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Data Curation and AI: Identifying Structural Gender Biases and Implications for the African AI Ecosystem

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Executive Summary

This report examines how structural gender inequalities may become embedded in artificial intelligence through the data curation processes on which AI systems depend, and why gender-responsive data and AI governance are necessary within the African AI ecosystem. Its central argument is that AI systems do not independently generate gender discrimination, but may inherit, reproduce, or amplify existing inequalities through the ways data are generated, collected, selected, classified, labelled, documented, and reused. This is significant because AI-assisted systems increasingly influence access to credit, online safety, public services and digital identity. Where the data used to develop and evaluate these systems underrepresent, misrepresent or inadequately contextualise women's experiences, errors and exclusion may be distributed unequally.

The report finds that structural inequality may affect data before and during AI development. Unequal digital access influences who generates data and which activities become visible; historical and incomplete datasets shape representation; annotation and classification involve social and interpretive judgments; and limited participation by women and affected communities may influence the categories, assumptions and intended uses adopted during curation. These pathways are examined through three manifestations within the African AI ecosystem. In credit scoring, characteristics produced by unequal economic conditions may be used as indicators of financial risk. In content moderation, limited African language and context-specific data may affect the recognition of gendered harm and women's participation in public life. In digital identity and public service systems, demographic gaps, biometric performance disparities and unequal access to registration may interact to reproduce existing exclusion. These examples do not establish that every AI system or African jurisdiction produces the same outcomes but demonstrate identifiable pathways through which structural inequality may become embedded in data-driven systems.

The report evaluates three continental instruments that address complementary aspects of this problem. The Continental Artificial Intelligence Strategy provides AI-specific policy direction on inclusion, diverse datasets, impact assessment, oversight and redress. The AU Data Policy Framework addresses the broader data ecosystem and expressly recognises representativity, data justice and the risks created by underrepresentation in datasets. The Malabo Convention provides the binding legal framework for states parties through personal data principles, data subject rights, and regulatory enforcement.

The report consequently identifies five observable policy and governance considerations concerning the operationalisation of dataset representativeness, the gender responsive application of impact assessments, sector-specific data curation safeguards, participation in dataset and classification decisions, and oversight of structural patterns of harm. These considerations do not duplicate the principles already recognised within the continental frameworks. They identify areas in which those principles have not yet been translated into common operational requirements for gender-responsive data curation across the AI lifecycle.

1.0 Introduction

Artificial intelligence is increasingly positioned within Africa's development agenda as a means of supporting economic and social transformation. The African Union's Continental Artificial Intelligence Strategy identifies agriculture, healthcare, education, financial services and public-service delivery among the sectors in which AI may contribute to African development.[1] The Strategy also recognises that achieving these benefits requires investment in data, infrastructure, skills and governance, alongside safeguards against the risks associated with AI adoption.[2]

The ability of AI systems to contribute meaningfully to these sectors depends substantially on the data used to develop, test and operate them.[3] Research on gender and AI in Africa highlights that the effectiveness of an AI system is influenced by the scope, quality and local relevance of its training and testing data.[4] Within this report, data curation encompasses the processes through which data are collected, selected, cleaned, organised, labelled, documented, maintained and updated to ensure that they remain suitable for their intended use.[5] Decisions made during these processes influence the people, activities, and experiences represented in the resulting dataset.[6]

African feminist research has challenged the treatment of data as a neutral or complete representation of society. It has highlighted that data are produced within existing relationships of power and that gender bias may be embedded in research design, sampling, data collection, classification and interpretation.[7] An Afro-feminist approach therefore directs attention to who produces data, whose experiences become visible, who determines the categories used, and whose knowledge is excluded or treated as irrelevant within data systems.[8]

The significance of these questions becomes clearer when considering women's participation in the sectors targeted for AI development. Evidence demonstrates women's substantial involvement in African agrifood systems and their increasing engagement with digital and mobile financial services.[9] African feminist organisations also work extensively across health, education, employment, subsistence, civic participation and access to public services,

1 African Union Commission, Continental Artificial Intelligence Strategy: Harnessing AI for Africa's Development and Prosperity (African Union 2024) 4, 17–18, 29 <https://au.int/sites/default/files/documents/44004-doc-EN-_Continental_AI_Strategy_July_2024.pdf> accessed 24 March 2026.
2 ibid
3 African Union Commission (n 1) 45–47.
4 Araba Sey and Shamira Ahmed, An African Perspective on Gender and Artificial Intelligence Needs African Data and Research (Policy Brief No 5, Research ICT Africa 2020) 1–3 <https://researchictafrica.net/wp-content/uploads/2020/10/an-african-perspective-on-gender-and-artificial-intelligence-needs-african-data-and-research.pdf> accessed 24 March 2026; National Information Standards
5 Leese M, 'Data curation: A conceptual framework for the study of data quality' (CURATE Working Paper No 2, ETH Zürich 2023) https://doi.org/10.3929/ethz-b-000597540 accessed 24 March 2026
6 ibid
7 Neema Iyer, Chenai Chair and Garnett Achieng, Afrofeminist Data Futures (Pollicy 2021) 6–8, 35–36 <https://pollicy.org/wp-content/uploads/2021/09/Afrofeminist-Data-Futures-Report-ENGLISH.pdf> accessed 24 March July 2026
8 Amber Sinha and Bobina Zulfa, Principles of Afro-feminist AI Data (Pollicy 2023) 3–5 <https://pollicy.org/wp->27 March 2026
9 Food and Agriculture Organization of the United Nations, The Status of Women in Agrifood Systems (FAO 2023) <https://doi.org/10.4060/cc5343en> accessed 24 July 2026; also see World Bank, Women and Financial Inclusion (Global Findex 2021 Gender Brief, World Bank 2023) 2–5 <https://thedocs.worldbank.org/en/doc/0254f-85d1cceceb6e72362a71eb600e4-0430062023/original/Findex2021-GenderBrief-030823.pdf> accessed 27 March 2026

demonstrating the importance of women's experiences within these areas.[10] Therefore, where AI systems are developed to address challenges in these sectors, their relevance will depend in part on whether the underlying data adequately reflect the people, activities, and conditions that constitute those sectors.

It must, however, be noted that participation in a sector does not necessarily result in equivalent representation in the data generated. Research has identified continuing gaps in gender-disaggregated information concerning digital access, technology use, skills and participation in African digital economies.[11] Evidence from financial inclusion research also demonstrates that unequal access to mobile phones, formal identification and digital financial services can affect women's ability to participate in data-generating digital systems.[12] These inequalities, therefore, influence which activities are recorded and subsequently available for use in the development of data-driven technologies.

The central thesis of this report is that AI systems rely on data produced within existing social and institutional conditions and that data curation processes may reproduce the structural inequalities present within those conditions. Gender bias in AI may therefore originate before algorithmic design, through unequal access to technology, limited participation in data production and curation, incomplete representation of women's experiences, and decisions concerning which data are collected, classified, labelled or retained.[13] Studies of AI ecosystems in Kenya and Ghana have similarly demonstrated how gendered assumptions may influence whether women's identities and perspectives are included, omitted or misrepresented in data used to build and train AI systems.[14] The report consequently identifies the points at which structural gender bias may enter data curation processes, examines its impact on African women and the African AI ecosystem. Further, the report considers the extent to which continental governance frameworks, particularly the AU Continental strategy, the Malabo Convention, and the AU Data Policy Framework, address gendered perspectives in Africa, thereby providing normative and/or instructional guidance on adequate safeguards against these risks.

