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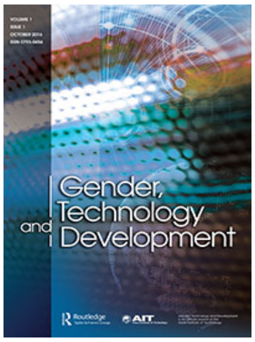

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Data science for empowerment: understanding the data science training landscape for women and girls in Africa

Claire Babirye[a], Chisenga Muyoya[b], Suvodeep Mazumdar[c], Andrea Jimenez[c], Ciira Maina[d], Jabhera Matogoro[e], Margaret Nyambura Ndung'u[f] and Dorothea Kleine[b]

[a]Artificial Intelligence Lab, Makerere University, Kampala, Uganda; [b]Department of Geography, University of Sheffield, Sheffield, UK; [c]Information School, University of Sheffield, Sheffield, UK; [d]Centre for Data Science and Artificial Intelligence, Dedan Kimathi University of Technology, Nyeri, Kenya; [e]Department of Computer Science and Engineering, The University of Dodoma, Dodoma, Tanzania; [f]International Institute of Information Technology, Kenya

ABSTRACT

The increasing datafication of African societies has led to a proliferation of data science-related training opportunities. These trainings provide young people with the opportunity to learn the skills to work on Data science, with some focused specifically on women and girls. While this is encouraging and brings new opportunities for women and girls to participate in the knowledge economy, it is important to understand the wider context of data science training in Africa, in particular, how women and girls experience their (data science) education, and how this knowledge can impact their lives, sustain livelihoods and bring empowerment. Through a review of the literature, as well as an examination of different pedagogical approaches and practices used by various formal and informal training programs in Africa, we examined the experience of women and girls. We conducted a mapping of the training and networks that have been set up to provide knowledge and skills and to empower women in data science. We highlight some of the facilitators that have positively contributed to a greater participation of women and girls in data science education, while also revealing some of the barriers and structural impediments to fair access to training for women in data science.

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Data science education; data science training; Africa; data science for women; empowerment

Introduction

Over the last three decades, the increasing penetration of ICTs across the African continent has led to a shift in the uptake and impact of ICT solutions, leading to transformational effects on societies and economies (Ponelis & Holmner, 2015). Within this ICT domain, data science tools have been shown to, in some cases, improve the

CONTACT Suvodeep Mazumdar s.mazumdar@sheffield.ac.uk Information School, University of Sheffield, Sheffield, UK

performance of businesses across sectors such as banking, agriculture, trade, telecommunications, health via data-driven decision making (Hersh, 2000; Provost & Fawcett, 2013). Much of this is evidenced in several application domains, such as the telecom industry, where data science has been used to predict non-payments (Yigzaw et al., 2010); in the banking sector, where data and AI-related innovation are applied to fintech and insurance (Adams et al., 2020); in the agricultural sector, data science has been used in real-time surveillance of crop diseases and for automated diagnosis of crops (Aduwo et al., 2010).[1] The use of wider access to telephone and internet services to enable networking and communication, improvements in social services and social inclusion, has been documented (Milek et al., 2011).

When used appropriately, ICTs can sometimes provide solutions to address issues faced by marginalized communities such as people with disabilities, the elderly and women (Al Dahdah, 2017; Ekdahl & Trojer, 2002; Guney-Frahm, 2018; Marcelle, 2004; Obayelu & Ogunlade, 2006; Trafford, 2021). ICT offers many opportunities for women and girls to gain the education and technical skills required for them to participate equally in the knowledge economy (Alha & Gibson, 2003; Tchombe, 2008). It is argued that ICTs can "provide diverse avenues for women's social, political and economic empowerment" (Marcelle, 2004; UNDAW & ITU, 2002, p. 3). Agenda 2063[2] Goal 17 (of full gender equality in all spheres of life), and the UN Sustainable Development Goal 5 (of Gender Equality)—highlight the significance of gender equality in all aspects of life. The importance of technology as a key enabler for attaining these development goals is also further recognized through high level documents such as the AU's Science, Technology and Innovation Strategy for Africa 2024, where developing a robust STEM workforce is critical to achieving these visions (Mare, 2021). There is evidence to suggest that ICT can therefore be a tool to promote gender equality and enhance women's empowerment (Anand, 2002; Guney-Frahm, 2018; Masika & Bailur, 2015; Obayelu & Ogunlade, 2006; Secretariat, 2002; Umukoro et al., 2020; Gurumurthy & Chami, 2014).

However, in spite of the clear need for the participation of women in ICT and STEM, many studies have identified lack of access to ICT as a key element in women's marginalization (Sey & Hafkin, 2019). With technologies and services becoming more sophisticated and expensive, and the need for greater levels of income and education, women's access to ICTs is increasingly challenged (Deen-Swarray et al., 2012). Women are widely under-represented in this field across the globe—only 30% of female students pursue STEM-related higher education studies (Ismail, 2018; Chavatzia, 2017). Only an estimated 30% of ICT workers in Europe are women, while creating only an estimated 9% of ICT applications (Mare, 2021). The broader picture of gender gaps in ICT access is however more complex, with limited internationally comparable sex-disaggregated official data, and, often, issues being framed in binary (male/female) terms (Sey & Hafkin, 2019, Brimacombe & Skuse, 2013). It is also important to note that affordance of ICT itself is insufficient for empowerment and that empowerment is a relative, and ongoing process (Bailur & Masiero, 2017). The mismatch in participation and access to ICT, also evident in Africa, can be attributed to some of the direct unfavorable conditions in relation to employment, education and income (Best & Maier, 2007), and once these variables are controlled, women can become the most active users of the digital tools (Hilbert, 2011; Ono & Zavodny, 2003; Tafnout & Timjerdine, 2009).

There is a high level of diversity (Gwagwa, 2020) and impact (Marivate & Moorosi, 2018) of AI deployment in Africa, despite a wide range of factors currently limiting the participation of women in data science. These factors impact negatively—both on the intrinsic right of women to shape digital futures and instrumentally, the limited participation of women has negative consequences for societies as a whole. For instance, economic development is impacted negatively (Ekine et al., 2013) and yet building on the potential of both men and women is vital in meeting the developmental needs of countries, and ensuring their competitiveness in the global economy (Gillwald et al., 2010; Milek et al., 2011).

While women in STEM earn more compared to women in non-STEM jobs (Beede et al., 2011), it is reported that fewer women participate in science education, and therefore have limited access to jobs in these fields (Mottin-Sylla, 2005). A girl who is 15 years old is two times less likely to aspire to a career as an engineer, a scientist or an architect and even when they successfully complete studies in any STEM field, they face a "glass-ceiling" preventing them from holding senior positions (Mishra, 2017).

