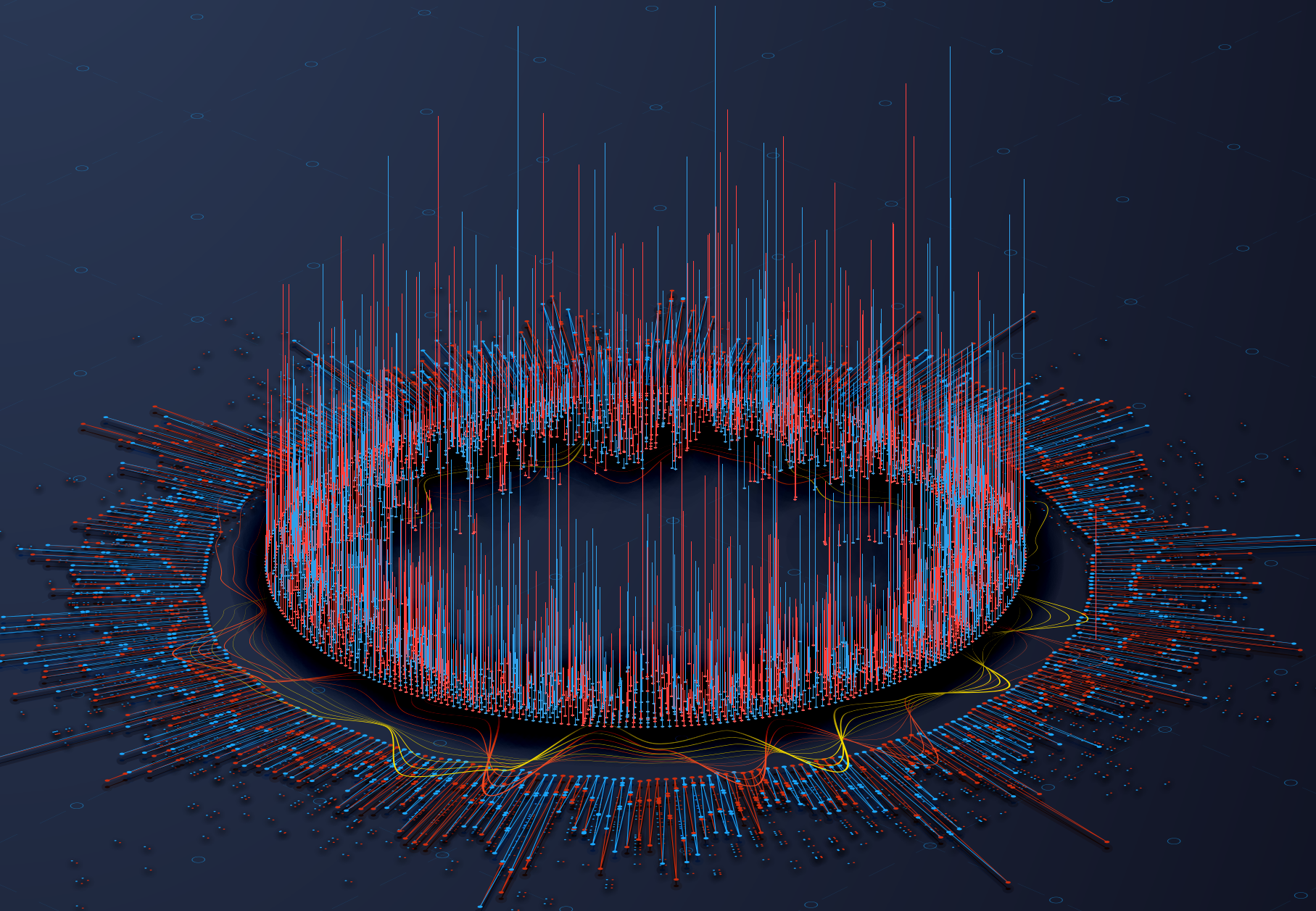


data science

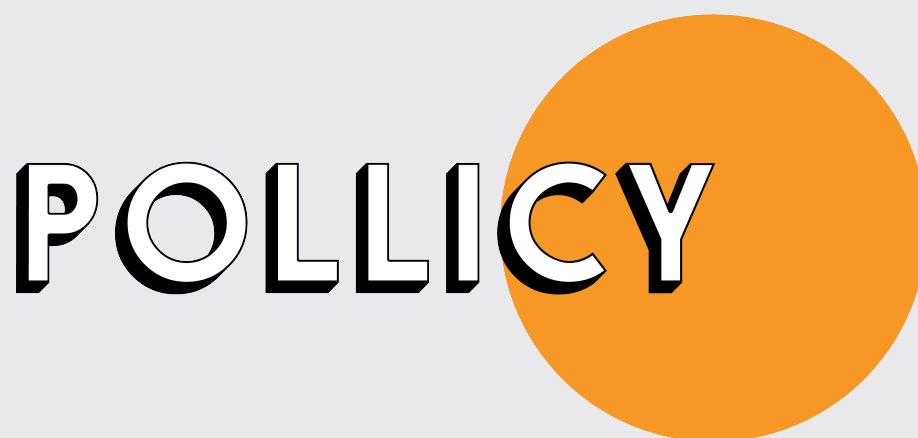
for empowerment



Understanding The Data Science Training Landscape In Uganda

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Definition of terms

Data Professional: These are workers who collect, store, manage and or analyse, interpret and visualize data as their primary or as a relevant part of their work.

Data science: Refers to the act of extracting value and actionable information from data, using a mix of traditional statistics and newer programming methodologies.

Marginalized communities: are groups and communities that experience discrimination and exclusion (social, political and economic) because of unequal power relationships across economic, political, social and cultural dimensions.

Data Engineer: are responsible for designing, maintaining, and optimizing data infrastructure for data collection, management, transformation, and access. They are in charge of creating pipelines that convert raw data into usable formats for data scientists and other data consumers to utilize.

Data Analyst: is a person whose job is to gather and interpret data in order to solve a specific problem.

Database developer: they deal with the design, development and optimisation of databases, preparing technical documentation and reports on database operations as well as maintaining the technological relevance of databases and their modernisation.

Database administrator: these are professionals involved in data storage and organisation, database maintenance and data infrastructure support, capacity planning, configuration, monitoring, \troubleshooting and database security as well as providing access to information for authorised users, organising backups and restoring data.

Data scientists: are professionals who design, train and test models and algorithms for data processing, prepare data sets for analysis, analyse datasets and algorithms and build statistical reports that become the basis for forecasting and decision-making.

List of Abbreviations

AI: Artificial Intelligence

AU: African Union

4IR: Fourth Industrial Revolution

FGD: Focus Group Discussion

ML: Machine Learning

NICT-Hub: National Information Communication and Technology-Hub

NLP: Natural Language Processing

STI: Science Technology and Innovation

STEM: Science Technology Engineering Mathematics

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Executive Summary

The increasing use of data across African countries has accelerated the need for data professionals training programs. These programs are designed to equip young people with the skills they need for careers in data in today's technological landscape. While this is a positive development that offers new career possibilities and community contributions, it is crucial to consider the broader context of data science training in Africa, especially in Uganda. As an organisation focused on the empowerment of women and girls, we need to understand women and girls' experience of this training and how it can impact their lives, help them secure their livelihoods, and empower them.

To gain insights into the training ecosystem in Uganda, we conducted interviews with both male and female data professionals and conducted secondary research on existing programs. We also looked at the different educational methodologies used in various formal and informal training programs. This research enabled us to map the training opportunities available and the networks that support data professionals. We also examined the specific data courses and career opportunities offered through these programs.

Our research highlights the factors that encourage greater participation of data professionals, particularly women and girls and other marginalized individuals, in data science professions. Additionally, it identifies barriers and structural obstacles that limit access to training in data professions for these groups. These findings can contribute to shaping national data professions curricula and anticipating the need for data related jobs. Additionally these findings could lead to developing actions needed to narrow the gender gap in science to avoid loss of vast human resources that could contribute to national development and further perpetuate gender inequality.

Introduction & Background

Globally, data has become the primary resource of our modern era, and its effective analysis is crucial for generating new knowledge. This demand for data professionals is evident across various industries, including government, private sector, security, academia, transportation, healthcare, finance, and banking. Data professionals play a vital role in virtually all sectors, from renewable energy to healthcare and public safety. They are at the forefront of technological advancements that shape our future, driving innovations in health, transportation, agriculture, smart cities, and financial technology. Their goal is to enhance people's quality of life and improve the efficiency of processes and services.

The significance of data professions gained widespread attention in 2020 during the COVID-19 pandemic. With a shortage of trained data professionals, many individuals found themselves attempting data analysis. Simultaneously, the proliferation of mobile applications and customer-facing apps generated vast amounts of data that were stored in diverse databases. Additionally, the academic field of data has been driven by the growing need to analyze the substantial amounts of data collected by governments and corporations.¹

In today's world, data-driven decision-making has become increasingly important as it helps decision-makers to better understand their operations and in turn make strategic decisions about changes in budgets, policies and management. However, the ability to harness these data and generate new knowledge is lagging in Africa due to the lack of well-trained data professionals.

