Realizing the Potential of AI in Africa: It All Turns on Trust

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Abstract Most nations have recognized the disruptive influence of artificial intelligence (AI) on all aspects of their economies, from manufacturing, to services, to governance, and the potential benefits that embracing AI technologies can bring. It is no different in developing countries and it is certainly the case that the countries of Africa have embraced AI, data science, machine learning, and robotics. However, the transition from recognition of potential to realization of benefits is not a straightforward matter. In this essay, we argue that this transition depends on turning technological invention into innovation, that technological innovation cannot happen without adoption, and that adoption depends on socio-cultural factors, in general, and on trust, in particular. We draw out the implications for AI in developing countries in Africa, arguing that, for Africa to realize the potential of AI in solving economic and social problems, the advancement and deployment of AI must be driven and executed by the peoples of Africa: if it is not, there will be little trust, less adoption, and minimal benefits.

1 Introduction

Humankind has always used tools to augment and amplify its capability for physical work. The computer age extended this to mental work but principally as a tool for greatly increasing the speed of processing. However, the developments in artificial intelligence (AI) over the past sixty five years, and in particular in deep learning

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approaches in the past ten, have ushered in what John Kelly at IBM refers to as the cognitive era [50], superseding the tabulating era and the ongoing programming era. He reminds us of J. C. R. Licklider's prediction in 1960 of a symbiotic partnership between man and computer that will "perform intellectual operations much more effectively than man alone can perform them" [56]. Today, that symbiotic partnership is realized through AI, a tool that both amplifies and extends human cognitive abilities.

While there is much debate about the ultimate destiny of that partnership and whether or not AI will prevail over humans after the technological singularity when the autonomous capabilities of AI exceed those of humans [78], there is far more discussion on a more practical level about how to harness AI for economic advantage and social development.

From an economic standpoint, AI forms the foundation of the so-called Fourth Industrial Revolution, Industry 4.0 [77]. Concerned about missing out on this revolution, countries and trading blocs around the world have prepared or are in the process of preparing AI strategies. Unsurprisingly, most of this activity occurs in developed economies, in the West, e.g. [3], Middle East, e.g. [7], and the Far East, e.g. [4],[1] where governments and organizations in the public and private sector seek to ensure that they have both a continued competitive advantage in global trade while maintaining or improving the standard of living of their citizens in economic and societal terms. The scope of these strategies is extensive. It embraces the research and development necessary to advance even further the capability of AI in disciplines, ranging from data science, to machine learning, to cognitive robotics, and much else in between. It also embraces strategies for promoting innovation—entailing the widespread adoption of scientific breakthroughs and related engineering inventions in AI—and ensuring that this is done in a trustworthy, ethical manner [28].

Amidst all this vigorous effort to investigate and exploit AI in developed countries, the relevance to developing countries is often neglected, except for a few cases where some agencies seek to assist developing countries, e.g. [23, 29], or initiatives taken in the developing countries themselves, e.g. [5]. Consequently the special role that AI can play in supporting developing countries doesn't always receive the attention it merits [88]. This essay attempts to shift the spotlight and highlight the ways in which AI is relevant for developing countries, focusing specifically on Africa.[2] In this essay, we refer mainly to the countries in Sub-Saharan Africa, that is, East Africa, West Africa, and Southern Africa. In doing so, we highlight the factors that influence the success or failure of efforts to leverage the benefits that AI can provide. As we will see, it all turns on trust and the crucial difference between invention and innovation.

[1] For an overview of national AI policies and strategies globally, see [69].

[2] Africa is a continent comprising fifty-four countries and many different cultures: it is not a homogeneous society and this needs to be borne in mind when speaking of "Africa". Indeed, the words of Horst Köhler, former President of Germany, in his speech on the impossibility of speaking of Africa sounds a cautionary note: "I would like, if I may, to clear up one misunderstanding right away: Horst Köhler is not an Africa expert … the reality on the ground in Africa is so much more complex than written accounts suggest … the more I learned about Africa, the more I realised how much there was still to learn" [51].