As a part of understanding the data science landscape, the data science and AI theme of the GeDIA project (https://gedia-network.org/) seeks to explore how data science and ICT provides opportunities for women to affect change in their social contexts. The project comprises 13 partners, including 4 universities in Africa, an African women in STEM network and a social enterprise focused on digital training. Our subgroup specialized in the aspect of women in IT and Data Science training and careers. This paper is based on our group deliberations and a literature review we conducted to inform our joint research agenda development.

In understanding how data science is shaping the lives of women, we seek to explore how data scientists (and, by extension, ICT professionals) are being trained (*pedagogical approaches*). We also explore some of the barriers and *structural impediments* to fair access to training for women in ICT and data science. Our research questions, therefore, are "What data science training opportunities are available in Africa for women and girls?" and "To what extent do these trainings provide opportunities for empowerment for women in Africa?"

We take inspiration from Naila Kabeer's (1999) women's empowerment framework, which depicts empowerment as a dynamic process of change in which women's ability to make strategic choices grows, giving them the option to articulate preferences and the agency to make decisions in order to achieve their own goals. The framework consists of three inter-related dimensions: *resources*, which includes "the various human and social resources which serve to enhance the ability to exercise choice" (p. 437) and are the pre-conditions for empowerment; *agency*, as "the ability to define one's goals and act upon them" (p. 438) and refers to the process for empowerment; and *achievements*, as the outcomes of empowerment. Further applications of this framework have extended this to consider the relevance of context (i.e., individual, household, community) and holistic approaches to empowerment, where women are engaged in identifying their own experiences of empowerment/disempowerment (Gressel et al., 2020). The paper is outlined as follows: in the next section, we initially describe the collaborative process of developing our research agenda and conducting a literature review. We then provide a description of the different pedagogical approaches employed in ICT and data science training in Africa. In "Data science training" section, we discuss the range of data science training opportunities available in different regions in Africa. We then discuss the barriers to fair access for women in ICT and data science ("Barriers, structural impediments to fair access for women in ICT and data science" section). We discuss these findings around the positive and negative factors that impact upon the participation of women and girls in ICT and data science ("Discussions—Understanding barriers and pedagogy" section) before concluding the paper and outlining our future work ("Conclusions and future work" section).

Methodology

The GeDIA project is aimed at uniting women change-makers and their male allies to ensure women can engage in shaping Africa's digital futures. As such, through peer-learning and knowledge sharing among project partners, we co-developed a research agenda, of which the data science pillar is one of three. The data science theme aims to understand how digital technologies, data science and artificial intelligence shape women change-makers and are, in turn, shaped by them. We organized a series of four one-hour online synchronous co-design workshops (21 July 2020, 23 July 2020, 17 September 2020, 25 September 2020), where collaborators (here, authors of this paper and other project members) shared their experiences of being data science educators or ICT professionals. Our reflections centered around how it was to be a researcher, professional or teacher in the data science and ICT training landscape, sharing some of the issues around participation and engagement of women and girls in ICT and data science training. Conversations also covered the need to highlight positive cases of capacity building centered around women. The co-design process was facilitated with the use of Google Jamboard and shared Google docs.

Following the first workshop, the authors agreed on the different themes that are critical to understanding the role of data science in the lives of women and girls and how data science can support women in shaping their digital futures. Once these topics were agreed, over the next few workshops, we discussed the gaps in knowledge that the team could study in more detail. Investigating the breadth of barriers and facilitators for women in data science emerged as an important first step. The knowledge gaps identified by the group that needed further exploration were primarily around the following themes:

- pedagogical approaches, tools and practices used in data science training for women in Africa;
- the role of data science knowledge for empowerment, dignity and social inclusion;
- specific case studies on women-centric data science training in Africa;
- barriers and structural impediments to fair access for women in data science;
- career outcomes and progression for women in data science.

The group co-design workshops led to a three-month literature review where we analyzed different types of literature including academic books, journal articles, conference proceedings and policy papers. Our aim was to center African scholarship amidst other works on this topic. Recognizing that African Scholars publish in a wide variety of journals (Murray & Clobridge, 2014) and also in other formats, the review included grey literature such as reports, working papers and case studies. The initial co-design reflective workshops, document review, and interviews resulted in a broader understanding of data science training around the identified themes.

The following set of keywords shaped the literature review:

- "data science pedagogy,"
- "data science/ICT training in Africa,"
- "gender and data science education,"
- "gender and capacity building,"
- "data science training experience" and
- "women-centric data science careers in Africa."

The following determined our Inclusion/Exclusion criteria:

- Journals, conference papers, and grey literature from Global North and Global South authors were included in our study.
- Papers on data science, IT, computer science, and ICTs were included as they were often discussed in relation to data science.
- The literature review excluded generic discussions on STEM education as these tended to have a broader focus.

Academic papers were accessed via searching Google Scholar and Scopus search systems, while grey literature were accessed through standard Google search queries. While a systematic review of the literature can offer deep insights into specific topics, we believe an exploratory search was most appropriate at this stage because of three primary reasons: (i) we wanted to be inclusive in our search of the literature to include contributions from African scholars (which are often exhibited in grey literature); (ii) we are currently scoping the data science education landscape to help us develop a research agenda; and (iii) the specific topic is relatively underexplored in only academic literature, and data science in Africa is a topic that is of growing interest. As such, an exploratory literature search was deemed the most appropriate method for this study, while future work will involve conducting participatory research with data science educators. We discuss our findings in the next sections.

Pedagogical approaches, tools, and practices used in ICT and data science trainings in Africa

Addressing gender gaps in technology and data science areas is critical to generating wider long-lasting impacts and hence, it is important to study the contexts in which data science is taught to women in Africa. Pursuing these inquiries around pedagogy can help better understand the wide ranges of methods through which data science training is delivered in Africa. In a future activity, we would like to explore this further, to possibly explain how different pedagogical practices could help alleviate gender gaps in data science. For instance, the GeDIA project worked with the Data Science Africa network to develop a gender equality themed summer school.