In the digital age, data professionals must possess proficiency in digital systems. The role of a data professional extends beyond interpreting extensive data sets to derive actionable insights. Some of the primary roles and responsibilities of data professionals include:

- Extract and source relevant data to align with project requirements.
- Gather both structured and unstructured data sets for data analysis.
- Develop machine learning algorithms and prediction systems.
- Utilize machine learning tools to enhance data quality.
- Analyze data and ensure consistency to uncover valuable trends and patterns.
- Collaborate with software developers and engineers to implement accurate analytical models.
- Propose refined solutions and strategies to enhance projects.²

A career in data is highly lucrative as the demand for professionals in this cutting-edge field is rising remarkably. Organisations are now truly understanding the power of big data and they want to leverage it to make smarter and more informed business decisions. Data careers are crucial because traditional analytical approaches are in themselves inadequate to tackle challenges posed by the unprecedented volume of large and unstructured datasets³.

¹ Beyene, J., Harrar, S. W., Altaye, M., Astatkie, T., Awoke, T., Shkedy, Z., & Mersha, T. B. (2021). A Roadmap for Building Data Science Capacity for Health Discovery and Innovation in Africa. *Frontiers in Public Health*, 9. <https://doi.org/10.3389/fpubh.2021.710961>

² Ibid

³ Ibid

Data professionals are responsible for a range of tasks, including collecting, storing, distributing, and analyzing raw data to derive valuable insights. These insights are vital for making data-driven decisions. Data professionals must possess the skills to effectively manage digital data using computer devices, as digital literacy is essential in today's fast-paced business environment for every company or organization.

The field of data career training is an amalgamation of mathematics, statistics, and computer science. However, many trainers specialize in only one of these areas, and the training often follows a practical, hands-on approach. One significant challenge is the shortage of qualified trainers, leading institutions to seek trainers from outside their country or even continent.

As a consequence, individuals aspiring to become data professionals often need to access expensive online resources or resort to informal educational paths to build their theoretical understanding and practical skills. This limitation can impact their career prospects, as formal qualifications tend to open up more employment opportunities compared to those who are self-taught in this field.⁴

Data Provides More Opportunities for African Talent

The increasing datafication of African societies has led to a proliferation of data science-related training opportunities. These training initiatives offer young people the chance to acquire the skills needed for careers in data science⁵. Big data, data science, machine learning and artificial intelligence are driving a revolution around the world as companies rush to take advantage of their data and turn it into a competitive advantage. However, there is a shortage of skilled data professionals worldwide and this shortage is much worse in Africa⁶.

By investing in data science education and training, African governments can attract more skilled professionals, provide better access to quality jobs for their citizens, and drive greater innovation and growth for their countries. The AU Science, Technology and Innovation Strategy for Africa 2024 (STISA-2024) places science, technology and innovation at the epicentre of Africa's socio-economic development and growth. The strategy continues to stress that a human capital base of engineers, science and technology professionals must be trained with the necessary competencies and capabilities to plan, organise, lead, coordinate and ultimately ensure that systems and resources are in place for implementation of innovations. The strategy further underpins the role of governments to make the necessary steps to ensure this enabling environment exists towards building research innovations⁸.

Data science tools have been shown to, in some cases, improve the performance of businesses and companies across sectors such as banking, agriculture, trade, telecommunications, health via data-driven decision making. Much of this is evidenced in several application domains, such as the telecom industry, where data science has been used to predict non-payments; in the banking sector, where data and AI-related innovation are applied to fintech and insurance; in the agricultural sector, data science has been used in real-time surveillance of crop diseases and for automated diagnosis of crops, in humanitarian crises and disasters data science has been used to anticipate and respond to arising needs⁹.

⁴ Jones, R. (2019, May 31). Data science: A challenging career with incredible potential for a financially inclusive Africa. Cenfri. <https://cenfri.org/articles/data-science-a-challenging-career-with-incredible-potential-for-a-financially-inclusive-africa/#:~:text=Businesses%20frequently%20resort%20to%20hiring>

⁵ Babirye, C., Chisenga Muyoya, Mazumdar, S., Jimenez, A., Maina, C., Jabhera Matogoro, Margaret Nyambura Ndung'u, & Kleine, D. (2022). Data science for empowerment: understanding the data science training landscape for women and girls in Africa. *Gender, Technology and Development*, 26(3), 437–462. <https://doi.org/10.1080/09718524.2022.2137562>

⁶ University of Nairobi. (2021). The Africa Data Science Intensive (DSI) program is a hands-on skills training data science course based on solving real-world problems. | Research, Innovation & Enterprise. Uonresearch.uonbi.ac.ke. <https://uonresearch.uonbi.ac.ke/node/530>

⁷ Africa Union Commission. (2024). On the Wings of Innovation, the Science, Technology and Innovation Strategy for Africa. https://au.int/sites/default/files/newsevents/workingdocuments/33178-wd-stisa-english_-_final.pdf

⁸ Ibid

⁹ Babirye, C., Chisenga Muyoya, Mazumdar, S., Jimenez, A., Maina, C., Jabhera Matogoro, Margaret Nyambura Ndung'u, & Kleine, D. (2022). Data science for empowerment: understanding the data science training landscape for women and girls in Africa. *Gender, Technology and Development*, 26(3), 437–462. <https://doi.org/10.1080/09718524.2022.2137562>

Increasing public awareness about the importance of data science could also help encourage more young people to pursue careers in this field, providing them with vital skills that will open up new doors for them professionally. Increasingly, data professionals in Africa are taking the lead in developing data-driven solutions to local challenges. They understand the social, cultural and political contexts. They are connected to the government departments, non-profit organisations and businesses that can put theoretical models into practice. As a result, they are well positioned to influence innovation on the continent¹⁰.

Training data professionals equips them with the skills and knowledge to engage in intellectual discussions and formulate strategies for enhancing their capacity to make substantial contributions to community development. The utilization of Big Data holds the potential to enhance government service provision, supplement official statistics, and support progress in various sectors, including education, healthcare, urban planning, transportation, and humanitarian relief services¹¹. While there is a significant need for Big Data analysis in different fields and industries, lack of human capital and equipment to conduct Big Data analysis is a serious hindrance to Africa's ability to use data science and analytics for purposes of human development, business and governance.

Women inclusivity in Data science

While careers in data are considered as one of the most highly recommended professions in 2020, reports indicate that only 30 percent of these positions are filled by women¹². Science, technology, and innovation (STI) are prerequisites to accomplishing the African Union's (AU) Agenda 2063¹³. There is a belief that more gender diversity, particularly in the field of data science, can translate to more significant innovation, increased productivity, and better decision making¹⁴.

The advent of the 4th industrial revolution (4IR) presents immense potential for the African continent to leapfrog its STI potential. However, despite this enormous potential for Africa to excel in STI-related socioeconomic development and growth, African women remain underrepresented¹⁵. In efforts to enhance the participation of women in Africa's STI-enabled socio-economic development and growth, the AU has augmented some empowerment programmes toward gender equality. For example, the AU proclaimed 2015 the Year of Women's Empowerment and Development Towards the African Union's Agenda 2063¹⁶. Furthermore, the AU has adopted frameworks such as the Science, Technology, and Innovation Strategy for Africa (STISA-2024) to boost the participation

¹⁰ Owoyokun, D. (2023): Data Analytics in Africa: Benefits and Challenges; <https://fettersonoff.com/data-analytics-in-africa-benefits-and-challenges/>

¹¹ Rasheva.K., Stefka T and Dimitar C. (2020): Data Science, Challenges and Trends: https://www.researchgate.net/publication/338106415_DATA_-_SCIENCE_CHALLENGES_AND_TRENDS/link/5e1ea972299bf136303acdc2/download

¹² Das, S. (2020, February 20). 5 Ways To Empower More Women In Data Science. Analytics India Magazine. <https://analyticsindiamag.com/5-ways-to-empower-more-women-in-data-science/>

¹³ Dugbazah, J., Glover, B., Mbuli, B., Kungade, C., & Shikwambane, N. (2022). Heightening The Participation Of African Women In Science, Technology, Engineering, And Mathematics Career Paths | AUDA-NEPAD. www.nepad.org. <https://www.nepad.org/blog/heightening-participation-of-african-women-science-technology-engineering-and-mathematics>

¹⁴ Duranton, S., Erlebach, J., Brégé, C., Danziger, J., Gallego, A., & Pauly, M. (2020). What's Keeping Women Out of Data Science? BCG Global. <https://www.bcg.com/publications/2020/what-keeps-women-out-data-science>

¹⁵ Dugbazah, J., Glover, B., Mbuli, B., Kungade, C., & Shikwambane, N. (2022). Heightening The Participation Of African Women In Science, Technology, Engineering, And Mathematics Career Paths | AUDA-NEPAD. www.nepad.org. https://www.nepad.org/blog/heightening-participation-of-african-women-science-technology-engineering-and-mathematics#_ftnref2

¹⁶ AU. (2021). Gender Equality & Development | African Union. [au.int](https://au.int/en/gender-equality-development). <https://au.int/en/gender-equality-development>

of women in STI-enabled socio-economic development and growth¹⁷. For example, efforts such as affording women and girls' equal opportunities to pursue data science-related career paths can substantially benefit Africa. This can potentially close the gender pay gap, improve women's economic security, ensure a diverse and competent data science workforce, and prevent biases in these disciplines and the products and services they generate¹⁸.