2.0 Scope and Limitations

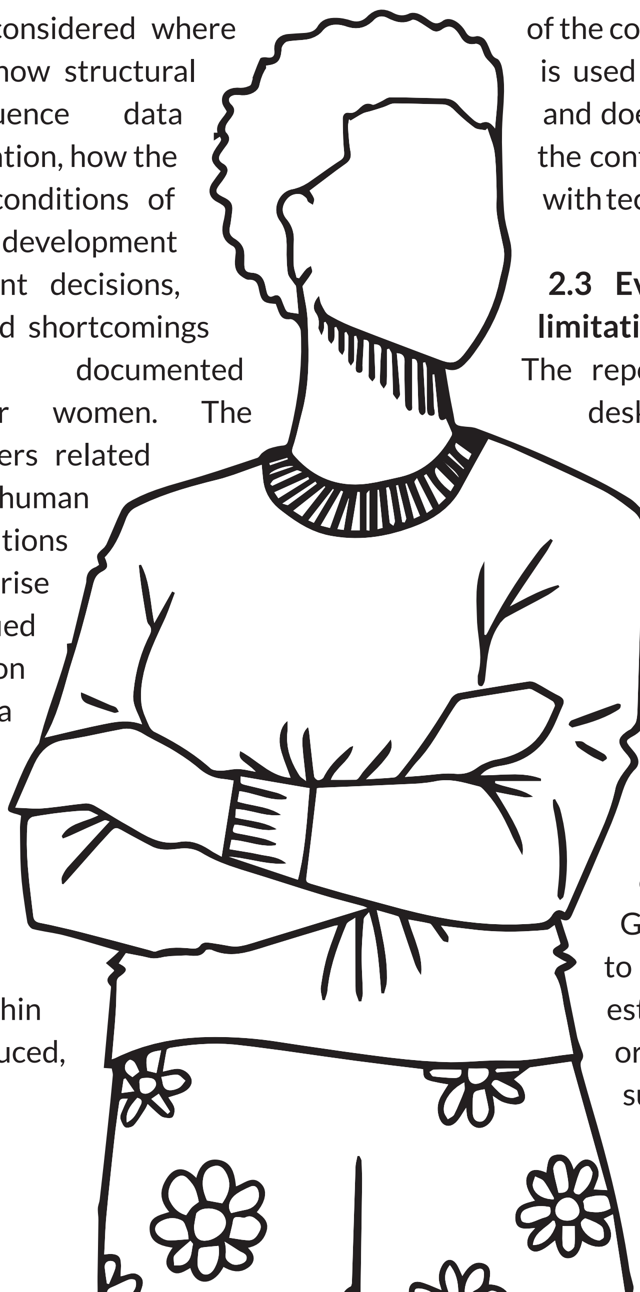
2.1. Subject-matter scope

The report focuses on how structural gender bias may enter AI systems through data curation. For this purpose, data curation encompasses the collection, selection, cleaning, classification, labelling, documentation, storage, maintenance and governance of data used to develop, test or operate an AI system. These processes are examined because they influence the quality, relevance and representativeness of the data made available for computational use.

10 Iyer, Chair and Achieng (n 6) 32–35.
11 Sey and Ahmed (n 4) 1–3
12 World Bank (n 9) 4–5; Uzma Alam and others, Gender Main Streaming in Artificial Intelligence Policy in Africa (Science for Africa Foundation 2025) 2–6 <https://scienceforafrica.foundation/sites/default/files/2025-03/Gender%20Mainstreaming%20in%20AI%20Policy%20in%20Africa%20v2.pdf> accessed 27 March 2026.
13 Sey and Ahmed (n 4) 1–3; Iyer, Chair and Achieng (n 7) 6–8, 35–36; Sinha and Zulfa (n 8) 3–5.
14 Angella K Ndaka, Harriet A M Ratemo, Abigail Oppong and Eucabeth B O Majiwa, 'Artificial Intelligence (AI) Onto-Norms and Gender Equality: Unveiling the Invisible Gender Norms in AI Ecosystems in the Context of Africa' in Damian Okaibedi Eke and others (eds), Trustworthy AI (Palgrave Macmillan 2025) 207–232 <https://doi.org/10.1007/978-3-0and/or,toContinental 31-75674-0_10>accessed 27 March 2026.

The analysis extends to digital access and data generation where inequalities in access affect who produces digital data and whose activities become represented in a dataset. It also considers participation in data collection, annotation, and other forms of curatorial work in which the people involved, the conditions under which they work, or the guidance available to them influence decisions about how data are selected, labelled, or interpreted.

The report does not provide a comprehensive examination of women's participation in the technology sector, online gender-based violence or all forms of algorithmic discrimination. These issues are considered where they help explain how structural inequalities influence data generation and curation, how the composition and conditions of those involved in AI development may shape relevant decisions, or how data-related shortcomings contribute to documented consequences for women. The report also considers related governance and human rights implications where they arise from the identified data curation pathways. Data curation remains the principal analytical focus of the report while recognising the wider conditions within which data is produced, used and governed.



2.2 Geographic and population scope

The report uses Africa as its geographical and policy frame while recognising that the continent does not constitute a uniform technological, social or data environment. Research on gender and AI has identified significant differences in the availability of gender-disaggregated data, digital infrastructure and relevant research across African countries. It has also cautioned that findings drawn from global or non-African studies may not accurately represent the configurations of gender and power present in particular African contexts. Accordingly, country and sector-specific examples are identified as such and are not presented as representative of the continent. The term *African women* is used as a broad analytical category and does not imply that women across the continent share a single experience with technology or data-driven systems.

2.3 Evidence and methodological limitations

The report is based on a qualitative desk review of peer-reviewed research, African feminist scholarship, policy and research reports, credible civil-society publications and relevant African governance instruments. Priority is given to African-authored and Africa-specific evidence where the report makes claims about African women or African AI ecosystems. Global sources are used primarily to support technical definitions, establish comparative standards or explain concepts for which sufficiently developed Africa-specific literature is not available.

The availability and depth of evidence differ across countries, sectors and AI applications. Some of the literature identifies general gender-data gaps, while other studies document particular experiences within specific jurisdictions or sectors. The report therefore distinguishes between evidence of an observed outcome, evidence of a possible risk and broader conceptual arguments concerning how structural inequality may be reproduced through data. Its conclusions identify and analyse documented processes, risks and governance gaps within the available literature. They should not be interpreted as evidence that every AI system disadvantages women or that the same conditions exist across all African countries, sectors or groups of women.

3.0 Conceptualising Data Curation and Structural Gender Biases

3.1 Data Curation

Data curation refers to the continuous practices through which data are made and maintained as trustworthy, intelligible and suitable for use.[15] The term curation originates from the Latin *curare*, meaning *to care*, and conveys the sustained work involved in organising, preserving and managing information. Within modern data systems, it encompasses the processes through which data are collected, selected, cleaned, organised, classified, labelled, documented, stored, maintained and updated for an intended purpose.[16] Data curation is therefore not a single stage that ends once a dataset has been assembled. It continues throughout the data lifecycle as information is reviewed, modified and prepared for new forms of use.[17]

Within this report, data curation is understood as a socio-technical practice rather than a purely technical process.[18] It involves distributed labour undertaken by data collectors, annotators, researchers, domain experts, system developers and institutions, whose decisions are mediated by technical tools, organisational priorities and available infrastructure.[19] Data does not therefore simply exist in a form ready for computational use, every dataset is shaped by prior interpretive decisions concerning what should be measured, which sources should be included, how variables should be defined, and which categories and classification systems should be applied.[20] These choices are also

15 Matthias Leese, 'Data Curation: A Conceptual Framework for the Study of Data Quality' (CURATE Working Paper No 2, 2023) 2 https://www.research-collection.ethz.ch/server/api/core/bitstreams/cdb35052-04d5-4ffe-bf0a-014a10b3d047/content accessed 27 March 2026

16 Ane Møller Gabrielsen, 'Gendering Data Care: Curators, Care, and Computers in Data-Centric Biology' (2024) 33(2) Science as Culture 256, 257 https://doi.org/10.1080/09505431.2023.2260830 accessed 25 July 2026.