Pedagogy, taken as an academic discipline, is the study of how knowledge and skills are imparted in an educational context, and it considers the interactions that take place during learning. Covering the art, science and profession of teaching, it includes the teaching styles and theories used, together with feedback and assessment (Stockard, 2018). Both the theory and practice of pedagogy vary greatly, as they reflect different social, political, and cultural contexts (Stockard, 2018). Teaching methods for computer science education can be applied in the context of specific learning theories (Zendler, 2019). Traditionally, learning theories provide recommendations that are the basis for the development of teaching methods. Today's teaching methods differ from those used in past generations because students have inherited a new social and technological culture (Zendler, 2019). Most learning theories for computer science-related courses such as ICT and Data Science, concentrate primarily on the outcome of learning, demands on didactic design, principle of teaching, role of the teacher and learner, role of the peers, control of the learning path and learning success (Zendler, 2019). In the majority of African classrooms and training, pedagogical approaches have been broadly categorized into two: teacher-centered pedagogy and student-centered pedagogy. In teacher-centered pedagogy, the teachers play an important role in the learning process by providing information to the students. The students are viewed as passive learners in a teacher-centered approach. Student-centered approaches, on the other hand, involve the teachers understanding the needs of the students, as a group and as individuals, and creating opportunities to participate in the learning activities at all times. In this approach the teachers' role is to facilitate not to instruct (Altinyelken, 2010; Dembele, 2005; Emaliana, 2017). While this binary proposition is simplistic, it invites researchers to focus on agency in the classroom.

Learning theories and approaches

Constructivist theory

Constructivist theory in the context of education acknowledges that the teacher is not a transmitter of knowledge but rather a facilitator and provider of experiences from which learners will learn. Similarly, pupils are not absorbers of knowledge but active participants in constructing their own meaning based on strongly held preconceptions (Aldridge et al., 2004). This theory is mainly based on a concept introduced in Piaget's (2001) pedagogical research and that is, the teachers prepare activities or tasks to facilitate the learning process of the students. Women in Machine Learning initiatives across Africa such as the Nairobi program,[3] use this approach while focusing on creating opportunities for members to engage in technical and professional conversations in a positive, supportive environment. The programs involve activities such as fireside chats, brain games and ice breakers, and all these fit into this theory, activating the minds of the learners for fruitful learning to happen. These activities are informal, yet they relate to the construction of knowledge. The informality helps in creating an intimate bond between the students and the facilitator or speaker, and this drives great discussions. Some of these could include storytelling of own experiences, insights which are relevant, and engagement which makes it an active and interactive session for both the students and the facilitator. This approach produces creative and self-motivated learners (Chandra & Briskey, 2012).

Behaviorist theory

Behaviorist approach is mainly teacher-centered, placing focus on the observable actions of learners, evaluating whether they are learning as effectively as possible through reinforcement learning (such as use of assessments, quizzes, test scores, take-home assignments) with constant feedback that informs learners whether what they are doing is right or wrong. This theory has been used in Computer Science Education to facilitate understanding complex problems by breaking them down into smaller tasks (Taylor, 2013). The form of pedagogical approach is frequently employed in formal training centers through use of lectures, assessments, take-home assignments and tests. Examples of the formal training centers where this form of pedagogy is used include: academic institutions offering master's degree and diploma courses in data science.

Collaborative learning

Collaborative learning is an educational approach to teaching and learning that involves learning in groups, working together to solve a problem, completing a task, or creating a product (Laal & Laal, 2012). It involves use of small group sizes, and at times a mixture of individual, pair and whole class instruction. AIR mentorship[4] is an example of an informal data science training based in Uganda that provides students with hands-on experience by engaging them in tackling real-world problems which are project-based. These projects are normally handled in groups of 2 to 3, depending on the size of the cohort. This facilitates learning in groups and collaborations amongst the students in the process of addressing the problem at hand. This approach is also commonly used in women-centric data science training as it fosters teamwork and knowledge sharing. Some of the women-centric data science training where it is used include: African Women in Data Science, AI & ML meetup in Nairobi,[5] Nairobi women in Machine Learning & Data Science[6] and R-Ladies Cape Town.[7]

Inquiry-based approach

With this approach, trainers play an active role throughout the process by establishing a culture where ideas are respectfully challenged, tested, redefined and viewed as improvable (Scardamalia, 2002). This culture has been institutionalized in the curriculum of some formal ICT and Data Science Training in Africa as research training. In the majority of the formal training offerings in Africa, research is part of the curriculum for not only STEM courses, but also other courses (e.g., arts, history, literature). The pan-African Data Science Africa[8] network not only aims at creating a platform for ICT and data science students to connect, but it also aims at training students and researchers to acquire skills that can enable them develop end-to-end solutions (starting from data collection phases to decision making and evaluation phases).

Pedagogical tools and practices

Various tools are used to train ICT and data science students in Africa to gain skills in various fields of ICT such as website designing, video editing, database management, data science, programming, among others. Some of these tools include: Microsoft applications such as Ms Word, Access; programming applications like: Python, Jupyter, Anaconda, Pytorch, TensorFlow Charts, Qlik Sense, R for data science; video editing applications like Adobe, Blender, Camtasia studio; gaming applications; website design applications like HTML, PHP, Content Management Systems. The use of ICT as a pedagogy tool in the STEM fields has presented new options and opportunities for learning concepts within these fields (Bell, 1993, as cited in Chandra & Briskey, 2012).

The methods and practices used are dependent on the theory or approach being used by the teacher or instructor. Some of the methods and practices used in Africa to train women in ICT and data science include: use of lectures, tutorials for practical sessions, field work or community engagement for case studies, hackathons and innovation challenges for knowledge construct and also assessing the learners.

The choice of a pedagogical approach and how it is implemented is critical to the success of teaching and learning STEM-related fields, where teaching concepts in STEM should incorporate the following (Chandra & Briskey, 2012):

1. Connectedness- which promotes the link between the existing and new concepts.
2. Structural and context- which helps in developing an understanding of the similarity between the underlying patterns in related topics.
3. Feedback, which is very important- especially if it is instant so that misunderstandings can be corrected at an earlier time within the teaching process.
4. Reflection and review, so as to give an opportunity to students to review and consolidate new ideas.
5. Intensity, which promotes rich experiences, thus enabling learners to engage in a;
6. Range of problems and exercises of high quality.

Data science training

As highlighted earlier, data science training on the continent falls under two main delivery modes—formal and informal training. We consider formal training as those that occur in a structured environment such as a higher learning institution. They are explicitly designed as education in terms of time, objectives and resources with learners earning degrees and certifications (Manuti et al., 2015). Informal training is the education that takes place outside of a traditional formal learning (Manuti et al., 2015) and is typically facilitated by community led initiatives.