2 The Benefits of AI Depend on Adoption and Trust

Rose [76] distinguishes between creativity, invention, and innovation. Creativity can lead to the invention of a novel idea or artefact but innovation carries the creativity and inventions into wider use: the diffusion of that invention and its widespread adoption, leading to substantial social change in the practices of a community of people. He frames this succinctly in a formula: "innovation = invention + exploitation + diffusion", where the invention is commercially developed and exploited, and, significantly, adopted in a wider community of users.

Successful innovation also depends on infrastructure. Rose notes that infrastructure is the unnoticed precondition for technology innovation [76]. There are two forms of infrastructure, the physical and the social. The physical infrastructure might include the availability of electrical power, communications networks, or internet connectivity, something that is taken for granted in developed countries but which cannot always be assumed in developing countries. Of equal importance is the social infrastructure which includes the social conventions that govern people's behaviour and the practices they find acceptable and unacceptable. Social infrastructure heavily impacts on whether or not an invention is adopted and becomes an innovation that can yield benefits for the local community. Crucially, social infrastructure includes trust and people's sense of what is trustworthy.

Hofman et al. [38] define trust as the expectation that a service will be provided or a commitment will be fulfilled, emphasizing the importance of *expectation* in their definition. Expectations, as they point out, depend on many things but, irrespective of what these expectations are, they are certainly grounded in the socio-cultural experience of those whose trust is required.

The importance of the cultural context in the evolution of trust is also emphasized by Lee and See [55], who define trust as "the attitude that an agent will help achieve an individuals goals in a situation characterized by uncertainty and vulnerability". They point out that there are many factors at play in the development of trust, including individual, organizational, and cultural context. They define culture as "a set of social norms and expectations that reflect shared educational and life experiences associated with national differences or distinct cohorts of workers". An awareness of these social norms and expectations, and the socio-cultural background from which they arise, is crucial to the development of trust in any new technology, including AI-based products and services, and by extension to their diffusion and adoption. For example, language as an important element of culture presents itself in multiple forms in Africa. There are about 1,500–2,000 officially recognised languages spoken across the 3,000 ethnic groups in Africa [70]. One needs to be alert to the biases that might surface if developers from a primary region, language, or tribe created a loan allotment algorithm for the remainder of the continent. This is worthy of concern because such scenarios have played out badly in other continents. In the USA, AI algorithms have been used in predictive policing, labeling residents based on location, social economic status, and name, resulting in cases where African Americans have been profiled, even though no crime was ever committed, no criminal record existed, and there was no recent contact with law enforcement [57].

Culture can be characterised in many ways. Hofstede identifies six dimensions in which an understanding of cultural issues should be addressed [39–41]. Others highlight the different ways that cultures perceive time and space, noting that concepts of time in the West and in Africa differ significantly [11]. Without wanting to fall into the trap of generalising across a multitude of cultures and ignoring ethnographic diversity, one can say that time in Africa has traditionally been tied to events, which may be regular or irregular, in contradistinction to the view in the West of time as continually moving from past, to present, to future. These factors have a bearing on how technology, generally, and information technology, powered by AI, in particular, can support an individual or a local community in Africa and whether or not that support, no matter how well intended, will be accepted, trusted, and adopted. Lack of trust can severely and negatively impact the adoption of these services and products, fatally undermining the achievement of the anticipated benefits: "Changes in the factors that affect users expectations will also impact users trust levels" [38]. Furthermore, AI brings its own special factors, e.g. explainability, transparency, lack of bias, all of which have their own influence on whether or not products and services that use AI will be trusted and adopted.

The consequence of this argument is that, if developing countries in Africa are to reap the rewards of adopting AI, innovation needs to be in the hands of those who understand the sociocultural factors that impact on trust, an understanding of which is essential for adoption and the realization of the benefits of the technological invention. In other words, as Michel Bézy puts it, it is imperative to "develop the African innovation market where new ICT solutions that are adapted to Africa's environment and needs will be developed by Africans for Africa" [16]. In the following section, we will ground this argument by looking more closely at the importance of AI to Africa.

