife conflict**: AI-enabled drone surveillance makes it easier to monitor large areas and detect potential issues for human-wildlife contact. ▪ **Early warning systems**: Predicting and notifying people about extreme weather events before they occur can minimize the effects of disasters on vulnerable communities. ▪ **AI-driven energy**: Microgrids with AI can automatically allocate renewable energy as needed.[108] These systems can analyze current weather conditions and energy demand to ensure even the most rural communities have access to clean energy.

Illustrative questions to incorporate gendered dimensions	**Minimizing human-wildlife conflict**: ▪ Do AI systems consider women's unique movement patterns as they disproportionately travel for water, foraging, wood collection, and other often-gendered tasks? ▪ Do AI systems inadvertently surveil and monitor the movements of women? **Early warning systems**: ▪ Do early warning systems disseminate information that is accessible and understandable to women? **AI-driven energy allocation**: ▪ Are AI-powered energy systems supporting the daily needs of women? ▪ Do women have access and control over AI-powered energy systems?

FINANCIAL SERVICES

Overview of gender concerns	Globally, women have disproportionate access to and power over financial resources with nearly 800 million women still unbanked and, of those that are, additional barriers exist. Limited access to formal financial institutions and gender bias in lending systems are two factors that prevent women from managing and growing their finances and having more stability and autonomy.[109]
Existing gender data gaps	▪ Lack of data on financial assets and use of financial services outside of established financial institutions (i.e., savings at home, financial services accessed through men in the household).[110] ▪ Lack of data on barriers to accessing financial assets like credit and land for women. ▪ Lack of women-specific data on spending patterns and financial transactions. ▪ Lack of data on women's involvement in the informal sector. ▪ Lack of understanding on the opportunity cost of women's labor outside of the home and poor quantification of the unpaid labor women perform in the home.[111] ▪ Vast gender inequalities reflected in existing data about entrepreneurship and startup funding.

Threats from persistent gender data gaps	AI systems may amplify gender inequities in access to financing, further excluding women from financial services and assets.[112] If this trend continues when scaled to emerging markets, barriers to finances will increase. This threatens to worsen women's access to financial products and services, which are key tools in increasing women's integration with the formal economy, financial freedom, and access to entrepreneurship opportunities.
Opportunities with high-quality gender data	With stronger financial gender data, the use of AI models that determine access to finances will be more gender equitable. Additionally, data on the gaps and opportunities for women to access financing enables these issues to be addressed. Both opportunities would result in improved livelihoods and greater financial autonomy for women.
Use case descriptions	▪ **AI models used to assess creditworthiness**: AI models are commonly used by financial service providers (FSPs) to assess individual creditworthiness for business, educational, and/or personal loans. ▪ **AI support for loan applications**: AI personal assistants and financial advisors support applicants to fill out loan applications, improving quality and likelihood of acceptance/approval. ▪ **Non-traditional credit scoring**: Predictive tools can use a variety of alternate data sources in underwriting models to assess loan applicants.[113]
Illustrative questions to incorporate gendered dimensions	**AI models used to assess creditworthiness:** ▪ Has the training data been assessed for gender bias? Have proper bias mitigation measures been taken?[114] ▪ How did the development team assess people and/or groups likely to be excluded from existing data? Did they seek out additional datasets to represent them? **AI support for loan applications**: ▪ Do AI advisors address the specific needs of women applicants? ▪ Are AI advisors, often accessed via digital tools, usable by women applicants? **Non-traditional credit scoring**: ▪ Do alternate data sources reinforce or amplify existing gender inequities in credit access? ▪ Are non-traditional credit scoring models using data that is available on women applicants?

HEALTH

Overview of gender concerns	Globally, women encounter numerous barriers to healthcare that stem from various biological and social factors, including a lack of evidence on the biological differences between men and women, a fundamental misunderstanding of women's health[115], and a global healthcare system that undervalues women in the health workforce.[116]
Existing gender data gaps	▪ Lack of understanding women's healthcare and how to define it, thinking beyond just reproductive health.[117] ▪ Existing data collection systems primarily collect healthcare information at health centers with data and digital infrastructure, failing to capture information from the smaller and more local health centers that provide most primary healthcare services to women and girls. ▪ Lack of sex disaggregated healthcare data with granularity (geography, race, age, etc.). ▪ Unequal gender representation in datasets that have downstream impacts, e.g., clinical trials (in the United States, including women participants was not mandated until 1993) and foundational health research (until today, most of mice-based research is performed only on male mice).[118] ▪ Household survey data on healthcare use and access often only captures head of household perspectives, which skew toward men.
Threats from persistent gender data gaps	AI systems may reproduce and amplify sex and gender-related health issues, providing additional care, services, and R&D to and for men, while women's needs are overlooked. For example, recent research demonstrated that liver disease prediction models stated to have high accuracy, when disaggregated by gender, false negatives for women were nearly double that of men. Meaning that women's liver disease goes undiagnosed and untreated, creating increased morbidity and mortality for women.[119] This may worsen health outcomes for women, whose needs are already underserved by existing health systems, service providers, and institutions.
Opportunities with high-quality gender data	With stronger gender data, healthcare for women and girls will be more evidence-based and informed, leading to overall improved health. Further issues that are specific to women's health will be included and advanced through AI applications, including efforts to overcome the stigma and shame that women can experience when seeking services.

Use case descriptions	■ **Diagnostic testing:** Using the latest advances in image recognition technology to analyze the results of medical testing, including radiology scans and lab tests. AI for diagnostics can support medical technicians interpret test results and screen for health issues. Tests specific to women's health include maternal/prenatal ultrasounds and mammograms. ■ **Surgical education and training:** Surgery AI-powered simulation programs can help medical professionals practice high-risk skills in a low-risk environment. These technologies can teach students surgical techniques and procedures for all types of surgery. Can also be used to support women entering the surgical field.[120,121] ■ **Health supply chain:** Forecasting demand for healthcare resources to help government and healthcare institution managers plan and allocate resources—labor, medications, etc. accordingly.
Illustrative questions to incorporate gendered dimensions	**Diagnostics** ■ Are women proportionately represented in training datasets for diagnostic tests? ■ Are AI solutions that perform diagnostic testing being built for women's health issues? **Surgical education and training** ■ Do AI-facilitated training programs advance women students as much as men? ■ Are AI-facilitated training programs as accessible to women students as much as men? **Health supply chain** ■ Are women-specific medical items included in AI-driven supply chain lists? ■ Are women health workers involved and trained in adoption and use of AI tools?

Endnotes

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