In this section, we discuss some of the available ICT and data science training in Africa. We highlight women-centric ICT and data science training initiatives and the approaches that they employ. We conducted a search for data science training opportunities using a standard search engine (Google) and investigated the responses from the search tool. Owing to the different regional languages in Africa and the possibility of training opportunities not having an online presence (or relying on having a presence in closed social networks), our search for data science training is not exhaustive. However, the variety of training that we identified highlights informal and/or formal training opportunities across all African regions (North, South, East, West, Central), along with the different languages of instruction (English/French). Our inclusion/exclusion criteria for identifying the data science training opportunities were as follows:

- The training should be on data science topics or technologies (e.g., as AI, Machine Learning, Python, R)
- The training must be delivered by instructors face-to-face in an informal or a formal setting (excluding online delivery mechanisms)
- The training details would have a visible online presence so that they could be looked up
- Medium of instruction or primary language used would be English/French as they were the most common languages (excluding other languages of instruction such as regional languages and/or other European languages)

As some members of the team conducting this research are heavily involved in data science in Africa (as practicing data scientists, organizers of training or collaborators), a final validation of the identified training opportunities was conducted based on previous experience and knowledge of the data science landscape in Africa.

Formal training

ICT training has been developed into a fully-fledged course at different levels of learning that is at both lower learning institutions (high school, colleges) and higher learning institutions (undergraduate, graduate/postgraduate).

Currently most institutions across Africa have quite a number of ICT related courses such as: Computer Science, Information Technology, Information Systems, Software Engineering, Computer Engineering. These courses can be undertaken at either undergraduate level (Certificate, Diploma, Degree) or at graduate/post graduate level (Master’s degree, PhD). Training is offered in both private owned and public (government) owned universities for example, African Masters of Machine Intelligence Rwanda, Masters in Data Science and Analytics (Chad), Data Science Analytics (Tunisia), Bachelors of Information Systems and Technology (Uganda).

However, because of some of the shortcomings in a formal setup such as: limited funds, limited time as a result of the resource-constrained environment, etc., informal training centers have been initiated[9] to boost the field, harness the potential of ICT and data science and also build a strong agile community for ICT and data science across the continent .

Informal training

Some of the (informal) training initiatives, for example Data Science Africa (DSA) or Deep Learning Indaba, are multi-country, hosted from different locations across Africa, targeting students and researchers across the regions. Data Science Africa (DSA), a registered nonprofit organization based in Kenya is among the training programs that have contributed to strengthening the Africa data science community by training participants in data science and machine learning methods; providing a platform for networking (between students, early career researchers, experts, practitioners); and supporting the design of solutions to real-world societal problems within the African context.

Table 1 presents a survey of the informal and formal training opportunities for students in Africa. Figure 1 presents a word cloud analysis of the motivations and methods of learning, as described by informal training organisations. It is important to note that informal training covers the majority of training surveyed, primarily due to the nature of formal training—most universities offer some form of training that would constitute either data science or a closely associated field (for example, Machine Intelligence, Data Science, Data Analytics, Artificial Intelligence or Business Intelligence).

Women-centered ICT and data science training

There is a pronounced gender imbalance in global and Sub-Saharan African STEM careers.[10] In Sub-Saharan Africa, various platforms have been created to support women in STEM-related fields including ICT and data science. Women-centered informal training programs build technical and leadership skills alongside self-confidence and voice in these fields.

Interventions that apply ICTs to women's empowerment have a long history in the development sector (Abubakar et al., 2017; Asiedu, 2006). Buskens and Webb (2009) use 17 such case studies in multiple African countries to highlight this. Many of the women-centered ICT and Data Science Training programs included in this review use the terms "empower," "empowering," or "empowerment" in publicly available descriptions of their activities. They often do not explicitly define what is meant by empowerment but share success stories of women who have been able to use their skills to improve their portfolios and acquire jobs or establish businesses. Using Kabeer's framework (as earlier discussed), we interpret their training activities as aiming to increase women's technical skills (resources), expose them to different career options and choices (agency) that may lead to their participation in the labor market (achievements).

Fifty-two percent of the (informal) training centers reviewed in this study are women-led and target women as their audience. These have been voluntarily setup by women who have surmounted social challenges and chosen to pursue STEM careers while facilitating opportunities for other women to do the same. Some of these training initiatives were founded by women based in Africa, for example: Django girls (Nairobi, Kampala), Women in Technology (Johannesburg), Gitgirl (Nigeria). Others were initiated by women who are based outside Africa, but now have ambassadors

Table 1. List of surveyed Informal and formal training opportunities in Africa.

Training organization	Country	Major language used	Region	Gender participation	Type
Abuja Women in Machine Learning & Data Science	Nigeria	English	Western Africa	Female	Informal
Accra Women in Machine Learning & Data Science	Ghana	English	Western Africa	Female	Informal
Africa Data Science Intensive Program	South Africa	English	Southern Africa	All	Informal
African Masters of Machine Intelligence	Rwanda	French	Eastern Africa	All	Formal
Agadir Kotlin User Group	Morocco	French	Northern Africa	All	Informal
AI Kenya	Kenya	English	Eastern Africa	All	Informal
AI Saturday Lagos	Nigeria	English	Western Africa	All	Informal
AIR Mentorship, Makerere	Uganda	English	Eastern Africa	All	Informal
Akira Chix/Code Hive	Kenya	English	Eastern Africa	Female	Formal
Algiers Women in Machine Learning & Data Science	Algeria	French	Northern Africa	Female	Informal
Asikana Network	Zambia	English	Southern Africa	Female	Informal
Blossom Academy	Ghana	English	Western Africa	All	Informal
Cape Town Data Science Meetup	South Africa	English	Southern Africa	All	Informal
Cape Town Python User's Group	South Africa	English	Southern Africa	All	Informal
Casablanca Big Data Meetup	Morocco	French	Northern Africa	All	Informal
Casablanca Startup: idea to IPO	Morocco	French	Northern Africa	All	Informal
Cassablanca Women in Machine Learning & Data Science	Morocco	French	Northern Africa	Female	Informal
Dakar Women in Machine Learning	Senegal	French	Western Africa	Female	Informal
Data Science Analytics, Tunisia	Tunisia	French	Northern Africa	All	Formal
Data Science Course: Moringa School	Kenya	English	Eastern Africa	All	Formal
Data Science Training in Tunisia	Tunisia	French	Northern Africa	All	Informal
Data Science Uganda	Uganda	English	Eastern Africa	All	Informal
Data Scientist Master's Program	Kenya	English	Eastern Africa	All	Formal
DataScienceAfrica	Multiple countries	English	Multiple regions	All	Informal
Deep Learning Indaba	Multiple countries	English	Multiple regions	All	Informal
Django Girls Kampala	Uganda	English	Eastern Africa	Female	Informal
Django Girls Nairobi	Kenya	English	Eastern Africa	Female	Informal
Explore Data Science Academy	South Africa	English	Southern Africa	All	Formal
Facebook Developer Circles	Uganda	English	Eastern Africa	All	Informal
Formation BI Tunisie	Tunisia	French	Northern Africa	All	Informal
Gaborone Women in Machine Learning & Data Science	Botswana	English	Southern Africa	Female	Informal
Gauteng Python Users Group	South Africa	English	Southern Africa	All	Informal
Gitgirl	Nigeria	English	Western Africa	Female	Informal
Innovate Her Africa	Uganda	English	Eastern Africa	Female	Informal
Joburg R Users Group	South Africa	English	Southern Africa	All	Informal
Johannesburg Women in Machine Learning and Data Science	South Africa	English	Southern Africa	Female	Informal
Kaggle Days Meetup Agadir	Morocco	French	Northern Africa	All	Informal
Kampala R Users Group	Uganda	English	Eastern Africa	All	Informal
Kampala Women in Machine Learning & Data Science	Uganda	English	Eastern Africa	Female	Informal
Kigali Women in Machine Learning & Data Science	Rwanda	French	Eastern Africa	Female	Informal
Lagos Women in Machine Learning & Data Science	Nigeria	English	Western Africa	Female	Informal
Masters in Data science and Analytics in Chad	Chad	French	Central Africa	All	Formal
Nairobi R Users Group	Kenya	English	Eastern Africa	All	Informal
Nairobi Women in Machine Learning	Kenya	English	Eastern Africa	Female	Informal