17 Mathias Leese (n15)

18 Socio -technical practice as noted is linked to the understanding of social technical systems which are 'systems that involve a complex interaction between technology and the social subsystems. These systems are open-ended and adapt to the ever-changing environment, they are significantly influenced by social components such as human, culture, organization, the context of use, usefulness, policies, and regulations. As such the practice is an approach studying the interrelatedness of social and technical elements, focusing on joint optimization and how humans and machines interact; see Lucas Ngowi, 'Socio-technical Systems: Transforming Theory into Practice' (Department of Computer Science and Engineering, University College of Information and Communication Technology 2017)<https://www.researchgate.net/publication/323958760_Socio_Technical_Systems_Transforming_Theory_into_Practice>

19 Mathias Leese (n15)

20 Ibid 4

influenced by the purposes for which the data is expected to be used and by the capabilities and limitations of the technical systems through which they are processed.[21] Curation consequently provides the process by which data is separated from their original context, reorganised and prepared for reuse within an AI system.

This understanding is central to the context of the discussions in this research report as curatorial decisions influence whose experiences become visible in data, how individuals and communities are classified, and which forms of knowledge are retained or excluded.[22] Where data is generated and curated within social and institutional conditions marked by structural gender inequalities, those inequalities may shape the composition, interpretation and treatment of the resulting datasets. Understanding data curation, therefore, provides an important analytical lens for identifying how gender bias may enter AI systems before or during model development. It also helps explain the wider implications of such bias for the African AI ecosystem, including the quality and local relevance of datasets, the performance of AI systems, participation in AI development, and the adequacy of existing data and AI governance arrangements.

3.2 Gender Bias and Structural Gender Bias

While the terms are sometimes used interchangeably, this report distinguishes between gender bias as an observable distortion in the operation or outcomes of a technological system and structural gender bias as a form of systemic exclusion embedded in the conditions under which data are produced and curated. Gender bias refers to systematic and unfair differences in the treatment or representation of women and men within technological systems.[23] Within machine-learning systems, such bias may become visible where decisions or outputs disproportionately favour one group because of limitations in the underlying data, system design or methods of analysis.[24]

On the other hand, structural gender bias operates at a more systemic level and arises from historical patterns of domination, exclusion and marginalisation that shape who can generate data, whose experiences are recorded, who participates in curatorial decisions and which forms of knowledge are treated as relevant.[25] scholars further note that, these conditions may be sustained through what is described as onto-norms, which refer to underlying conceptions of reality that determine which identities, forms of knowledge and courses of action are treated as normal or authoritative. Consequently, where women's perspectives are excluded from the design, curation and use of AI systems, they may be represented primarily as sources of data without receiving equivalent recognition as participants in knowledge production and decision-making.[26]

It should be noted that this report uses an analytical perspective, rather than an absolute distinction, to differentiate between gender bias and structural gender bias. These concepts interact throughout the AI lifecycle, for instance, while a gender imbalance in a dataset may be addressed through technical interventions

21 ibid

22 Jerlyn QH Ho and others, 'Gender Biases within Artificial Intelligence and ChatGPT: Evidence, Sources of Biases and Solutions' (2025) 4 Computers in Human Behavior: Artificial Humans 100145, sections 1.1 and 3.1 https://doi.org/10.1016/j.chbah.2025.100145 accessed 3 April 2026.

23 Ho and others (n 22) sections 1.1 and 3.1.

24 Ndaka and others (n 5) 210.

25 Kutoma Wakunuma and others, 'Decoloniality as an Essential Trustworthy AI Requirement' in Damian Okaibedi Eke and others (eds), Trustworthy AI (Palgrave Macmillan 2025) 256 https://doi.org/10.1007/978-3-031-75674-0_12 accessed 3 April 2026.

26 Ndaka and others (n 14) 210.

such as improved sampling, labelling, or model evaluation, addressing structural bias requires broader attention to the institutional and social conditions that produce such imbalances, including unequal digital access, limited participation in data governance, and unequal authority over the definition and use of data.

3.3 How Data Curation Produces Gender Bias in AI

The relationship between gender bias and structural gender bias becomes visible across the stages through which data are selected, classified, labelled, prepared and applied within AI systems.[27] At the point of data selection, curators may rely on historical datasets that reflect the norms, priorities and institutional practices of earlier periods or dominant social groups. Where such data are used without sufficient contextual evaluation, they may reproduce historical gender inequalities and fail to reflect changes in women's participation in areas such as employment, education and public life.

Bias may also enter through annotation and labelling. Annotation involves human judgment in determining how information should be categorised and made comprehensible to an AI model.[28] The social assumptions, cultural perspectives and personal judgments of annotators may influence the labels assigned to people, activities and experiences. Where annotation teams are not sufficiently diverse or are provided with inadequate guidance, gendered stereotypes may be incorporated into datasets and subsequently reproduced through outputs that appear technically neutral.[29] The influence of structural bias persists during data preparation for model training. The composition of development teams, the priorities of the institutions responsible for the system and the categories adopted during curation can determine which experiences are represented and how they are interpreted. Where these processes lack meaningful participation by women and other affected groups, male-centred assumptions about concepts such as leadership, intelligence, work and social responsibility may become embedded in the training pipeline.[30] Women may consequently be treated as sources of information without being accorded comparable authority to define categories, interpret data or determine how the resulting systems should be used.[31]

The consequences of these curatorial choices may become visible when an AI system is implemented. Biased data can contribute to allocation or representational bias where systems associate genders with specific occupations, characteristics or social roles. This is illustrated by automated translation systems that assign masculine terms to occupations such as *doctor* or *engineer*, even where the original language is gender neutral. Notably, allocation bias is not itself a stage of data curation, but it is a downstream consequence that may be traced to the data and classifications through which the system was developed.[32]

27 Ho and others (n 22) section 3.1.3.
28 ibid
29 ibid

30 Ndaka and others (n 14) 209; Ho and others (n 22) section 1.1.
31 Ndaka and others (n 5) 224
32 Ndaka and others (n 14) 215; Orfeas Menis−Mastromichalakis and others, 'Gender Bias in Machine Learning: Insights from Official Labour Statistics and Textual Analysis' (2026) 60 Quality & Quantity 619, 623 https://doi.org/10.1007/s11135-025-0 can recognise,2261-0 accessed 3 April 2026.

4.0

Manifestations of Structural Gender Bias arising from Data Curation Practices in the African AI Ecosystem

The preceding discussion identified the stages at which structural gender bias may enter data curation, including data generation, selection, classification, annotation and preparation for computational use. This section considers how those conditions may become visible when data-driven systems are applied within African contexts. It does not suggest that every AI system produces the same effects or that the examples examined are representative of all African countries. This section focuses on circumstances in which a documented outcome or credible risk may be connected to the representation, classification or treatment of African women within the data used to develop, evaluate or operate an AI system.

Three manifestations are considered, namely, financial exclusion in AI-driven credit scoring, unequal content moderation and its implications for online safety and women's political participation, and exclusion arising from digital-identity and public service systems. Across these areas, the recurring concern is not the existence of gender imbalance in the abstract, but the manner in which pre-existing inequalities may be converted into data features, classifications and evaluation standards. The examples therefore connect curatorial decisions to their potential economic, political, and public-service consequences within the African AI ecosystem.