While women account for roughly 55 percent of university graduates on average across countries, only two-thirds of this valuable talent pool pursue a career in a STEM-related sector like engineering, software development, or analytics, and even fewer pursue a career in data science. Women make up only approximately 15 to 22 percent of all data science professionals, according to various surveys from WEF, Global Gender Gap Report and BCG research¹⁹.

Barriers to Entry and Widening Gaps in Data Science

The factors that lead to fewer women in data science start early with barriers to women entering the field, and they grow more entrenched as women work to make their mark as leaders in the field²⁰. The value of data science for girls is not emphasised in society as a whole. There are stereotypes and prejudices that place fine art in the hands of girls and data science topics in the hands of boys. Views such as women's nature to give birth and have care responsibilities act as barriers to women's participation in data science courses. The direct and indirect costs for studying technical courses are much higher, compared to non-technical courses. Due to the high son preference in most African societies, families might invest more in supporting boys to enroll on technical courses, than girls²¹.

For most of the data science trainings less than 30 percent of participants are women, thus the need to target more women early in their careers for skill development and matching them with appropriate mentors to encourage them to stay in the field²². Factors such as the cost of programs and limited internet accessibility have hindered women's access, with only 28 percent of women compared to 42 percent of men in Uganda having internet access in 2020. Similarly, people with disabilities face challenges related to facility access and suitable equipment. This gender gap widens as one goes away from the capital city and urban areas to rural areas²³. The broader picture of gender gaps in data science is however more complex, with limited comparable gender disaggregated official data.

Implications of Underrepresentation and Lack of Diversity

Globally, men outnumber women as students, educators, researchers, and workers in STEM fields yet women scientists have an important role to play in Africa's development, including pushing the envelope on gender equality. For example, in 121 countries across the world with available data, women make up 29 percent of science researchers²⁴. The under representation of women and girls in data science perpetuates gender inequality by making it harder for women and girls to get ahead in fields that are linked to digital technology²⁵. The underrepresentation of women and the lack of diversity in the field of data science raise concerns about the potential for biased algorithms and suboptimal outcomes. This imbalance may lead to the development and implementation of data-driven policies that disadvantage women and underrepresented groups²⁶. Additionally, underrepresentation means women will not realize their full

¹⁷ Jackson, J. C., Chirawu, P., Payumo, J. G., Jamison, A. J., & Conteh, M. L. (2022). Perspectives on Gender in Science, Technology, and Innovation: A Review of Sub-Saharan Africa's Science Granting Councils and Achieving the Sustainable Development Goals. <https://www.frontiersin.org/articles/10.3389/frma.2022.814600/full>

¹⁸ Ibid

¹⁹ Ibid

²⁰ Thota, B., Kaul, A., & Ghosal, A. (2022). Women in data science: breaking the glass ceiling - Article. Kearney. <https://www.kearney.com/service/analytics/article/-/insights/women-in-data-science-breaking-the-glass-ceiling>

²¹ ESSA. (2021). The Gender Gap in Universities and Colleges in sub-Saharan Africa. [essa-africa.org](https://essa-africa.org/node/1421). <https://essa-africa.org/node/1421>

²² Martin, K. (2021, February 1). Women in Data Science: Why They're Critical to the Data Science Workforce. UW Extended Campus. <https://u-wex.wisconsin.edu/stories-news/women-in-data-science-critical-to-workforce/>

²³ Nyesigire, S. (2023, March 20). Intersectionality of women's digital rights. Monitor. <https://www.monitor.co.ug/uganda/oped/letters/intersectionality-of-women-s-digital-rights-4166212>

²⁴ Mukhwana A.M., Abuya T., Matanda D., Omumbo J., Mabuka J. (2020). Factors which Contribute to or Inhibit Women in Science, Technology, Engineering, and Mathematics in Africa. Nairobi. The AAS

²⁵ Nyesigire, S. (2023, March 20). Intersectionality of women's digital rights. Monitor. <https://www.monitor.co.ug/uganda/oped/letters/intersectionality-of-women-s-digital-rights-4166212>

²⁶ Bezanson, S. (2021, March 30). Closing the Gender Gap in STEM Education in Africa. Mastercard Foundation. <https://mastercardfdn.org/closing-the-gender-gap-in-stem-education-in-africa/>

potential in academia, personal development and broader socio-economic development in Africa. It can also potentially affect the pool of professionals and leaders in the job market, hence maintaining the current gender gap if not worsening and resulting in exclusion of feminine perspective in creating and developing solutions²⁷. Additionally, educational background is increasingly important in appointment to positions of where technological profiles are in high demand and , because of low representation, women will be less likely to compete for positions with men and more likely to earn less, hence increasing income inequality²⁸.

The 'Role Model Effect'

African women' contribution in the fields of science, technology, engineering and mathematics remains low. One of the factors behind this is inadequate encouragement of girls to pursue math and science at an early school going age. Female role models in traditionally male-dominated positions inspire women, and combat gender discrimination and sex segregation in their communities. This has been referred to as the "role model effect." Evidence shows that women who have access to relatable role models are more likely to prosper in academia, compared to those who lack access to them. A research study conducted in Poland in 2017 to understand the contextual factors in women's education decisions showed that female students who pursued engineering and technology careers had the presence of a significant role model close in their social network. In this case, a role model is defined as a person who is more advanced in the field of study and who has a long-lasting interaction with the individual making the decision. According to this study, a role model in STEM "infects" other individuals in their social network with the idea of pursuing STEM-related careers²⁹.

The role model provides accurate information that allows students to realistically estimate the potential costs and benefits of making a decision that goes against gender role stereotypes. The decision to pursue a career in STEM is a process that begins relatively early in life and that then must be maintained on an ongoing basis. The gender differences in course choice promote gender stereotypes about suitable courses for men and women³⁰.

²⁷ <https://www.frontiersin.org/articles/10.3389/fpsyg.2020.02204/full>

²⁸ Ibid

²⁹ Guenaga, Mariluz, Andoni Eguíluz, Pablo Garaizar, and Ander Mimenza. 2022. "The Impact of Female Role Models Leading a Group Mentoring Program to Promote STEM Vocations among Young Girls" *Sustainability* 14, no. 3: 1420. <https://doi.org/10.3390/su14031420>

³⁰ ESSA. (2021). The Gender Gap in Universities and Colleges in sub-Saharan Africa. *Essa-Africa.org*. <https://essa-africa.org/node/1421>

Mapping Data Science Training Programs & Initiatives in Africa

In recent years, data science training programs have emerged in fields of artificial intelligence like machine learning, deep learning, computer vision, speech recognition, neural and natural language processing (NLP). These advancements are shaping the future of work. The changing landscape of work calls for Africa to take proactive steps to be a leader in creating impact and fostering innovations that empower its citizens in the Fourth Industrial Revolution (4IR).

In this digital era, the synergy between data scientists and AI engineers is essential. They collaborate to identify and address societal challenges using data from both private and public sources. This collaboration results in cutting-edge solutions that benefit various sectors across the continent.

Various academic institutions across the African continent are offering data science courses with the purpose of solving uniquely African problems as well as creating a new exciting employment pipeline. Academic institutions in Africa have recently begun creating structures, networks and training programs that stimulate research and capacity development in data science. Some of the examples that we will discuss here aptly in this paper include the African Center of Excellence in Data Science in Rwanda, the AI and Data Science Research Group at Makerere university Uganda, the School of Data Science and Computational Thinking at the Stellenbosch in South Africa. Other events include the Deep Learning Indaba as well as initiatives established by Google and Microsoft in Africa for training data scientists.

Higher Education Programs

The African Institute for Mathematical Sciences (AIMS), a pan-African network of centres of excellence for post-graduate training, research and public engagement in mathematical sciences that are providing training through a series of short course to young African data scientists to boost capacity in data science, particularly, big data analytics, machine learning, data science as well as providing a platform for practitioners to interact, work on innovative development solutions, collaborate and exchange ideas³¹.

The School for Data Science and Computational Thinking at Stellenbosch University (SU) in South Africa, opened in July 2019 with a multidisciplinary approach embracing subjects including mathematics, computer science, mathematical statistics and AI. With growing interests in data science, machine learning, artificial intelligence, more and more students and those already in the employment market are looking to pivot their career into this space. To facilitate capacity -building in data science and computational thinking, in and around the african continent, the Stellenbosch University (SU) established the African Data Science Academy (ADSA) to facilitate human capacity building in data science and computational thinking for industry and academia as well as researchers and professionals who want to build their skills in data science-related fields. Training classes are hybrid in nature which allows for students in any part of the world to take these courses³².