(*continued*)

Table 1. Continued.

Training organization	Country	Major language used	Region	Gender participation	Type
NorthAfrican Summer School in Machine Learning	Multiple countries	English	Multiple regions	All	Informal
PyData Casa/Rabat	Morocco	French	Northern Africa	All	Informal
Python Data Science Training—Chad	Chad	French	Central Africa	All	Informal
Python Kampala	Uganda	English	Eastern Africa	All	Informal
Pythontz	Tanzania	English	Eastern Africa	All	Informal
R Ladies Abuja	Nigeria	English	Western Africa	Female	Informal
R Ladies Addis Ababa	Ethiopia	English	Eastern Africa	Female	Informal
R Ladies Al-Khartum		English		Female	Informal
R Ladies Cotonou		French		Female	Informal
R Ladies Lagos	Nigeria	English	Western Africa	Female	Informal
R Ladies Nairobi	Kenya	English	Eastern Africa	Female	Informal
R Ladies Yaounde	Cameroon	French	Central Africa	Female	Informal
R Users Group Kenya	Kenya	English	Eastern Africa	All	Informal
R-Ladies Cape Town	South Africa	English	Southern Africa	Female	Informal
R-Ladies Johannesburg	South Africa	English	Southern Africa	Female	Informal
Tech4Her Africa	Nigeria	English	Western Africa	Female	Informal
Tensorflow User Group Casablanca	Morocco	French	Northern Africa	All	Informal
Vacoas—Phoenix Women in Machine Learning & Data Science	Mauritius	French	Eastern Africa	Female	Informal
Women in Tech Africa	Multiple countries	English	Multiple regions	All	Informal
Women in Tech JHB	South Africa	English	Southern Africa	Female	Informal

Figure 1. Word cloud analysis of informal training organizations as they describe the motivations and methods of learning on their websites and online platforms..

across the continent, for example Women in Machine Learning which now has ten ambassadors running the ten chapters across the continent, R Ladies with nine ambassadors running nine chapters across the region.

Regardless of their origin, these training initiatives share a common belief that the ICT and data science sectors can benefit from increased representation of women from diverse backgrounds. The initiatives use pedagogical approaches that promote gender equality through social and collaborative learning discussed below.

Capability building approaches

Similar to other informal training initiatives, a large component of program delivery at women-centered initiatives is focused on technical capacity building. They use collaborative learning approaches to develop knowledge and skills in ICT and Data Science. This is done through short or long term programs, workshops, themed learning sessions and hackathons. Many of the initiatives also include training in business, entrepreneurship and marketing and place emphasis on women leading their own startups and being creators of the technologies.

Initiatives such as ZimbaWomen[11] and Asikana Network[12] have been supported and funded through partnerships with global technology corporations such as Google, Microsoft and Facebook to provide skills and training so as to build capacity toward coding technology.[13] Through these partnerships, some of the programs have scaled to other countries, for example, ZimbaWomen has supported more than 300 girls in Kenya, Uganda and Ethiopia.

Mentorship approaches

Unlike other informal training initiatives, women-centered initiatives place a strong emphasis on mentorship. Their mentorship programs are designed to support and encourage young women to pursue careers in STEM-related fields. They challenge gender stereotypes by linking women with role models, most of whom look and sound like them and are from similar backgrounds. Through interaction with those who are further in their careers, participants are able to see that it is possible to aspire to roles that they may have otherwise been socialized to believe are reserved for men. Mentorship activities across the women-centered training initiatives take on many different forms, including group mentorship, talk series, and one-to-one mentorship programs. For example, some of the programs enable young girls to learn from and interact with female professionals in STEM in networking sessions, then assign them to mentors (Guney-Frahm, 2018). These programs create opportunities for participants to develop and strengthen their support networks of women in STEM, access career advice and grow into the people they desire to be.

Employment opportunities

In addition to technical skills and mentoring, women-centered training initiatives also address soft skills and workplace preparedness. They conduct activities such as CV writing workshops, practical sessions on designing data project portfolios, and inviting HR personnel to speak on employer expectations and other relevant topics. Some initiatives also participate in advocacy and work on improving the perception of women in STEM amongst potential employers. They partner with companies to provide internship and work experience opportunities that often improve employability. Some programs are able to quantify this contribution to employment opportunities for young women, for example, Women in Technology Uganda (WITU) has reached 8000 girls, and of these 74% have found work in various sectors including ICT, Business and Entrepreneurship.[14]

Barriers, structural impediments to fair access for women in ICT and data science

Recently, there has been considerable work done to ensure fair access to education, training and employment for women in STEM-related fields (Mukhwana et al., 2020). This has been facilitated through raising awareness, targeted capacity building and networking opportunities, among others. However, women's participation in STEM careers remains low. In this section, we discuss some of the barriers and structural impediments for women in ICT and data science.