4.1 Financial Exclusion in AI-Driven Credit Scoring

This manifestation is best explained through gender misrepresentation, noting that gender misrepresentation may arise throughout the data curation lifecycle where women are underrepresented, inaccurately represented or classified through gendered assumptions.[33] When such datasets are used to develop and evaluate AI systems, they may contribute to models that reproduce or amplify existing gender biases. In financial services, structural gender bias may manifest where credit-scoring systems treat characteristics produced by unequal social and economic conditions as neutral indicators of financial risk.[34] A simulation-based audit of credit-scoring models associated with African fintech markets used synthetically matched SME profiles with equivalent financial fundamentals but different gender-associated sectoral, network and leadership characteristics.[35] The study reported a 37.2 percentage point lower approval rate for female coded profiles and identified sector classification, network valuation and linguistic assessment as possible proxy mechanisms through which gendered disadvantage entered the credit-scoring

33 Harini Suresh and John V Guttag, 'A Framework for Understanding Sources of Harm throughout the Machine Learning Life Cycle' (2021) Proceedings of the 1st ACM Conference on Equity and Access in Algorithms, Mechanisms, and Optimization 1–9 https://doi.org/10.1145/3465416.3483305 accessed 25 July 2026; 2026.Joy Buolamwini and Timnit Gebru, 'Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification' (2018) 81 Proceedings of Machine Learning Research 77, 77–78, 81–87 https://proceedings.mlr.press/v81/buolamwini18a.html accessed 24 March 2026

34 Simon Suwanzy Dzreke and Semefa Elikplim Dzreke, 'Double Discrimination: Algorithmic Amplification of Gender Bias in African Fintech Credit Scoring: A 10-Algorithm Audit Reveals 37% Underfunding Penalty against Women-Led SMEs' (2025) 8(1) Advanced Research Journal 58–81 https://doi.org/10.71350/3062192576 accessed 24 March 2026.

35 ibid 73–76.

process.[36] Viewed through a data curation lens, the study's reported findings illustrate how features such as limited access to formal collateral, concentration in particular economic sectors and reliance on community-based financial networks may originate in structural barriers affecting women entrepreneurs.[37] Consequently, when these features are selected, classified and weighted as indicators of risk without considering the social and institutional conditions that produced them, credit-scoring systems may interpret structural disadvantage as evidence of lower creditworthiness. Further, this may result in lower loan approval rates, smaller credit allocations, higher borrowing costs and reduced opportunities for women-led businesses to invest and expand. These outcomes may also reinforce future bias by limiting women entrepreneurs' ability to accumulate assets and develop the formal credit histories represented in subsequent lending datasets.

4.2 Unequal Content Moderation, Online Safety and Women's Political Participation

Structural gender bias within the African AI ecosystem also becomes visible in online spaces, particularly where AI-assisted content moderation systems are developed using data that do not adequately represent African languages, social contexts or gendered forms of abuse. Research by the Association for Progressive Communications found that 28% of women interviewed across Kenya, Senegal, Uganda, South Africa and Ethiopia had experienced online violence, while 95% of online aggressive behaviour was directed at women.[38] These findings describe the wider gendered environment in which automated moderation systems operate. The connection to data curation arises from the fact that the datasets used to train these systems are trained to identify, classify and respond to harmful content.

Automated content moderation depends on datasets that contain sufficiently representative examples of the languages, expressions, and social contexts in which online harm occurs. Where a language or community is insufficiently represented during data collection and curation, a moderation system may be unable to recognise abuse expressed in that language or context.[39] For many African languages, including Swahili, the datasets available for training and evaluating moderation systems remain limited, with some relying substantially on web-scraped or machine-translated content that does not adequately reflect local dialects and code-mixed communication.[40] These limitations affect not only the overall accuracy of content moderation but also the forms of harm that the system can recognise.

The gendered implications arise where training datasets contain insufficient or inadequately classified examples of the coded, contextual and language-specific forms of abuse directed at African women.[41] In such circumstances, the resulting systems may provide unequal protection because the experiences of those affected are not adequately represented within the data used to identify harmful content. Social

36 ibid
37 ibid
38 Neema Iyer, Bonnita Nyamwire and Sandra Nabulega, Alternate Realities, Alternate Internets: African Feminist Research for a Feminist Internet (Pollicy 2020) 22–23 https://ogbv.pollicy.org/report.pdf accessed 15 February 2026.

39 Farhana Shahid, Mona Elswah and Aditya Vashistha, 'Think Outside the Data: Colonial Biases and Systemic Issues in Automated Moderation Pipelines for Low-Resource Languages' (2025) 8(3) Proceedings of the AAAI/ACM Conference on AI, Ethics and Society 2331, 2333–2338 https://doi.org/10.1609/aies.v8i3.36719 accessed 3 April 2026.
40 ibid 2333–2338.
41 Mona Elswah, Aliya Bhatia and Dhanaraj Thakur, Content Moderation in the Global South: A Comparative Study of Four Low-Resource Languages (Center for Democracy & Technology 2025) https://cdt.org/insights/content-moderation-in-the-global-south-a-comparative-study-of-four-low-resource-languages/ accessed 3 April 2026.

media users in the Global South have raised concerns regarding the spread of hate speech and harassment, together with the inconsistent moderation of such content.[42] While companies increasingly deploy language models to support content moderation, limited data for low-resource languages and the models' reliance on English language associations can restrict their ability to moderate content across different linguistic contexts.[43] Within the African AI ecosystem, this constitutes a manifestation of structural gender bias where unequal representation in language and moderation datasets affects whose experiences of harm are identified and addressed.[44]

These limitations also have implications for women's political participation and safety online. Deepfake technologies and other AI-enabled tools may be used to produce or circulate gendered disinformation, harassment and other forms of technology-facilitated violence. During Kenya's 2022 general elections, more than half of the women surveyed experienced technology-facilitated gender-based violence, including hate speech, disinformation and sexual harassment.[45] The Inter-Parliamentary Union similarly reported that 46% of women parliamentarians surveyed in Africa had experienced attacks, while research concerning women journalists indicates that 73% had experienced online violence in the course of their work, contributing in some cases to withdrawal from public conversations.[46] These findings do not establish that AI systems caused the documented harms; however, they demonstrate the pre-existing gendered conditions into which such systems are introduced and the consequences that may arise when AI-assisted detection and moderation tools are not equipped to recognise the languages, contexts and forms through which those harms are expressed.

4.3 Public Service and Digital Identity Exclusion

Structural gender bias within the African AI ecosystem may become visible where systems used to identify individuals or mediate access to public services are developed from data that do not adequately represent the populations they serve. Automated facial analysis and facial-recognition systems provide one example, as available evidence has documented racial and gender disparities in their performance, with particular implications for darker-skinned women.[47] Buolamwini and Gebru's evaluation of three commercial gender classification systems

42 Gabriel Nicholas and Aliya Bhatia, 'Toward Better Automated Content Moderation in Low-Resource Languages' (2023) 2(1) Journal of Online Trust and Safety https://doi.org/10.54501/jots.v2i1.150 accessed 25 July 2026.
43 Shahid, Elswah and Vashistha (n 39) 2333–2338; Nicholas and Bhatia (n 42) 2–4.
44 Shahid, Elswah and Vashistha (n 39) 2333–2338; Nicholas and Bhatia (n 41) 2–4.