³¹ Matekenya. D., Kimpolo. M.L.C., & Monroe.T., (2020) Preparing Africa's next generation for leadership in digital data and innovation <https://blogs.worldbank.org/opendata/preparing-africas-next-generation-leadership-digital-data-and-innovation>

³² Viljoen , M. (2020, June 3). Non-conventional approaches for SU's African Data Science Academy. Dst.gov.za.

<https://www.dst.gov.za/index.php/media-room/latest-news/3086-non-conventional-approaches-for-su-s-african-data-science-academy>

The *African Center for Excellence in Data Science* in Rwanda at the University of Rwanda and the *AI and Data Science Research Group* at Makerere University in Uganda are offering specialized programs at both undergraduate and graduate level with the aim of providing a research hub stimulating collaboration between academia, government and the private sector as well as computational and AI methods to improve efficiency in health, transportation and agriculture among others³³.

Private Sector Initiatives

One of the leading start-ups training data scientists on the African continent is a South African based initiative *Zindi* that has trained over 49,000 data scientists across the continent since its inception in 2018. Additionally, Zindi hosts the largest machine learning hackathon UmojaHack where more than 1000 university students from about 300 universities across the continent gather annually to compete and learn about data science. Zindi's work has been particularly focused in some sectors like agriculture where data scientists and AI engineers have helped develop systems to track and assess the health of crops including those infected with diseases, tracking pests as well as performing analysis for better yield management. Additionally Zindi links data scientists to organizations for placements to learn, connect and find employment³⁴.

There are initiatives by big tech companies like IBM, Microsoft, and Google as they expand across the continent in search for skills that will help them generate revenue and create impact. They offer internship programs with hands-on training to data scientists. In Lagos, Microsoft launched the first Africa Development Centres (ADC) to serve as a premier centre of engineering for Microsoft, where world-class African talent can create solutions for local and global impact. In 2020, the global giant proved its further commitment by setting up the Microsoft Africa Research Institute (MARI), which is co-located in the ADC with the aim to understand how innovative technologies, like cloud and AI, are helping to solve local challenges, and how we can then use this understanding to influence product creation and unearth opportunities³⁵.

Google on the other hand set up a center in both Accra in Ghana and Lagos in Nigeria as AI training centers to train engineers that can help to address African data science challenges and create solutions for local and global impact. Other initiatives include the Decision Science Accelerator, a subsidiary of Blue Label Telecoms, which closed down in the wake of the Covid-19 pandemic³⁶. Training is offered in a hybrid model and at a cost.

Events

Deep Learning Indaba is another initiative that is leading the way in bringing researchers, computer scientists and other data scientists to interact and strategise a way of addressing challenges on the African continent including crop and human diseases, election prediction among others using data science. There are more events like workshops, summits that take place in different countries on the African continent throughout the year to accelerate data science and AI innovations. Examples include the African Symposium on Big Data Analytics Data Science Africa Summer Schools, and Artificial Intelligence hosted by Young Affiliates Network(TYAN).

³³ Ibid

³⁴ WOUGNET, (2020): Bridging the Digital Gender Gap in Uganda: An Assessment of Women's Rights online based on Principles of the African Declaration of Internet Rights and Freedoms

³⁵ Ibid

³⁶ Ibid

Objectives

In our examination of how data science is influencing the lives of young people, we aim to investigate the training methods employed for data scientists and ICT professionals. We also delve into the barriers and structural obstacles that hinder equitable access to data science training.

The primary goal of this research is to assess the data science skill development programs offered in Uganda and identify opportunities for action and improvement. Specifically, we intend to:

1. Identify the existing data science programs available in Uganda.
2. Examine the gender representation within these programs.
3. Explore the pool of data experts in the Ugandan job market and the landscape of employers seeking these experts.
4. Document the challenges aspiring learners encounter in accessing and completing data skills development programs.

Finally, we aim to provide recommendations to improve the existing data science skill development programs, with a focus on supporting underrepresented groups and building a more robust community of data scientists in Uganda.

Methodology

This research study used four key approaches which combined secondary and primary data collection and analysis. The combined approach allowed for an understanding of the existing data science landscape, existing training initiatives as well as barriers to these training.

Desk Review

To gain a deeper appreciation of past and ongoing educational initiatives in the field of data science, we conducted an extensive review of existing literature and reports related to data science capacity-building programs and initiatives in Africa, with a specific focus on Uganda.

Survey

An online survey was distributed to a total of eighty-five data scientists within Uganda. These respondents were carefully selected from various data specialisations that encompass activities such as data collection, storage, and management. This pool of data professionals included roles such as data architects, data engineers, data quality assurance engineers, database developers, and database administrators.

The survey also included individuals engaged in data analysis, interpretation, and visualization, representing data scientists and data analysts. Additionally, individuals who had expressed interest in data skills development programs but had not yet enrolled were part of the survey sample. It is worth noting that the research team paid special attention to incorporate data scientists from minority groups, including refugees and individuals with disabilities.

Key Stakeholder Interviews

Key Stakeholder or Informant Interviews (KIIs) were conducted with seven important stakeholders from Uganda. These interviews aimed to gain insights into the current gaps, challenges, successes, and demands in data science training. The interviewees represented trainers of data scientists offering data skills development programs in Uganda, as well as Civil Society Organizations and other organizations working on issues related to access and inclusion in education and training programs in Uganda. These discussions provided valuable perspectives on the state of data science training in Uganda, incorporating the viewpoints of those directly involved in training and organizations striving for inclusive education and training programs.

Focus Group Discussions (FGDs)

In addition to the data collected through the methods previously mentioned, four Focus Group Discussions (FGDs) were organized. These FGDs involved additional data scientists who hadn't participated in the previous interviews. The purpose of these discussions was to collectively envision the current state and future prospects of data science in Uganda.

Similar to the survey approach, participants from underrepresented minority groups, including persons with disabilities (PwDs) and refugees, were purposely sampled to ensure their experiences and insights were included in the FGDs.

Study Limitations

There are several important considerations to note in this study. Firstly, we acknowledge that the sample size is relatively small, which limits the generalizability of the study's findings. Nevertheless, we believe that these findings can provide valuable insights to inform decisions aimed at enhancing data science training in Uganda.

Secondly, the focus group discussions, which were employed to gain a deeper understanding of gender-related issues, have certain limitations. They did not delve into the complexities of various gender identities and the intersections of different forms of inequality. Instead, the discussions primarily focused on issues of equality and gender mainstreaming with regard to both women and men in a broader sense. However, this could serve as a foundational step for future research, which could expand upon these concepts and findings to be more inclusive and responsive to a wider range of marginalized identities and groups.

Findings

Key Demographics

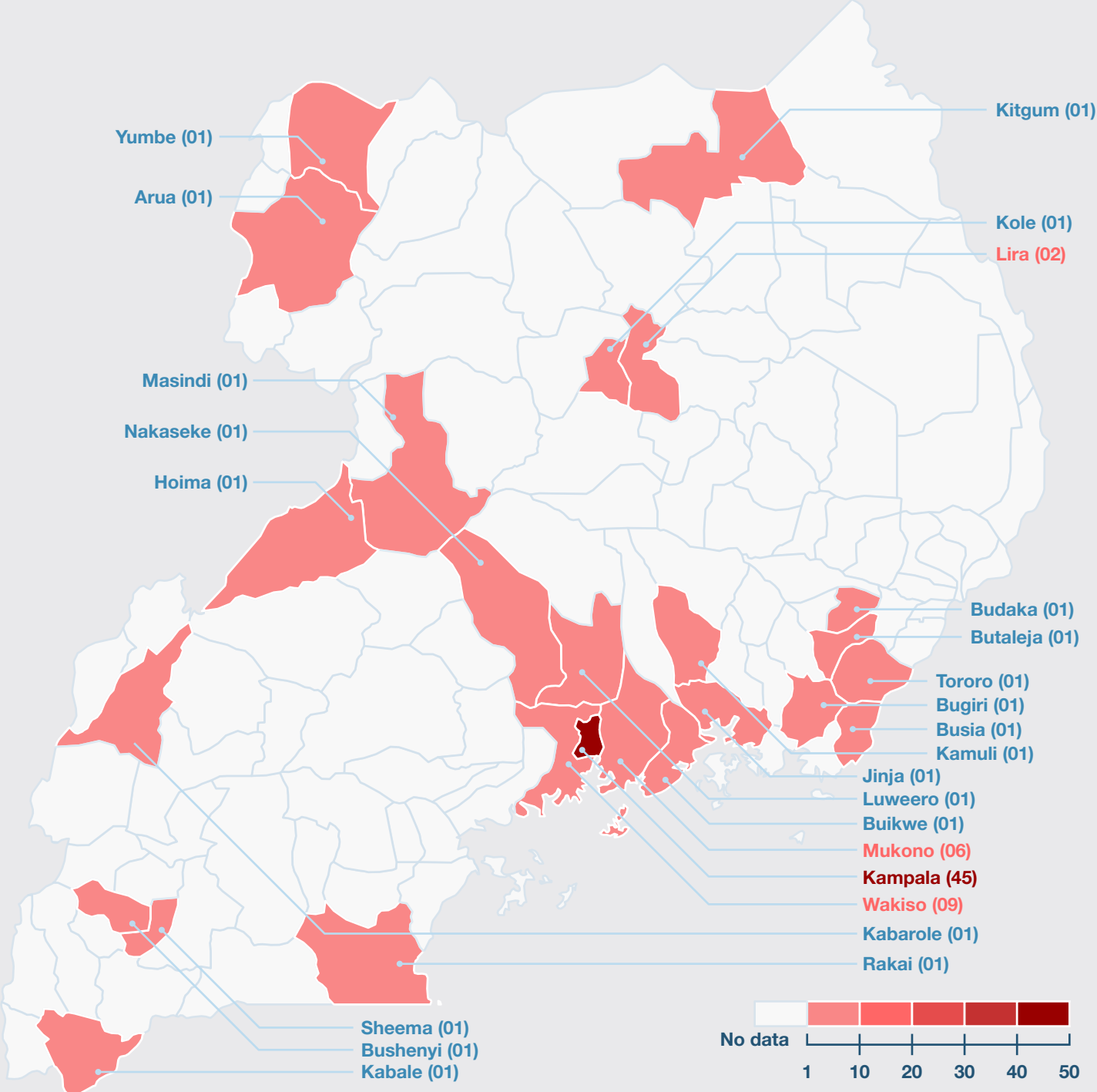
The research targeted young individuals within the field of data science. Using a convenience sampling approach, we selected a sample of 85 research participants from various districts across the country. The findings revealed that 53 percent of the respondents were from Kampala district, while 11 percent were from Wakiso district. The remaining 36 percent came from different districts spread across all four regions of the country.