Social norms

In many countries, the sociocultural beliefs and practices are largely connected to the construction of feminine identities, ideologies of domesticity, gendered family responsibilities and resulting gender stereotypes (O'Brien & Crandall, 2003). These institutional and sociocultural barriers contribute to low participation of women in these disciplines (Pretorius et al., 2015). These social norms and gender stereotypes underpin the rest of the barriers and are discussed further below.

Academic performance, enrollment, and retention

Sociocultural norms and gendered expectations about the role of women in society significantly affect girls' educational opportunities, learning outcomes and decisions about study (Beede et al., 2011). Research shows that girls assess their mathematical abilities lower compared with boys with similar mathematical achievements (Scardamalia, 2002). In some cases, negative stereotypes about the ability of girls to excel in STEM contributes to substantially lowering women's test performance and thus increasing gaps in academic performance between the girls and boys (Moss-Racusin et al., 2012; Sinnes, 2012; Zafar, 2013), in STEM subjects.

In higher education, women's enrollment and retention rates are also typically lower in STEM-related courses (Rathgeber, 2000). According to a study done by ICT consultants at Makerere University, and other African universities, the ratio of female to male students in the ICT programs is 1:3 (Nsibirano, 2009; Rathgeber, 2000). Women are discouraged from choosing and staying on STEM courses (Nsibirano, 2009). Gender biases are not only revealed in inequality in enrollment and completion but also in policies that favor male students in STEM disciplines (Moss-Racusin et al., 2012).

To add to these challenges, sexual abuse and sexual exploitation in return for grades or promotion exist illegally in some African education institutions (Adeniyi, 2020; Devers et al., 2012). These have greatly affected the number of students enrolling for STEM-related courses as some of the facilitators use this platform to ask for sex for marks or for other gain (Devers et al., 2012).

Workplace bias and discrimination

Due to stereotyping, people associate STEM with men and humanities and arts fields with women, and some hold negative opinions of women in what they perceive as masculine positions such as scientists or engineers (Hersh, 2000; Hill et al., 2010; A. C. K. Lee, 2003; Mitter, 2004; Tanwir & Khemka, 2018; United Nations Educational, Scientific and Cultural Organization [UNESCO], 2018). This bias manifests itself in discriminatory recruitment practices. For example, a randomized double-blind study on science faculty from research-intensive universities in Africa found male applicants for a position of laboratory manager were routinely rated more competent for the job than equally qualified female candidates (Manuti et al., 2015). Once women are recruited, they are often restricted to entry level roles, or to gendered types of work. For example, within the STEM fields, professions such as engineering have been associated with men while women have been associated with specializations like human-computer interaction, user design and website design (Saloma, 2002).

Discriminatory practices in the work place have also been found to discourage women from staying in STEM jobs and careers (Ceci, 2009; Eccles, 2009; Wang et al., 2013). Male dominated workspaces can hold macho work cultures that celebrate stereotypically masculine traits like over-competitiveness at the expense of inclusion and collaboration[15] (Mare, 2021). While women in STEM earn higher than women in non-STEM fields (Beede et al., 2011), women in identical positions with men often earn considerably less (Nedomova et al., 2017). Research repeatedly finds this gender pay gap and inequality in wages as a factor in driving women away from STEM careers (Ferriman et al., 2009; Howes, 2002).

Men continue to outnumber women, especially at the upper levels of STEM professions (Tanwir & Khemka, 2018). The under-representation of women in STEM careers leads to a dearth of role models and mentors, which in turn makes young women less likely to aspire to STEM careers (Derbyshire, 2003) and has a negative impact on the pipeline of women in STEM (World Economic Forum, The Global Gender Gap Report, 2016).

Family responsibilities

Girls encounter gendered roles and expectations at an early age (Steele & Aronson, 1995) and are socialized to be helpful, sociable and friendly and to focus on children and family (Brown et al., 2000; Stewart, 2004). Childcare is frequently constructed as women's responsibility. Thus, women who aspire to be both mothers and have careers in STEM have to consider the significant implications for their time and in some cases, their finances (Martinez et al., 2007). For example, with a growing availability of private childcare in Swaziland the cost of employing domestic assistance has risen since independence to a cost that is beyond what many professional young women, including those who work in STEM fields, can afford, while traditional community-based childcare support is limited or not available in cities and university towns (Okeke et al., 2017). These domestic pressures on female scientists are rarely documented, and systematic information on the effects of responsibilities outside the workplace is difficult to come by, even though it may be a significant factor depleting the pipeline of female scientists and mentors (Okeke et al., 2017). Slow career progression for women who decide to have children, social pressure and household commitments discourage or hamper their progress in science (Miller & Shrum, 2011; Okeke et al., 2017). The problem of female under-representation is compounded by the fact that, in many

African societies, women shoulder most of the responsibility for other work in the home (Mitter 2004; Okeke-Ihejirika & Okeke-Ihejirika, 2004; Pearson, 2015).

While women-centered training initiatives focus on improving women's skills and confidence, it is pertinent that the structural and systemic barriers discussed above are addressed to improve participation of women in STEM careers. From a social point of view, non-access to the Internet cannot be corrected primarily by women changing their attitudes toward technology at an individual level ("fixing women"); only a more gender-balanced educational and labor system prove effective to this end ("fixing systems") (Hafkin & Huyer, 2008; Naivinit & Onta, 2006).

Discussions—understanding barriers and pedagogy

Low female participation in Computer Science (CS) related courses is a known problem (Medel & Pournaghshband, 2017). Trends of gender inequality have long affected the STEM field, across all levels. Perceptions of a masculine environment and notions regarding nerd culture" continue to deter women from entering the field (Irani, 2004). Even amongst women who do transgress these stereotypes and enter the STEM field, low confidence tends to characterize their educational experience (Cohoon, 2007; Irani, 2004). Despite performing as well as men, women consistently believe they are performing at lower rates (Beyer, 1999; Irani, 2004). However, research on the effects of societal beliefs and the learning environment on girls' achievements and interest in STEM shows that when teachers and parents interact with girls and support their effort, girls perform better in mathematics and are more likely to pursue STEM-related fields in the future.

In this section, we examine the linkage between pedagogy and structural barriers to fair access of women to training in STEM. Our contribution is twofold—firstly, we discuss the extent to which ICT training and networks have helped to overcome some of the existing structural barriers and secondly, we discuss how pedagogy has (perhaps unwittingly) increased some of the existing structural barriers to fair access for women in ICT and Data Science.