45 Arthur Kakande and others, A Report on Online Violence against Women in the 2022 Kenya General Election (Pollicy 2023) 23–24 https://pollicy.org/wp-content/uploads/2023/05/Byte_Bullies_report.pdf accessed 15 February 2026.
46 Inter-Parliamentary Union and African Parliamentary Union, Sexism, Harassment and Violence against Women in Parliaments in Africa (Issue Brief 2021) https://www.ipu.org/resources/publications/issue-briefs/2021-11/s,,exism-harassment-and-violence-against-women-in-parliaments-in-africa accessed 25 July 2026; Julie Posetti and others, The Chilling: Global Trends in Online Violence against Women Journalists (UNESCO 2021) https://unesdoc.unesco.org/ark:/48223/pf0000377223 accessed 3 April 2026.
47 Amnesty International Canada, 'Racial Bias in Facial Recognition Algorithms' (21 March 2023) accessed 25 July 2026.

found error rates of up to 34.7 per cent for darker-skinned women, compared with a maximum error rate of 0.8 per cent for lighter-skinned men.[48] Their study also found that the facial-analysis benchmark datasets examined were overwhelmingly composed of lighter-skinned subjects, illustrating how imbalances introduced during dataset collection and curation can contribute to uneven system performance.[49]

The consequences of these representational disparities may extend beyond errors in classification. In the law-enforcement context, the reliance placed on an incorrect facial-recognition match contributed to the documented wrongful arrest of a Black woman in the United States.[50] While this case did not occur in Africa, it demonstrates how limitations originating in facial-image datasets and recognition systems may produce significant legal and social consequences when their outputs are relied upon in consequential decision-making.

Within the African context, these concerns are illustrated by their intersection with existing inequalities in access to legal and digital identity. Nearly 500 million people in Sub-Saharan Africa lack foundational legal identification. Because many digital-ID systems depend upon an existing foundational identity, their introduction may reproduce or deepen established identification gaps.[51] Limited internet coverage, the cost of connectivity and low levels of digital literacy may create further barriers for women, refugees, internally displaced persons, persons with disabilities and other marginalised groups.[52] These conditions are especially consequential where biometric digital-ID systems are made a condition for accessing services and rights, including healthcare, education, social-protection payments and voting.[53] Evidence from ten African countries indicates that disability, illiteracy, registration costs and limited access to the necessary infrastructure can prevent already marginalised groups from enrolling in or using biometric identification systems.[54]

Facial recognition is not the only biometric technology employed in digital ID systems, and exclusion cannot therefore be attributed to facial image datasets alone. Nevertheless, concerns about demographic performance disparities remain relevant where facial recognition is used for enrolment, verification or authentication.[55] In South Africa, for example, analysis of biometric identification and digital payments has cautioned that facial-recognition bias affecting darker skin tones may result in the exclusion or misidentification of Black users, alongside broader barriers arising from connectivity and affordability.[56]

Gender disparities may also arise before biometric matching occurs, through unequal access to identity registration. In Nigeria, a 2021 ID4Africa discussion reported that eight million fewer women than men held a National

48 Buolamwini and Gebru (n 33) 81–87.
49 ibid
50 American Civil Liberties Union, 'Woodruff v Oliver' (5 December 2024) https://www.aclu.org/cases/woodruff-v-oliver accessed 7 April 2026.
51 Melody Musoni, Ennatu Domingo and Elvis Ogah, Digital ID Systems in Africa: Challenges, Risks and Opportunities (Discussion Paper No 360, ECDPM 2023) 1, 6 https://ecdpm.org/application/files/5517/0254/4789/Digital-ID-Systems-in-Africa-ECDPM-Discussion-Paper-360-2023.pdf accessed 7 April 2026.
52 ibid
53 Gbenga Sesan and Tony Roberts (eds), Biometric Digital-ID in Africa: Progress and Challenges to Date: Ten Country Case Studies (Institute of Development Studies 2025) https://doi.org/10.19088/IDS.2025.051 accessed 7 April 2026.
54 ibid
55 Ajen Sita, 'Biometrics and the Future of Payments in South Africa' (EY, 24 October 2025) https://www.ey.com/en_za/insights/technology/biometrics-and-the-future-of-payments-in-south-africa accessed 7 April 2026.
56 ibid

Identification Number.[57] World Bank research further identified gender specific registration barriers, including household and childcare responsibilities, the need for permission to enrol in some circumstances, and greater difficulty obtaining supporting documents. These barriers were compounded by travel costs, distance to registration centres, long waiting times and informal fees.[58]

Considered through the report's data curation framework, these patterns demonstrate how structural gender bias can operate at two interconnected levels. First, inadequate demographic representation in the datasets used to develop and evaluate biometric systems may contribute to uneven technical performance. Second, where women encounter barriers to registration or authentication, their experiences may be less visible in administrative datasets that are subsequently used to design, assess, and deliver data-driven public services. This may create a reinforcing pattern in which existing inequalities shape both the data available to public institutions and the operation of the systems developed from those data. The concern is therefore not that every digital-ID system necessarily produces gender discrimination, but that dataset composition, biometric-system design and unequal conditions of access may interact in ways that reproduce structural gender inequality.

The highlighted manifestations demonstrate that structural gender bias does not arise from a single technical failure or produce a uniform consequence. Across credit scoring, content moderation and digital identity, the recurring pathway is that unequal access, incomplete representation, context-poor classification and other curatorial choices may translate existing inequalities into the data used to allocate credit, recognise harmful content or verify identity. The examples also demonstrate why technical correction alone may be insufficient where the underlying data gaps arise from broader institutional and social conditions. The resulting question this report therefore identifies as a focus area is one of governance, specifically, whether the continental frameworks on AI and data establish sufficiently clear standards, oversight mechanisms and remedies to identify and address these risks throughout the data and AI lifecycle. The following section examines how the principal continental AI and data governance instruments address that question.