Regarding age distribution, the majority; fifty two percent of participants fell within the 25-34 years age category, followed by thirty one percent in the 18-24 years bracket. The remaining seventeen percent fell between the ages of 35 to 44. This age diversity highlights the significant interest among different age groups in pursuing careers in data science and acquiring essential skills that can open up new professional opportunities for them, as emphasized by one of the key stakeholder respondents:

In terms of age, I think what we are seeing is that a lot of young people are into data science training. So, early career and university at 23 to 29. We also have an executive part of this course, and this is targeting people who are in senior and middle management careers. So, 29 to 43 years. Because of our skills gap, our analysis with the stakeholders showed that there was a strong desire for managers to understand even basically what this data science, AI and machine learning thing is all about and I think that's important, because they offer direction to the people who are below them.

- Key Stakeholder Interview

A Map Showing the distribution of Research Participants



To understand the existing pool of data professionals, we inquired about their current data profession. The responses showed that out of eighty five data professionals that responded to the survey, sixty seven percent are data analysts, twenty percent are database administrators, and the remaining thirteen percent are database developers, data architects, data engineers and data quality assurance engineers.

During our focus group discussions with data scientists, they emphasized the importance of data science degrees at all levels for acquiring essential programming skills. However, they also highlighted that instructor-led data science training programs and seminars offer additional insights into various aspects of the field, providing practical knowledge that is highly valuable in the job market³⁷.

The findings of this research reveal a significant disparity in gender representation within the field of data science. Only twenty five percent of the participants identified as female, while seventy four percent identified as male. The remaining one percent did not specify their gender.

As anticipated, these results indicate that the number of men in data science is three times higher than that of women, which is not surprising but certainly concerning. It mirrors the broader trend in many science and tech spaces where women are underrepresented. The underrepresentation of women in the data science profession could be attributed to factors such as limited career growth opportunities for women, the dominance of males in this field, and societal gender stereotypes and biases.

One key stakeholder respondent highlighted that most science, computer, and data science programs, both at the undergraduate and postgraduate levels, tend to have more male participants compared to females:

Let me start with the highest level, if you look at Masters. In computer science, we have four Masters students who enrolled for first year and out of the four, there is one who is a lady, no one who is special needs. At undergraduate, we have 11 students and there is one lady, the rest are male students. So, almost 90 percent are male.
- Key Stakeholder Interview

Key respondents from data science training institutions we spoke to mentioned having limited or no gender related strategies or programs to promote gender representation in data science or eliminate barriers that women data scientists face³⁸.

The study revealed several noteworthy trends among study participants from marginalized communities. A significant proportion, seventy five percent of them, had less than three years of working experience in the field. Moreover, it was concerning to note that an equal proportion, seventy five percent, lacked awareness of any government initiatives or policies aimed at promoting and supporting data professionals from marginalized backgrounds.

Additionally, sixty three percent of them reported infrequent attendance at workshops, seminars, or similar skill-enhancing programs, which suggests potential barriers to skill development. Equally concerning, fifty percent of them indicated that the available training programs were inaccessible, primarily due to issues related to location and availability.

³⁷ Focus Group Discussion_4

³⁸ Key stakeholder Interview_1

These findings underscore the importance of addressing the specific needs of data professionals from marginalized communities. It's crucial to focus on providing professional development opportunities that are more inclusive and accessible to individuals from these backgrounds to ensure greater diversity and inclusivity in the field.

Data Science Training initiatives and Employer Landscape in Uganda

The increasing demand for accessible data necessitates a shift from traditional statistical processes to embrace new technologies, including machine learning, for statistical analysis. To gain insight into the data science career trajectory and the job market in Uganda, we examined the current training programs and the landscape of employers in the country.

Our discussions with participants revealed that data science in Uganda is still in its early stages, which contributes to the absence of a clearly established career trajectory in the field.

Sixty-four percent of the survey respondents had a bachelor's degree in a technical field that covered fundamental aspects of mathematics, computer science, and statistics. These individuals then progressed into various roles, such as:

1. Data Engineer: Responsible for designing, building, and managing big data infrastructure.
2. Data Analyst: Tasked with interpreting data sets to identify new trends and insights.

The courses provided in data science training programs encompass a wide range of topics. These include machine learning algorithms, statistics and data analysis, data visualization, sampling techniques, mathematical sciences, and programming languages such as JAVA, JavaScript, R, and Python. Additionally, there is a focus on natural language processing, with an emphasis on hands-on training, soft skills development, and problem-solving capabilities.

It's important to note that most data science training programs are conducted in person, but there are a few online options available. The duration of these programs varies, with long-term programs lasting up to three years for a bachelor's degree. In contrast, short-term programs typically span from three months to six months, and there are even more condensed options lasting 7 to 10 days. For example we inquired about their current data science training. The responses showed that sixty seven percent are engaged in short courses lasting between 3-6 months in data science, while thirty three percent have not enrolled in any further training after completing their first-degree programs. These flexible program durations cater for the diverse needs and preferences of individuals seeking to develop their data science skills.

Participants from both the focus group discussions and a significant eighty percent of survey respondents emphasized the importance of staying current with the latest trends in data science to excel in their careers and succeed in the job market. To achieve this, many individuals engage in self-guided learning through various online platforms, ensuring they remain up-to-date with the ever-evolving field of data science. They thus learn from tutorials on online platforms like Youtube and Azure Data Factory which is an online platform where data scientists take free online short courses in data analysis. Other online learning platforms mentioned were LinkedIn Learning, ADX, DataforDev, Udemy, Coursera³⁹. These platforms have free online short courses that cover a wide range of data science courses that help learners to master data science⁴⁰.

Other forms mentioned that data scientists we spoke to use to keep up with the trends and latest advancements in the industry included peer group learning, attending conferences and events related to data science as well as reading data science publications⁴¹.

³⁹ Focus group discussion#4

⁴⁰ Statistics Foundations 1: The Basics Online Class | LinkedIn Learning, formerly Lynda.com. (2021). LinkedIn. <https://www.linkedin.com/learning/statistics-foundations-1-the-basics>

⁴¹ Brouwer, J., & Engels, M. C. (2021). The role of prosocial attitudes and academic achievement in peer networks in higher education. European Journal of Psychology of Education <https://link.springer.com/article/10.1007/s10212-020-00526-w>

An example was given by one of the participants:

I attended DataFest in 2022 and I saw Pollicy and Sunbird AI doing amazing work. They were talking about things they are doing in the data space as well sharing knowledge in the data area. There was also UCU and Refractory sharing about the work in Artificial Intelligence.
- Focus Group Discussion #3

As both public and private institutions across the country begin to recognise the power of data and the need to employ a greater level of data analytics in the design of product innovations, capable data scientists are required to meet this demand. Participants recognized the surge in research, innovation, and creativity within the country, which has been instrumental in influencing policy changes. This has consequently led to an amplified demand for data scientists. However, the current supply of data scientists in the country is insufficient and often lacks the necessary quality. This situation results in many data scientists seeking further training after their initial training or degree to bridge this gap and meet the industry's requirements⁴².