Positive factors

Accessibility to mentors and role models

The majority of the women-centric ICT and data science training initiatives in Africa were established to support women who have an interest in ICT to expand their skills and knowledge base and consider pursuing careers in STEM fields. The initiatives normally host mentorship talks and series where women who have progressed on their career path encourage and motivate other fellow women to pursue these careers as well. Thus the choice made by some women to pursue STEM-related careers has been influenced by other women who are already studying or working in STEM and these have acted as role models (Mukhwana et al., 2020).

Scholarships

From the study carried out on women-centric-ICT and data science trainings in Africa, we found out that 90% of the informal training centers have been voluntarily set up by other women who have surmounted some of the barriers and social challenges within their communities and are passionate about increasing the participation of women in science and technology. Training centers like DigiGirlz, Women in Technology Uganda (WITU), Data Science Africa (DSA) have obtained funds from big tech-companies like Microsoft, Facebook and Google so as to provide a platform, free to the participants, for women in STEM fields to develop their skills and knowledge, thereby increasing opportunities for women and girls in pursuing data science and STEM careers.

Peer-to-peer support

According to the survey carried out, the majority of the informal ICT and data science training institutions in Africa use the collaborative learning approach. This has been evidenced through participation in some of these trainings, but also through the survey that was carried out with some of the organizers and participants in the training. Collaborative learning enables peer-to-peer support as it involves learning in teams to solve a problem or accomplish a given task (Laal & Laal, 2012). Peer support from students of the same gender (and frequently age) is effective in enabling women to succeed in STEM fields (Mukhwana et al., 2020). This kind of support has enabled women, especially young girls, to develop their esteem, confidence and their capability in STEM fields.

Negative factors

Representations as used in course materials

Although these representations are useful tools for conceptualizing material (Medel & Pournaghshband, 2017), they frequently reinforce gender stereotypes while setting standards for consequent papers and teaching materials.

An example of a negative representation is the one which has been used to introduce and explain cryptographic protocols in upper-level computer security courses. The names and associated roles of the characters in this classic teaching method are problematic due to their unfair distribution of positive and negative roles for men and women (Medel & Pournaghshband, 2017).

The method is based on a scenario: "Alice sends a message to Bob" and is developed with other characters: Eve and Mallory. Eve, the "eavesdropper," attempts to invade privacy by eavesdropping on the message between Alice and Bob. Mallory, another character, is the perpetrator in the man-in-the-middle attack. Evidently, both of the most well-known adverse characters are female.

The institutionalization of negative representations of women in CS demonstrates a severely unbalanced male influence in the field (Medel & Pournaghshband, 2017). Since CS has long faced a shortage of women, it is unsurprising that the materials reflect predominantly male-centered perspectives. This results in continuous generations of students learning from materials that are rooted in inequality. Subsequently, the continued use and advancement of the field using biased standardized materials, forms a vicious cycle (Medel & Pournaghshband, 2017).

Language and imagery

There are negative implications of using male oriented generic pronouns in the context of CS lectures and course materials (Medel & Pournaghshband, 2017). This reinforces and perpetuates gender inequality, many investigations have supported this argument, and demonstrated that the use of the generic "he" invokes male bias in a significant proportion of subjects (Lee, 2003; Pauwels, 2003). Some imagery in course materials objectifies women's bodies or projects gender stereotypes. Objectifying imagery affects women's confidence, and therefore academic performance, in two ways: deteriorating their perceptions of self, and lowering others' perceptions of them (Medel & Pournaghshband, 2017).

Participation of all stakeholders in the policy process

The policy making process is commonly made up of the government which is not a comprehensive representation of all stakeholders. Gender advocates, for example, who would take self-education in gender analysis of ICT are not included in all levels of decision making (Secretariat, 2002).

Conclusions and future work

In this paper, we present our findings from a document review process, exploring the data science training landscape in Africa from a variety of perspectives. The document review process was necessitated following a series of four workshops, where the authors and the GeDIA project members set out to co-develop a research agenda focused on data science and gender equality. The broader topic of interest, as drawn out from our discussions, was data science training, as it is important to understand how barriers in learning the skills can potentially reinforce the gender gaps observed within the data science and tech sector. The document review initially identified a variety of pedagogical approaches employed by the different formal and informal training offered in Africa. We further discuss the causal pathways that link ICT and data science and women's empowerment. We also highlighted some of the informal and formal data science training programs that exist in Africa, following which, we discussed the different barriers to fair access for women in ICT and data science. Finally, we discuss our findings based on how data science training pedagogy can impact on the barriers that women experience.

The GeDIA project is seeking to explore further avenues of this research, where we will investigate the individual perspectives of students and educators. For future work, we aim to interview current and previous students of a sample of the identified informal and formal training organizations (Table 1). We also plan to conduct a survey and interview educators to understand the experience of being a data science teacher in Africa. Based on the co-developed research agenda, funding has been obtained to undertake this work.

Notes

1. While bringing new efficiencies and opportunities for a wide range of domains, Data science and AI innovations have also brought in new debates and concerns around ownership and use of data, bias and transparency, ethics, inclusivity, participation, and so on.
2. Agenda 2063 is Africa's strategic plan for transforming Africa into the global powerhouse of the future stewarded by the African Union: https://au.int/en/agenda2063/overview.
3. See https://www.meetup.com/Nairobi-Women-in-Machine-Learning-Data-Science/.
4. See https://airmentorship.github.io/.
5. See https://www.meetup.com/African-Women-in-Data-Science-AI-and-ML-Meetup-Group/.
6. See https://www.meetup.com/Nairobi-Women-in-Machine-Learning-Data-Science/.
7. See https://www.meetup.com/rladies-cape-town/.
8. See http://www.datascienceafrica.org/.
9. See http://www.datascienceafrica.org/.
10. See https://en.unesco.org/news/empowering-african-girls-be-next-generation-stem-leaders.
11. See https://www.zimbawomen.org/.
12. See https://www.asikananetwork.org/.
13. The involvement of big technology corporations is a welcome development, where sharing practice, learning from real-world experiences is essential to learning data science. As critical researchers, however, we also acknowledge wider debates around controversies and wider implications of AI (mis)use, ethical and legal implications, bias and so on. The role that technology corporations can play is immensely important, particularly in sharing experiences around the negative consequences of AI and data science and not only limiting activities to capacity building in programming.
14. See http://witu.org/.
15. See https://www.weforum.org/agenda/2020/02/gender-imbalance-women-data-science-stem-jobs/.