5.0

Continental AI and Data Governance Frameworks

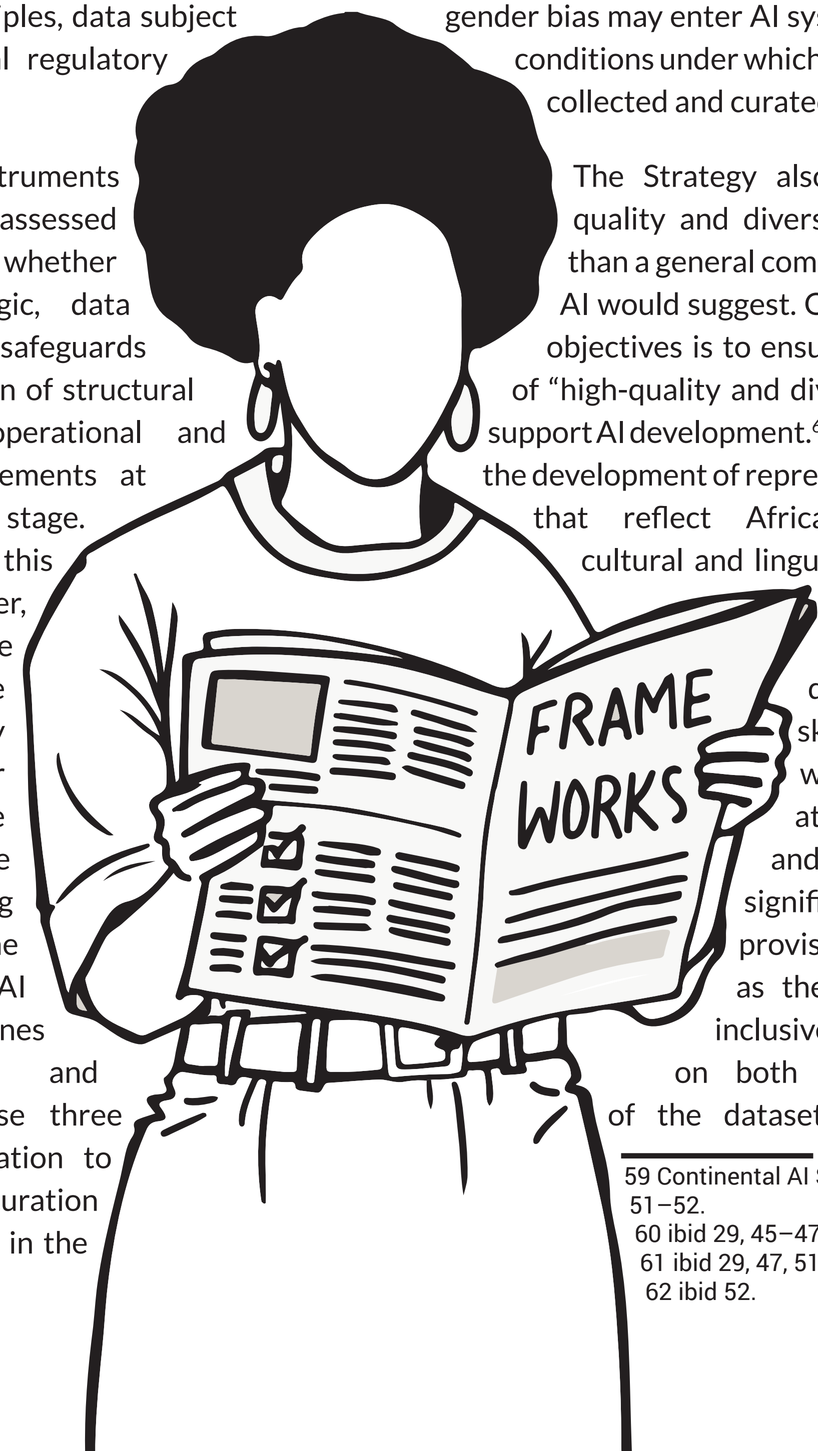
The preceding discussion identifies how data quality, dataset representativeness, and gender accountability emerge through data curation processes as governance concerns that can shape how AI systems allocate opportunities, determine outcomes, and influence access to resources and services. The analysis therefore turns to the continental governance architecture within which these concerns may be addressed. Three instruments are examined because they regulate complementary layers

57 Javad Jarrahi, 'Massive Gender Disparities in Digital ID Systems Persist, ID4Africa Panel Says' Biometric Update (12 March 2021) https://www.biometricupdate.com/202103/massive-gender-disparities-in-digital-id-systems-persist-id4africa-panel-says accessed 8 April 2026.

58 World Bank, Barriers to the Inclusion of Women and Marginalized Groups in Nigeria's ID System: Findings and Solutions from an In-Depth Qualitative Study (World Bank 2021) https://documents.worldbank.org/en/publication/documents-reports/documentdetail/881401618990982108 accessed 8 April 2026.

of that architecture. The Continental Artificial Intelligence Strategy provides the principal AI-specific policy direction on datasets, inclusion, impact assessment and oversight. The AU Data Policy Framework addresses the wider conditions governing the production, use and governance of data, including representativity, non-discrimination and data justice. The African Union Convention on Cyber Security and Personal Data Protection, commonly referred to as the Malabo Convention, provides the binding legal framework for states parties through personal data principles, data subject rights, and national regulatory authorities.

The identified instruments are therefore assessed to examine whether continental strategic, data policy and legal safeguards translate recognition of structural inequality into operational and enforceable requirements at the data curation stage. The discussions in this section, however, do not constitute a comprehensive review of every African AI or data governance instrument but the select key anchoring instruments in the African data and AI ecosystem. It examines the contribution and limitations of these three frameworks in relation to the specific data curation pathways identified in the report.



5.1 African Union Continental Artificial Intelligence Strategy

The Continental AI Strategy recognises the relationship between AI data, gender inequality, and discriminatory outcomes. It identifies bias arising from the collection and use of training data as a risk that may result in discrimination against women and other vulnerable groups.[59] It further recognises that AI systems can reproduce bias where data is sourced inequitably or where development teams are insufficiently diverse.[60] These observations align with this finding that gender bias may enter AI systems through the conditions under which data is generated, collected and curated.

The Strategy also addresses data quality and diversity more directly than a general commitment to ethical AI would suggest. One of its strategic objectives is to ensure the availability of "high-quality and diverse datasets" to support AI development.[61] It further calls for the development of representative datasets that reflect Africa's demographic, cultural and linguistic diversity and emphasises the need to promote diversity in AI skills and talent, with particular attention to women and girls.[62] The significance of these provisions is noted, as they recognise that inclusive AI depends on both the composition of the datasets used and the

59 Continental AI Strategy, (n1) 4, 26, 51–52.
60 ibid 29, 45–47.
61 ibid 29, 47, 51–52.
62 ibid 52.

participation of women in the institutions and teams responsible for developing AI systems.

Further, the Strategy includes measures for accountability across the AI lifecycle. It recommends the adoption of governance mechanisms that respect diversity and gender equality through ex ante and ex post impact assessments intended to identify, measure and mitigate bias and discrimination [63] and additionally calls on member states to establish independent institutions capable of overseeing the use of AI, enforcing emerging standards and providing access to redress where violations occur.[64] The Strategy therefore does not merely recognise gender equality at the level of principle but identifies impact assessment, independent oversight and redress as components of responsible AI governance.

The limitation of the strategy, however, lies in the level of operational detail and the legal status of these commitments. The Strategy does not define the methodology, minimum indicators or evidentiary thresholds that should govern its proposed impact assessments. It does not specify how gendered effects should be identified, whether assessments must use gender-disaggregated data, or what degree of demographic underrepresentation would require altering or withdrawing an AI system. Similarly, its requirement for high-quality and diverse datasets is not accompanied by standards for measuring dataset quality, representativeness or relevance within sectors.

The Strategy's implementation framework also remains dependent on subsequent action by the African Union, regional institutions and member states. It envisages the development of an African AI readiness index, a monitoring and evaluation portal and a further normative governance framework to guide implementation.[65] These are important institutional measures, but their future-oriented character confirms that several of the mechanisms required to monitor compliance are still to be developed. Accordingly, the Strategy establishes a strong normative and policy basis for gender-responsive AI governance. Still, it does not itself create binding or directly enforceable standards for dataset representativeness, gender-disaggregated testing or gender impact assessment.

5.2 African Union Data Policy Framework

The AU Data Policy Framework approaches the issue from the broader perspective of data governance. Its principal contribution is its recognition that the value and fairness of data-driven systems depend on data quality, representativeness and non-discrimination.[66] The Framework expressly identifies quality, integrity, representativeness and non-discrimination among its guiding principles.[67] Its principle of fairness and inclusiveness requires member states to ensure that the Framework benefits all Africans and responds to the voices of persons marginalised by technological development. The related principle of integrity and justice requires data collection, processing and use to be lawful and just and prohibits the unfairly discriminatory use of data.[68]

The Framework also recognises the specific problem examined in this report. In its assessment of the African data ecosystem, it identifies discriminatory automated decision-making as a risk arising from the invisibility or

63 ibid 34.
64 ibid 61.

65 ibid 60–64.
66 African Union Commission, AU Data Policy Framework (African Union 2022) vi, 19 https://au.int/sites/default/files/documents/42078-doc-DATA-POLICY-FRAMEWORKS-2024-ENG-V2.pdf accessed 7 July 2026.
67 ibid 19.
68 Ibid

underrepresentation of certain categories of people in datasets, as well as from shortcomings in algorithmic modelling.[69] Its discussion of data justice similarly considers whether individuals and communities are visible, represented or underrepresented in data and whether reliance on data in automated decision-making perpetuates historical injustice and structural inequality.[70] Notably, this closely aligns with the report's argument that the underrepresentation of African women in digital and administrative datasets is not merely a statistical limitation but a governance concern that can produce discriminatory outcomes.