Regarding entities that provide employment to data scientists, a larger percentage; forty one percent, are employed by research firms and academic institutions that conduct research. Thirty three percent are employed in government departments while the remaining interviewees are employed in banks, insurance companies, telecom companies and human rights organisations. Data scientists play a big role in research as they communicate and demonstrate the value of the data that they collected and analysed to facilitate improved decision-making processes. Coupled with this is that data science knowledge and skills can be applied across all sectors including health, financial sector, agriculture, education but how it is applied or used in each industry may differ.

A lot of the data scientists are being absorbed in different sectors here in Uganda and outside the country where they work remotely. We've seen a lot of organizations now, like utility or service-driven organisations, banks, seem to be employing data scientists as well as private organizations. Yes, setups companies like somebody I- Labs like Pulse lab and large inter-government organizations also employ a lot of data scientists.
- Key Stakeholder Interview

Mapping Existing Initiatives

Data science has become an essential component of many industries, from healthcare to finance to marketing. As a result, there is an increasing demand for professionals who have the skills and knowledge to work with data effectively. While data scientists acquire some of these skills in the course of studies and work, attention is turning to additional training. Additional data science training can provide individuals with the necessary skills to become data scientists or analysts, or to simply enhance their existing skill set⁴³ as well as keep up to date in the job market with the best efficient methods of data analysis that produce results within a short period that subsequently helps to reduce the turn-around time within which the data scientists provide results to organizations to use in decision making⁴⁴.

Additionally, building data science knowledge, capacity, and skills sits at the heart of digital transformation in Uganda, enabling innovation and driving evidence-based policies across the country⁴⁵. By gaining more skills in data science individuals can position themselves for career advancement opportunities.

⁴² Focus Group Discussion#1

⁴³ Talentedge. (2023, March 13). Benefits of Data Science Course. Talentedge. <https://talentedge.com/articles/benefits-data-science-course/>

⁴⁴ Focus Group Discussion#4

⁴⁵ Focus Group Discussion#4

In the globalized world of today, data scientists need diverse competences, and must be able to understand and solve problems with multidisciplinary approaches, as well as assimilating and generating new knowledge. Data scientists therefore must go further and acquire skills that are logically interconnected so as to prepare them for the present-day job market.

Whilst the number of data professionals in Uganda is unknown, we do recognize the presence of initiatives that contribute to data science skills development and the empowerment of Ugandans in a field that is increasingly providing opportunities for career advancement. Data science initiatives bring data scientists, enthusiasts and students in Uganda together such that they are not isolated but work together to cascade data science skills and knowledge to a wider community⁴⁶. Through the researchers' networks and with support from the National ICT Hub Uganda, data training initiatives in Uganda and across other African countries were mapped out. Various entities in the country are emerging with programs to skill data scientists. For this research these will be categorised as academic, government or civil society or non-governmental organisations.

Civil society organizations

Pollicy | Refractory | Fundi Bots | Sunbird AI | Data Science Africa
UN Global Pulse Lab | Code For Africa | Zindi

Government Institutions

National ICT Hub | Ministry of Energy | Ministry of Agriculture

Academic institutions

These offer degree and diploma programs both at undergraduate and graduate level in data science.

APTECH | Makerere University AI Lab | ISBAT University
Busitema University-AI and Machine Learning | Uganda Management Institute (UMI)
Trans African Management Institute

Most of the training initiatives for data scientists are not given free of charge, learners have to pay for the program they are undertaking in addition to bringing digital devices to use during the training by themselves⁴⁷.

⁴⁶ Key Stakeholder Interview_2

⁴⁷ Key Stakeholder Interview_Busitema University

Barriers Faced By Data Scientists In Accessing And Completing The Data Science Training

As the demand for data scientists grows globally, a shortage of talent exists and remains high in Uganda and Africa at large. Aspiring African data scientists face numerous challenges as they pursue a career in data science.

The scarcity of formal educational opportunities in data science, such as undergraduate and graduate degrees, is a major factor contributing to the shortage of skilled data scientists on the continent. Consequently, individuals aspiring to become data scientists often face the challenge of accessing expensive online resources or resorting to informal education routes, such as e-learning or professional training, to develop their theoretical knowledge and practical skills. This situation places limitations on career prospects, as employment opportunities tend to be more accessible to individuals with formal qualifications, rather than those who are self-taught⁴⁸.

Coupled with this was the limited access to the training, especially the informal ones. A good number of participants said they were not aware of some of the existing initiatives that offer data science training⁴⁹. There is therefore a need to provide a platform and living repository that will give more targeted and filtered access to these initiatives to potential data scientists or professionals that want to enhance their skills.

The field of data science is ever-changing with new tools, library resources, and innovations arising frequently. Several data science networks and groups in Uganda seem not to take a standardised form of practice. Keeping up with the latest trends can be difficult for data scientists. Data scientists we spoke to in this research attributed this to the curriculum used.

For some institutions that are offering training the course content was perceived as shallow to benefit the data scientist in their work⁵⁰. Most of it was said to be introductory content for much of the course units⁵¹. The knowledge given is very basic, they do not go in depth as one participant shared:

Some of these training institutions do not go in-depth into sharing knowledge, for example when you look at data analysis, the programs we are taken through are really so basic and you reach the job market and it's really more than that they tend to assume that all of who are attending their data science programs already have more knowledge yet we have more of foundational knowledge and that's why we come to them looking for more knowledge, that we are not yet exposed to. - Focus Group Discussion #2

⁴⁸ Focus Group Discussion#4

⁴⁹ Focus Group Discussion#3

⁵⁰ Focus Group discussion#2

⁵¹ Focus Group Discussion#1

A key stakeholder respondent acknowledged this gap created by the lack of a curriculum revealing that there are efforts underway by data science practitioners and academic institutions across Uganda to design a standard curriculum to train students to solve Uganda and African challenges to make learning and practicing data science efficient and practical. A framework needs to be defined that will align the current job market needs with the Data Science curricula and skills provided by formal and non-formal institutions.

While most academic institutions were said to be using conventional statistical packages and programming language software like STATA, SPSS, Excel in instruction, the job market on the other hand is embracing new software packages like Python, R, JAVA, among others that produce results much faster and improves overall performance⁵². Additionally, training was said to be more theoretical which then introduces a disconnect between what data scientists find in the job market and what they learnt in training.

What we learn in class is not really aligned to what we find in the job market and that is why we as data scientists need more and more training so that we get those skills for which we did not acquire during academic training. They expose us to a lot of theory while in school. They need to expose us to more practical things. The software packages used in academic institutions are not what we find on the job market. This misalignment affects us when we begin working. - Focus Group Discussion #1

The emergence of new statistical packages and programming language software has transformed the way data scientists and researchers conduct their statistical analysis. Therefore, performing complex and at times erroneous statistical analysis using software packages that have been in existence longer is becoming a thing of the past⁵³. Despite the emergence of new statistical and programming language software and the speed with which these tools are produced, it may be important for data scientists to acknowledge that all the available software tools strive to accommodate almost all features data scientists need to analyse their data⁵⁴.

Programs available for data scientists at most of the training institutions have to be paid for and most people have limited funds. Similarly, the programs available online too tend to also be constraining financially. For some programs, if enrollment is cheap, exams to complete the program and be given a certificate is costly⁵⁵. Examples of costs that were given for data science courses range from 100 USD per month to 200+ USD per month for a nine months course. Given the dynamic and ever-evolving nature of the data science industry, it's crucial for data scientists to stay up-to-date with the latest developments and emerging trends. While some courses may provide a foundational understanding of data science, they may not always offer in-depth knowledge that keeps pace with industry advancements⁵⁶. As such, the learners have to invest more money in another institution to learn more which is costly.

⁵² Focus Group Discussion#4

⁵³ Focus Group Discussion #3

⁵⁴ Masuadi, E., Mohamud, M., Almutairi, M., Alsunaidi, A., Alswayed, A. K., & Aldhafeeri, O. F. (2021). Trends in the usage of statistical software and their associated study designs in health sciences research: A bibliometric analysis. *Cureus*, 13(1). <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7872865/>

⁵⁵ Focus Group Discussion#2

⁵⁶ Ibid

Data Scientists Stories

Male Data scientist

Opio, a 27-year-old university graduate, is a data scientist. His journey towards becoming a data scientist began during high school when he explored online resources. He discovered a website that offered free training in using Python for data analysis.

Upon entering university, Opio had a general idea about data analysis but was faced with a choice between pursuing a career as a programmer, a biostatistician, or a mechanical engineer. Ultimately, he decided to enroll in a statistics degree program. Opio's decision was influenced by his early interest in statistics, which he had developed as a child watching statisticians handle data in films and documentaries.

After successfully earning his degree in statistics, Opio started his career as a data collector with various research firms. As he gained experience and expanded his professional network, his interest in data analysis grew. In his role as a data collector, he not only collected data but also managed it using Microsoft Excel, performed data cleaning, and conducted basic data analysis.