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Notes on contributors

Claire Babirye is a Computer Science professional with vast experience in different computing modules: from computer networks, computer security, network monitoring to machine learning, data science, deep learning technologies, and use of technology for improved service delivery. She serves as a Research Assistant at the AI and Data Science Research Lab of Makerere University. Her role is to: (1) tap into the revolution to obtain more and better data so as to support development and humanitarian work; (2) support data analytics and data visualization of real-time surveillance data so as to provide insights for decision making; and (3) develop machine learning models that can be used to perform classification on tasks such as crop disease diagnosis. She is also a lecturer at Uganda Technology And Management University. Claire is a tech enthusiast who is interested in empowering people via technology and community engagements, such as voluntary training. She is currently a co-organizer of the Artificial Intelligence (AI) Saturday classes that are facilitated under the AI Mentorship Program at the AI and Data Science Research Lab of Makerere University and IndabaXUG. She is also a member of the Data Science Africa Community.

Chisenga Muyoya is a proactive leader with a deep passion for social change. She is an experienced software programmer and a multidisciplinary ICT for Development researcher. She co-founded Asikana Network in Zambia, a social enterprise that increases the participation of women and girls in technology. Asikana Network holds free training sessions for young women in marketable skills like mobile app programming and web development skills as well as video production and editing using innovative and experimental teaching methods. In a country where negative perceptions of women's capabilities are rife, she purposefully uses technology as a tool to challenge cultural gender norms. She holds a BSc in Computing and a Master's degree in ICT for Development (University of London) which was awarded a distinction and an academic prize for research on gender and technology. She is currently a Commonwealth PhD Scholar researching feminist approaches to data science at the University of Sheffield. Named one of the top 30 young women leaders in Africa, she is a Mandela Washington Fellow, MILEAD Fellow, Global Shaper, Vital Voices Fellow, Chevening Scholar, TOYP Honoree and continuously demonstrates a strong commitment to service through her activism, volunteer work and research.

Suvodeep Mazumdar is a lecturer in Data Analytics. His research explores developing techniques and mechanisms for reducing the barriers that impede user communities' understanding of vast complex multidimensional datasets. He conducts interdisciplinary research on highly engaging, interactive, and visual mechanisms in conjunction with complex querying techniques for seamless navigation, exploration, and understanding of complex datasets. He applied his research in a wide range of application domains, such as Aerospace Engineering, Sports Informatics, Crisis/Emergency Management, Smart Cities, and Mobility Planning. As a part of his research, he collaborates with large multidisciplinary teams of academics, industry partners, city councils, and planners. He has worked in several extensive research and industrial projects funded by the UKRI, European Union, Innovate UK, and the European Space Agency. His research includes: (1) Studying and developing data and visual analytic techniques to analyze massive volumes of dynamic data in near real-time; (2) Citizen Science and Crowdsourcing Techniques for observing physical phenomena, events and environments; (3) User Interface Development, Human-Computer Interaction and user-centered Design; and (4) Assistive technologies to support independent activities of daily living.

Andrea Jimenez is a lecturer in Information Management at the University of Sheffield's Information School. She holds a PhD from the School of Management at Royal Holloway University of London, and a Master's degree in Sustainable Development, with a focus on social innovation and ICTs for Development (ICT4D). As part of her PhD, she has been conducting in-depth qualitative research on technology and innovation hubs, focusing on innovation processes occurring within hubs in both the Global North and Global South. Her interest revolves around intersectionality, decoloniality, and innovation. She complements this academic career with industry experience, having worked for the United Nations in both the Food and Agriculture Organization (FAO) and the International Telecommunications Union (ITU), in addition to the Alliance for Affordable Internet (A4AI). Her research interests revolve around the impact of digital innovation, social innovation and entrepreneurship.

Ciira Maina graduated from the University of Nairobi, Kenya with a BSc degree in Electrical Engineering in 2007 and with a PhD from Drexel University in Philadelphia (USA) in September 2011. Between October 2011 and August 2013 he was a postdoctoral researcher in machine learning and computational biology at the University of Sheffield. Since September 2013 he has been a Lecturer in Electrical Engineering at the Dedan Kimathi University of Technology in

Nyeri, Kenya. He is a member of the organizing committee for Data Science Africa which aims to improve knowledge of machine learning in Africa and served as program chair for DSA 2017 and general chair for DSA 2015 and 2018. He is currently involved in several projects aimed at applying machine learning and the internet of things to problems relevant in the African context.

Jabhera Matogoro holds PhD in Telecommunications Engineering and MSc in Computer Science from the University of Dodoma and Bsc in Computer Science from University of Dar es Salaam, respectively. Dr Matogoro is working as a Lecturer in the Department of Computer Science and Engineering of the College of Informatics and Virtual Education. Jabhera Matogoro is the Founder and Chairperson of Tanzania Community Networks Alliance, an umbrella organization for community networks in Tanzania. Dr Matogoro is an Open Internet Engineering Mozilla Fellow for the year 2019–2020. Jabhera Matogoro is working to scale-up community-owned cooperative societies in Tanzania, aimed at making cooperative attractive for youth and young girls in Tanzania, while at the same time addressing challenges associated with broadband Internet access.

Margaret Nyambura Ndung'u is an Information Scientist with over 20 years of work experience. Her PhD, obtained in 2011, is in Information Systems. She has consulted widely with National, Regional, and International organizations in the area of ICT strategy development, e-governance, Internet Governance, and the digital economy. She has been a lecturer in Information Systems in Kenya and supervised MBA students in South Africa, where she was a postdoctoral fellow. She is the lead Kenya Partner for Research ICT Africa, where she is also a research associate. Since 2018, she is a member of the Communications & Multimedia Appeals Tribunal (CAMAT), the tribunal that arbitrates disputes in the ICT & Multimedia Sector in Kenya, as spelt out in the Kenya Information & Communications Act (KICA), 2013.

Dorothea Kleine is Co-Director of the Sheffield Institute for International Development, University of Sheffield, where she leads the Data, Digital and Innovation group. Her research investigates sustainable human development, global justice, and the role of ICTs in making progress toward these aims. Themes such as gender equality, participation, justice, and choice run strongly through her work. She has published widely and is particularly well-known for her theoretical work on applying the capabilities approach to digital development, as laid out in Technologies of Choice (MIT Press). She has undertaken research with partners in Africa (Kenya and South Africa) and Latin America (Brazil and Chile), as well as advising UNICEF, UNCTAD, UNEP, DFID, GIZ, IDRC, Nokia, GSMA, and Oxfam. She holds a PhD from the London School of Economics. Before joining Sheffield, she worked at Cambridge and Bonn universities and was director of the ICT4D Center, Royal Holloway, University of London. Together with four other female co-directors, she leads the GeDIA project (https://gedia-network.org/) as PI.

ORCID

Suvodeep Mazumdar http://orcid.org/0000-0002-0748-7638

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