The Framework further recommends several measures relevant to data quality and accountability. It calls for integrated national data systems governed by principles that include quality and integrity, encourages the development of sector-specific data codes and guidelines, and promotes the establishment of independent and adequately resourced data protection authorities.[71]It also recommends that member states require impact assessments for high-risk data processing activities and emerging technologies and recognises regulatory impact assessments, ethical frameworks and sectoral regulation as possible governance tools.[72] The provisions as outlined provide a foundation upon which more specific gender responsive data governance measures could be developed; a notable limitation within both the AI and data governance ecosystem in addressing gendered perspectives.

However, the Framework does not consistently translate its recognition of underrepresentation into gender specific operational requirements. Although it identifies representativity and non-discrimination as principles, it does not require gender-disaggregated data collection, establish demographic representativeness thresholds, or prescribe procedures for testing whether datasets adequately capture women's experiences. Its references to impact assessment similarly do not establish a distinct gender impact assessment or specify how gendered and intersectional harms should be assessed before an AI system is deployed.

This limitation reflects the Framework's scope and function as a principle-based instrument intended to guide domestication by Member States, rather than operate as a directly applicable regulatory regime. Its broad focus on the data economy means that it does not establish detailed sector-specific requirements for every use of data or emerging technology. While the Framework recognises discriminatory automated decision-making and underrepresentation as risks, it provides limited guidance on how to assess and address these risks in practice. It therefore provides a continental basis for considering data justice and representativeness, while leaving national legislation, sectoral codes and regulatory standards to translate these principles into operational and enforceable gender responsive obligations.

5.3 Malabo Convention

The Malabo Convention differs from the two policy instruments because it establishes binding legal obligations for states that have ratified or acceded to it. Adopted on 27 June 2014, the Convention entered into force on 8 June 2023 following the deposit of the fifteenth instrument of ratification.[73] As of 2 February 2026, 20 of the

69 ibid 13.
70 ibid 29.
71 ibid ix–x, 51.
72 ibid 36, 51.

73 African Union, African Union Convention on Cyber Security and Personal Data Protection (adopted 27 June 2014, entered into force 8 June 2023) art 36 https://au.int/

African Union's 55 member states had ratified or acceded to the Convention and deposited the relevant instruments.[74] Its continental application is therefore not uniform.

The national data protection landscape is nevertheless broader than the Convention's ratification record. The African Commission on Human and Peoples' Rights reported that 39 African states had enacted data protection laws and 34 had established regulatory authorities to oversee compliance.[75] Regulations, regulatory guidance and sector-specific instruments also supplement some national regimes. These national frameworks may give effect to principles comparable to those contained in the Convention or provide additional safeguards relevant to data quality, automated decision-making, biometric processing and regulatory oversight. They are not examined individually in this report, and the assessment of the Malabo Convention should not therefore be interpreted as an assessment of the protections available under every national legal framework.

Within this defined scope, the Convention applies to automated and non-automated processing of personal data and may extend to AI systems where their development or operation involves such data.[76] It establishes safeguards relevant to data quality, biometric processing, automated decision-making, and regulatory enforcement, although these safeguards were not specifically framed around AI, data curation, or structural gender bias.

Article 13 requires personal data to be processed lawfully and fairly and establishes an accuracy principle under which personal data must be accurate, kept up to date where necessary, and erased or rectified where it is inaccurate or incomplete.[77] As a legally significant data quality obligation, the provision can protect women where discriminatory outcomes arise from inaccurate or incomplete personal information. The Convention further requires prior authorisation from national data protection authorities for certain sensitive forms of processing, including biometric data and data used in national identification systems.[78] The provision lends itself to the identified discussion on facial recognition and digital identity systems.

The Convention also provides a notable safeguard against solely automated decision-making under Article 15, which provides that a person should not be subject to a decision that produces legal effects or substantially affects them where the decision is based solely on automated processing intended to evaluate personal aspects.[79] The Convention additionally provides rights of access, objection, rectification and erasure, which may enable individuals to identify and challenge the personal data underlying an adverse decision.[80]

Institutionally, the Convention requires each state party to establish an independent national data protection authority. These authorities are empowered to receive complaints, audit personal data processing, issue warnings, withdraw

sites/default/files/treaties/29560-treaty-0048_-_african_union_convention_on_cyber_security_and_personal_data_protection_e. pdf accessed 7 July 2026.

74 African Union, List of Countries Which Have Signed, Ratified or Acceded to the African Union Convention on Cyber Security and Personal Data Protection (status as of 2 February 2026) https://au.int/sites/default/files/treaties/29560-sl-AFRICAN_UNION_CONVENTION_ON_CYBER_SECURITY_AND_PERSONAL_DATA_PROTECTION_0.pdf accessed 25 July 2026.

75 African Commission on Human and Peoples' Rights, 58th and 59th Combined Activity Reports (EX.CL/1659(XLVIII), 2026) 31 https://achpr.au.int/sites/default/files/files/2026-03/ex-cl-1659-xlviiieng.pdf accessed 7 July 2026.

76 African Union Convention (n 74) art 9.

77 ibid art 13.

78 ibid art 10(4)(c)–(d).

79 ibid art 14(5).

80 ibid arts 17–19.

authorisations, impose monetary penalties and order the suspension or prohibition of unlawful processing.[81] These provisions establish both an oversight body and a pathway through which individuals may seek regulatory intervention, with decisions and sanctions imposed by the authorities also subject to appeal.[82] The Convention therefore provides more extensive enforcement and remedial mechanisms than the two continental policy instruments.

Its limitations arise primarily from its personal data focus and the absence of AI-specific and gender responsive requirements. The accuracy principle concerns whether personal data is factually accurate and complete. It does not necessarily address whether a dataset is demographically representative of the population on which an AI system will be used. A dataset may contain accurate information about each person included in it while still underrepresenting African women as a group. The Convention does not expressly require gender disaggregated testing, dataset documentation, assessments of sampling bias or continuous monitoring of AI systems for disparate gender effects.

Similarly, although the restriction on solely automated decision-making provides an important safeguard, its scope is limited to decisions based solely on automated processing that produce legal effects or substantially affect an individual. It does not comprehensively address AI-assisted decisions involving nominal human participation or systems whose harmful effects emerge cumulatively across groups rather than through a single legally significant decision. The Convention's individual rights and complaints mechanisms may therefore provide remedies in particular cases without necessarily addressing structural patterns of gender underrepresentation within AI datasets.

Its continental effect is further limited by uneven ratification and domestic implementation. Its obligations apply directly to state parties rather than uniformly across all African states. The existence of binding provisions at the continental level must therefore be distinguished from their effective availability within each national jurisdiction.

5.4 Overall Finding[83]

The three instruments make distinct contributions to gender responsive AI and data governance. The Continental AI Strategy most directly recognises gender inequality within AI development and expressly recommends diverse datasets, impact assessments, independent oversight and access to redress. Its principal limitation is that these measures remain high-level policy recommendations without detailed compliance standards. The AU Data Policy Framework provides a broader data justice foundation and directly identifies underrepresentation in datasets as a cause of discriminatory automated decision-making. However, it does not convert this analysis into gender specific requirements governing data collection, curation and testing. The Malabo Convention supplies the binding legal layer through principles of data accuracy and fairness, restrictions on solely automated decision-making, data subject rights and regulatory enforcement. Its protections are nevertheless centred on personal data and individual rights and do not comprehensively address demographic representativeness or collective and structural gender bias.