Opio's journey towards data science took a significant step when his supervisor recognized his potential and encouraged him to pursue formal data science training. Additionally, his friends, who were also involved in data collection and had undergone data science training, motivated him to enhance his data collection skills, especially in using programmed software like Kobo Collect.

Initially, Opio opted for self-training by watching YouTube tutorials and working on data science projects. However, he later discovered free data science training programs on various online platforms and eagerly joined them. This additional training equipped him with valuable skills.

Opio's career as a data analyst took him to both non-governmental organizations and government entities. Even while being employed, he continued to take online courses to meet the increasing demand for data science skills and knowledge in his workplace. Through his continuous dedication to learning and professional development, Opio positioned himself to seize the abundant job opportunities available in the data science field.

Female Data scientist

Anna, a female data scientist, initially had dreams of pursuing mathematics at the university level. However, influenced by the belief that studying mathematics would lead to a career only in teaching, she decided to study engineering for her first degree. Anna's colleague, Judy, also a data scientist, had no specific inspiration for her initial degree in statistics; it was a course assigned to her during university admission. During her undergraduate studies, Judy discovered the vast potential in data science, which included data visualization, programming, and analysis. She became inquisitive and developed a strong desire to learn more about the field.

Anna and Judy have a friend, Liz, who is currently pursuing a master's degree in Artificial Intelligence and Machine Learning at one of the public universities in Uganda. Unlike Anna and Judy, Liz had a long-standing interest in science subjects, which was nurtured by her father's encouragement. While Liz initially considered a bachelor's degree in civil engineering, her father advised her to pursue computer science due to concerns about occupational hazards in engineering. Although Liz had heard misconceptions about computer science being solely about typing, she found the subject fascinating during her undergraduate studies. While studying computer science, Liz lacked female mentors in her program, but she found guidance and encouragement from two male mentors who motivated her to pursue a master's degree. Liz mentions that the absence of female mentors and mentoring programs together with undefined career paths for girls tend to make it difficult to attract and maintain women scientists.

In her current master's program, Liz is one of only four female students out of a class of 48. The other female who was the fifth left the program after studying for one month. Liz and her colleagues tried to reach out to her to find out why she was not attending the program and she informed them that she was no longer interested in continuing with the masters program since she is already employed and it would be difficult for her to strike a balance between work and school. Efforts from Liz and her colleagues to convince her fell on deaf ears and they have since given up on following her up. Liz goes on to mention that her masters coordinators are concerned about the underrepresentation of women and are eager to implement initiatives to motivate more women to join similar programs. Anna, Judy and Liz think that data science training institutions must intentionally enroll and promote female leaders in order to provide women and girls with more role models. They also feel that there is a need for the government and other stakeholders to create incentives like scholarships and grants to motivate women and girls and increase enrollment into data science professions.

Discussion

Many African companies are plagued by ‘brain drain’ – the en masse departure of skilled workers to markets with more opportunities. By investing in data science education and training, African governments can attract more skilled professionals, provide better access to quality jobs for their citizens, and drive greater innovation and growth for their countries. Increasing public awareness about the importance of data science could also help encourage more young people to pursue careers in this field, providing them with vital skills that will open up new doors for them professionally. To address gaps and opportunities in the data ecosystem, it is essential to review the current data skills development programs in Uganda. By doing so, we aim to build a stronger cohort of data scientists and analysts, with a specific focus on supporting historically marginalized participants such as women.

There is a pronounced gender imbalance in data science in Uganda as shown by the results that requires development of strategies that can empower women to join the data science field. For example, there are women-led data science initiatives in Uganda and outside the country on the African continent where women interested in data science can be linked to like Django women, women in Machine learning, R Ladies that have opportunities for women to pursue STEM careers⁵⁷.

Disparities in gender representation resonates with what most researchers across the globe have found that most STEM fields still have a daunting gender diversity problem. Across countries, women make up around fifty five percent of university graduates but they account for just over one-third of STEM degrees⁵⁸. From this precious talent pool, only two-thirds go on to a career in a STEM-related field such as engineering, analytics, or software development, and even fewer move into a career in data science⁵⁹. This then shows that women interested in data science have fewer role models to look up to which has a compounding effect, on limiting awareness of role models. Most data scientists know only one female role model or leader, which makes it difficult for women who are new to the field to visualize their own career track. Having a role model may not be a prerequisite for a successful career in data science, but its importance cannot be discounted. For example a 2018 Microsoft study found that having STEM women role models increases women’s interest in STEM careers by up to fifty two percent⁶⁰.

Further to this, low representation of women in data science is susceptible to bias and subsequently undermines evidence-based policy making based on information shared by male data scientists as a wide range of views and experiences of women will be lacking. Data scientists’ choices regarding data measurement, collection, organization and analysis can impact the insights they gain and can potentially introduce bias at every stage of the data process. Whether intentionally or not, data scientists may incorporate their personal values, interests and experiences into the data they work with, influencing the outcomes in alignment with their own understanding of the world. In this way, datasets and algorithms can be seen as containing “encoded sets of values.” And when the people who create and work with data are not representative of the general population, they can inadvertently introduce bias. This suggests that if datasets and algorithms that are less biased are to be created, there is a need for more gender diversity in data science.

⁵⁷ Babirye, C., Chisenga Muyoya, Mazumdar, S., Jimenez, A., Maina, C., Jabhera Matogoro, Margaret Nyambura Ndung’u, & Kleine, D. (2022). Data science for empowerment: understanding the data science training landscape for women and girls in Africa. *Gender, Technology and Development*, 26(3), 437–462. <https://doi.org/10.1080/09718524.2022.2137562>

⁵⁸ Duranton, S., Erlebach, J., Brégé, C., Danziger, J., Gallego, A., & Pauly, M. (2020). What’s Keeping Women Out of Data Science? BCG Global. <https://www.bcg.com/publications/2020/what-keeps-women-out-data-science>

⁵⁹ Ibid

⁶⁰ Thota, B., Kaul, A., & Ghosal, A. (2022). Women in data science: breaking the glass ceiling - Article. Kearney. <https://www.kenarney.com/service/analytics/article/-/insights/women-in-data-science-breaking-the-glass-ceiling>

Empowering women with the necessary skills will enable them to be part of a data science cohort that is available to meet the growing demands of data and contribute to making more data-driven decisions, thereby driving Uganda's progress. Additionally, 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. Future research can further explore this further to possibly explain how different pedagogical practices could help alleviate gender gaps in data science.

Conclusion

As the data science landscape in Uganda matures, where organisations and institutions are gradually realising the value of adopting evidence-based practices, there is a clear need for capable Ugandan data scientists who understand the context in which challenges will need to be solved. The potential for data science to spur socio-economic discoveries and catalyse innovation is enormous. Improvements in data availability and quality, better infrastructure and capacity and increased engagement from a variety of academic, government, non-government and private sector actors suggest significant progress is on the horizon in Uganda, though significant challenges remain. Faced with a myriad of industrial and institutional bottlenecks Uganda needs data scientists more to create tailored solutions to the challenges the country is facing. Data scientists are crucial for the recently launched digitalization roadmap that serves as a way leading Uganda to realizing growth from the Fourth Industrial Revolution(4IR) through creating its own talent to help both the public and private sector make informed decisions, predict markets as well as prepare for unforeseen calamities.

Recommendations

For Government

Efforts to promote gender diversity and inclusivity in the data science field are essential. The Ministry of Education and Sports as well as the Ministry of ICT should consider taking the following initiatives.

Support Women in STEM Initiatives

Encourage discussions and initiatives to support women in STEM (Science, Technology, Engineering, and Mathematics) starting from primary to secondary schools and higher institutions of learning. By introducing these discussions early on, in both public and private educational institutions, you can inspire young girls to pursue data science and related fields. Creating female role models within the data science community is crucial to providing younger girls with inspiring figures to look up to.

Policy Frameworks for Gender Equity

Establish policy frameworks that provide increased funding for training and mentorship programs, enabling women to pursue leadership roles in scientific fields. Implement gender-friendly policies, such as offering on-site childcare services and career re-entry programs. These initiatives can help women scientists continue their careers, even after fulfilling important societal duties such as starting a family.

Empower Female Data Science Trainers

Encourage and empower female data science trainers to be role models and mentors for young girls interested in data science careers. By promoting female trainers and mentorship programs, you can inspire and motivate young girls to explore data science-related career paths and provide guidance on their journey. This could include involving these data science trainers in school tours to the National ICT Hub, class talks and seminars, summer boot camps, internship placements etc.

Varied Academic Opportunities

Introduce diverse academic opportunities, including online education and short courses, to increase accessibility for young people, especially girls, interested in data science. Additionally, provide training for teachers on gender-sensitive instruction and strategies to engage girls in data science, making the field more inclusive. It would also be helpful for stipend and bursaries to be provided for online learning, especially for courses not offered nationally in academic institutions.

These initiatives can contribute to a more balanced and diverse representation in the data science field, offering opportunities for all aspiring data scientists, regardless of gender.

For Civil society Organizations

Civil society also has a role to play in supporting data science careers.