81 ibid arts 11–12.
82 ibid art 12(2)– (6).

83 These findings relate to the content of the three continental instruments and do not establish that comparable or more detailed safeguards are absent from national legislation, regulations or regulatory guidance.

6.0

Observable Policy and Governance Considerations

The analysis of the manifestations of structural gender bias and the governance instruments gives rise to several policy and governance considerations. These considerations do not suggest that gender equality, data quality, representativity or accountability are absent from the continental framework. They, however, relate to areas in which the instruments examined do not establish common operational requirements for addressing structural gender bias at the data curation stage. Their relevance and application may vary according to national legal frameworks, sectoral conditions and the evidence available within contexts.

A. Operational Criteria for Dataset Representativeness

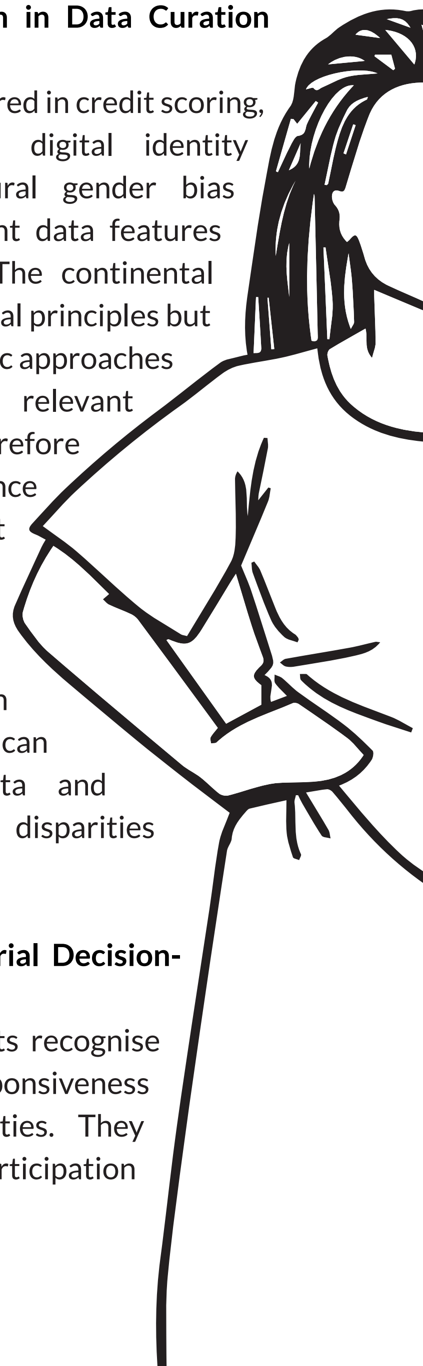
The Continental AI Strategy and AU Data Policy Framework recognise the importance of diverse, representative and locally relevant datasets. However, the instruments do not establish common criteria for assessing or documenting demographic composition, dataset provenance, known representation gaps and contextual limitations. This raises a policy consideration concerning how representativeness may be evaluated in relation to the purpose of a dataset, the population affected and the context in which an AI system is intended to operate.

B. Gender-Responsive Methodologies for Impact Assessment

The Continental AI Strategy already provides for impact assessments before and after the deployment of an AI system to identify, measure, mitigate and address adverse effects on women and other affected groups. The observable concern is therefore neither the recognition nor the introduction of impact assessment, but the methodology through which gendered effects would be examined. The instruments do not specify gender-disaggregated indicators, approaches for identifying intersectional effects or the circumstances in which identified disparities would require further review, modification or discontinuation of a system.

C. Sectoral Differentiation in Data Curation Governance

The manifestations considered in credit scoring, content moderation and digital identity demonstrate that structural gender bias may arise through different data features and curatorial practices. The continental instruments establish general principles but do not set out sector-specific approaches to these differences. A relevant consideration is therefore how data governance arrangements may account for structurally produced financial characteristics used as risk indicators, limited representation of gendered harm in African language moderation data and demographic performance disparities in biometric systems.

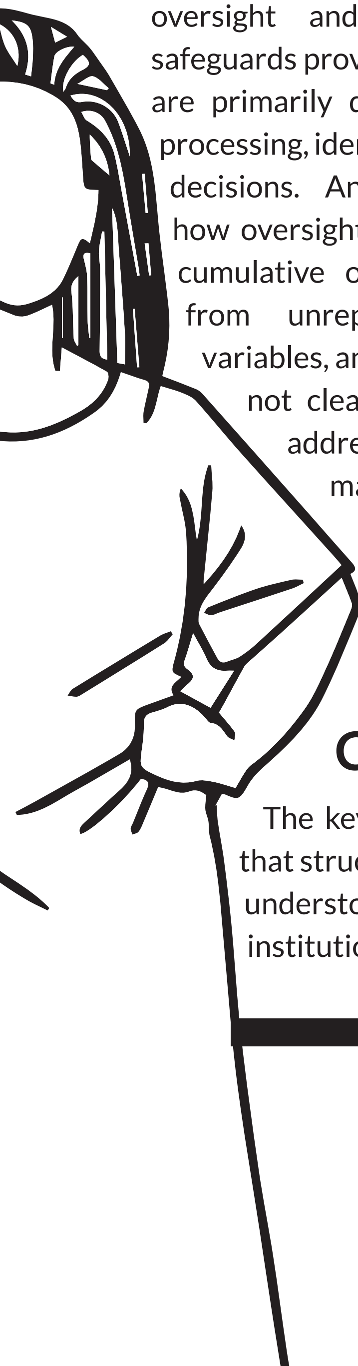


D. Participation in Curatorial Decision-Making

The continental instruments recognise inclusion, diversity and responsiveness to marginalised communities. They provide less detail on participation in the specific decisions through which datasets are designed, classified, annotated and evaluated. This raises a governance consideration concerning how the knowledge and experiences of African women and other affected communities may inform the categories, contextual judgments and evaluation standards applied during data curation.

E. Regulatory Treatment of Structural and Cumulative Effects

The Malabo Convention provides data-subject rights and regulatory remedies, while the Continental AI Strategy recognises independent oversight and access to redress. These safeguards provide an important foundation but are primarily directed towards personal-data processing, identifiable violations and particular decisions. An observable consideration is how oversight arrangements may respond to cumulative or group-level patterns arising from unrepresentative datasets, proxy variables, and AI-assisted decisions that may not clearly fall within protections that address only automated decision-making.



7.0 Conclusion

The key consideration in this report is that structural gender bias in AI should be understood in relation to the social and institutional conditions within which data are generated, curated and governed. Decisions concerning access, selection, classification, annotation and computational reuse determine whose experiences become visible and how those experiences are interpreted within an AI system. The manifestations considered in credit scoring, content moderation and digital identity show that the consequences may differ across sectors but share a recurring pathway through which existing inequalities may become represented as apparently neutral data characteristics or technical outcomes.

The Continental Artificial Intelligence Strategy, AU Data Policy Framework and Malabo Convention provide a significant foundation for responding to these concerns. Their contribution is nevertheless limited by the incomplete translation of their principles into harmonised, measurable and enforceable requirements for gender-responsive data curation.

The analysis consequently points to five areas requiring further policy and governance consideration: dataset documentation and representativeness, the gender-responsive application of impact assessments, sector-specific safeguards, participation in data curation decisions, and oversight and remedy for structural patterns of harm. The objective is not demographic balance in the abstract, but an African AI ecosystem in which the conditions that shape data are made visible and African women participate meaningfully in defining, governing and challenging the systems developed from those data.

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