Networking Conferences

Organise conferences and workshops that facilitate networking among data scientists. These events, both in-person and online, encourage knowledge exchange, idea-sharing, and career development in the field. Such networking could uncover ideas and could spark inspiration among peers.

Mentorship Programs

Promote mentorship to enhance skills and career readiness. Connect young data professionals with experienced mentors who can bridge knowledge gaps, improve skills, and guide them in their data science careers. Having a right mentor would help learners to prepare for work-readiness before embarking on a full-time job. Alongside it allows learners to upskill themselves according to industry requirements as well as get guidance to look for the right job.

For Policy and NICT Hub

Scale up our established and free Data Science trainings

Support Data Ladies Ambassadors who can nurture and promote the growth and development of university and institutional AI clubs, data science clubs, networks, and machine learning meet-ups. These ambassadors can act as mentors and role models for aspiring data scientists, helping to share knowledge and insights from Data Ladies sessions. Data Ladies Ambassadors can play a crucial role in extending the impact of their knowledge and experiences to individuals interested in data science who may not be affiliated with academic institutions, making the field more accessible and inclusive. Data Ladies is a monthly meet-up organised by Pollicy creating a space for women to dialogue around their experiences with data, share knowledge and create an atmosphere of togetherness.

Strengthen Sustainable Partnerships

Maintain and strengthen existing partnerships that aim to address societal challenges affecting data science, such as funding constraints and limited training spaces. These collaborations can be harnessed to find innovative solutions to these challenges, furthering the growth and development of data science in the community. Continue to leverage partnerships for economic growth and development opportunities related to data science. This could involve initiatives to promote entrepreneurship, job creation, and innovation within the data science sector, thereby contributing to economic prosperity.

For Data Science Trainers

Enhancing Data Science Training Methods

Continuously improve data science training methods by ensuring a balance between theoretical and practical sessions. Include fieldwork, community engagement for case studies, hackathons, and innovation challenges to construct knowledge and assess learners' capabilities effectively. Encourage trainers to use statistical and programming language software commonly employed in the job market. This helps learners develop skills that align with industry demands and trends.

Standardise Data Science training Curriculum

Trainers need to work hand in hand with the Ministry of ICT as well the Ministry of Education and Sports to standardize data science training content and guidelines on minimum areas to be covered during data science training. This will ensure that all data scientists in their various professions receive the same necessary knowledge and skills during training and have access to the same resources which will help to improve the overall quality and consistency of data science training.

Gender-Inclusive Training

Develop women-centered initiatives that actively support and encourage young women to pursue careers in STEM-related fields. Challenge gender stereotypes by connecting women with role models who share their backgrounds and experiences. These role models can serve as inspirational figures, demonstrating that women can excel in roles traditionally considered male-dominated.

Create and Participate in Mentorship Opportunities

Implement various forms of mentorship activities within women-centered training initiatives, including group mentorship, talk series, and one-to-one mentorship programs. These activities create valuable opportunities for learners to build strong support networks, access career guidance, and become the professionals they aspire to be in the field of data science.

Cited Works

Africa Union Commission. (2024). On the Wings of Innovation, the Science, Technology and Strategy for Africa. https://au.int/sites/default/files/newsevents/workingdocuments/33178-wd-stisa-english_-_final.pdf

AU. (2021). Gender Equality & Development | African Union. Au.int. <https://au.int/en/gender-equality-development>.

Babirye, C., Chisenga Muyoya, Mazumdar, S., Jimenez, A., Maina, C., Jabhera Matogoro, Margaret Nyambura Ndung'u, & Kleine, D. (2022). Data science for empowerment: understanding the data science training landscape for women and girls in Africa. *Gender, Technology and Development*, 26(3), 437–462. <https://doi.org/10.1080/09718524.2022.2137562>

Beyene, J., Harrar, S. W., Altaye, M., Astatkie, T., Awoke, T., Shkedy, Z., & Mersha, T. B. (2021). A Roadmap for Building Data Science Capacity for Health Discovery and Innovation in Africa. *Frontiers in Public Health*, 9. <https://doi.org/10.3389/fpubh.2021.710961>

Bezanson, S. (2021, March 30). Closing the Gender Gap in STEM Education in Africa. Mastercard Foundation. <https://mastercardfdn.org/closing-the-gender-gap-in-stem-education-in-africa/>

Brouwer, J., & Engels, M. C. (2021). The role of prosocial attitudes and academic achievement in peer networks in higher education. *European Journal of Psychology of Education*. <https://doi.org/10.1007/s10212-020-00526-w>

Das, S. (2020, February 20). 5 Ways To Empower More Women In Data Science. *Analytics India Magazine*. <https://analyticsindiamag.com/5-ways-to-empower-more-women-in-data-science/>

Dugbazah, J., Glover, B., Mbuli, B., Kungade, C., & Shikwambane, N. (2022). Heightening The Participation Of African Women In Science, Technology, Engineering, And Mathematics Career Paths | AUDA-NEPAD. *Www.nepad.org*. <https://www.nepad.org/blog/heightening-participation-of-african-women-science-technology-engineering-and-mathematics>

Duranton, S., Erlebach, J., Brégé, C., Danziger, J., Gallego, A., & Pauly, M. (2020). What's Keeping Women Out of Data Science? BCG Global. <https://www.bcg.com/publications/2020/what-keeps-women-out-data-science>

ESSA. (2021). The Gender Gap in Universities and Colleges in sub-Saharan Africa. *Essa-Africa.org*. <https://essa-africa.org/node/1421>

Gonzalez, S., Mateos de Cabo, R., & Sáinz, M. (2020). Girls in STEM: Is It a Female Role Model Thing? *SSRN Electronic Journal*, 11(1664-1078). <https://doi.org/10.2139/ssrn.3541939>

Jackson, J. C., Chirawu, P., Payumo, J. G., Jamison, A. J., & Conteh, M. L. (2022). Perspectives on Gender in Science, Technology, and Innovation: A Review of Sub-Saharan Africa's Science Granting Councils and Achieving the Sustainable Development Goals. <https://www.frontiersin.org/articles/10.3389/frma.2022.814600/full>

Jones, R. (2019, May 31). Data science: A challenging career with incredible potential for a financially inclusive Africa. *Cenfri*. <https://cenfri.org/articles/data-science-a-challenging-career-with-incredible-potential-for-a-financially-inclusive-africa/#:~:text=Businesses%20frequently%20resort%20to%20hiring>

Martin, K. (2021, February 1). Women in Data Science: Why They're Critical to the Data Science Workforce. UW Extended Campus.

<https://uwex.wisconsin.edu/stories-news/women-in-data-science-critical-to-workforce/>

Masuadi, E., Mohamud, M., Almutairi, M., Alsunaidi, A., Alswayed, A. K., & Aldhafeeri, O. F. (2021). Trends in the usage of statistical software and their associated study designs in health sciences research: A bibliometric analysis. *Cureus*, 13(1). <https://doi.org/10.7759/cureus.12639>

Matekenya. D., Kimpolo. M.L.C., & Monroe.T., (2020) Preparing Africa's next generation for leadership in digital data and innovation

<https://blogs.worldbank.org/opendata/preparing-africas-next-generation-leadership-digital-data-and-innovation>

Rasheva.K., Stefka T and Dimitar C. (2020): Data Science, Challenges and Trends:

https://www.researchgate.net/publication/338106415_DATA_SCIENCE_CHALLENGES_AND_TRENDS/link/5e1ea972299bf136303acdc2/download

Nyesigire, S. (2023, March 20). Intersectionality of women's digital rights. Monitor.

<https://www.monitor.co.ug/uganda/oped/letters/intersectionality-of-women-s-digital-rights-4166212>

Owoyokun, D. (2023, July 9). Data Analytics in Africa: Benefits and Challenges - Fetters Off.

<https://fetersoff.com/data-analytics-in-africa-benefits-and-challenges/>

Statistics Foundations 1: The Basics Online Class | LinkedIn Learning, formerly Lynda.com. (2021). LinkedIn.

<https://www.linkedin.com/learning/statistics-foundations-1-the-basics>

Talentedge. (2023, March 13). Benefits of Data Science Course. Talentedge. <https://talentedge.com/articles/benefits-data-science-course/>

Thota, B., Kaul, A., & Ghosal, A. (2022). Women in data science: breaking the glass ceiling - Article. Kearney.

<https://www.kearney.com/service/analytics/article/-/insights/women-in-data-science-breaking-the-glass-ceiling>

University of Nairobi. (2021). The Africa Data Science Intensive (DSI) program is a hands-on skills training data science course based on solving real-world problems. | Research , Innovation & Enterprise.

[Uonresearch.uonbi.ac.ke](https://uonresearch.uonbi.ac.ke). <https://uonresearch.uonbi.ac.ke/node/530>

Viljoen , M. (2020, June 3). Non-conventional approaches for SU's African Data Science Academy. Dst.gov.za.

<https://www.dst.gov.za/index.php/media-room/latest-news/3086-non-conventional-approaches-for-su-s-african-data-science-academy>