3 AI in Africa

AI is having an increasingly positive impact in Africa, in sectors such as energy, healthcare, agriculture, public services, and financial services [68]. It has the potential to drive economic growth, development, and democratization, reducing poverty, improving education, supporting healthcare delivery, increasing food production, improving the capacity of existing road infrastructure by increasing traffic flow, improving public services, and improving the quality of life of people with disabilities [72].

In the energy sector, AI and internet of things (IoT) technology have been proactively supported financially and adopted. Companies such as Engie [26], the French electricity provider, have funded several energy tech startups such as Fenix International [30], Mobisol [63], PowerCorner [73], and partnered with Equatorial Power [27], among others. Through pay-as-you-go energy products in Uganda, Zambia, Kenya, Tanzania, Rwanda, Nigeria, Benin, Ivory Coast, Côte d'Ivoire, and Mozambique, AI is being used to score users and predict demand, making the products more affordable and adaptable. For example, Fenix uses predictive analytics to extend energy services and products to those who previously lacked access. Because of solutions like these, more of the over 600 million people in Sub-Saharan Africa who lack electricity can now be connected [74]. Initially targeting East Africa, the Electricity Growth and Use in Developing Economies Initiative [25] is using data analytics and deep learning, drawing on a broad base of historic consumption data and satellite imagery, with the goal of providing an open electricity consumption growth prediction service for individual businesses and residences. It is also using daily night-time illumination satellite imagery to provide wide-area, long-term estimates of grid stability across Sub-Saharan Africa.

In the healthcare sector, AI helps address the shortage of doctors through telemedicine and access to medical supplies through drone delivery [15]. In Kenya and South Africa, Tambua Health is providing an AI-assisted handheld tool that uses deep learning algorithms to assess the health of the heart and lungs with minimal training and minimal wait-time [82]. The government of Rwanda recently announced plans to open a robotics cancer training centre [49] in collaboration with a France-based research institute for digestive cancer [48]. This centre will offer laparoscopic training and R&D for minimally-invasive surgery. It has already recruited software developers and research engineers from local universities, leveraging graduate education in robotics and computer vision. In conjunction with the United Nations Development Programme, Rwanda has also recently deployed smart anti-epidemic robots in their successful fight against COVID-19 [85]. The use of drones in healthcare also has significant potential. For example, Silicon Valley-startup Zipline [90] partnered with the Rwandan government to deliver more than 50 types of blood products to rural hospitals and clinics using custom-designed drones [24]. The Zipline drones have a range of more than 100 km and, as of 2018, 12,000 units of blood had been delivered on more than 6,000 flights. As soon as a drone leaves the launch catapult, it is fully autonomous [1]. More than 30 of its 100 employees are Rwandan. The authors of an IEEE Spectrum article sum up the Zipline operation up well: "In the distance, we can hear the faint buzz of another Zip returning home after making its delivery of blood. Anywhere else on Earth, it would be futuristic. In rural Rwanda, it's just routine" [1].[3]

In the agricultural sector, AI has the potential to improve productivity and efficiency at all stages of the value chain, allowing small-holder farmers to increase their income through higher crop yield and greater price control, detection and precision treatment of pests and diseases, monitoring soil condition and targeted deployment of fertilizer, creation of virtual cooperatives to aggregate crop yield, broker better prices, and exploit economies of scale. There are a few companies already deploying AI in agriculture. Gro Intelligence, for example, is an analytics company in Kenya which is filling a global gap in the world of agricultural data by deploying artificial

[3] To see a Zipline drone drop blood packs to a clinic in rural Rwanda, see https://bit.ly/2pfnB6l (time interval 0′ 52″–1′ 22″).

intelligence systems for food security and climate stability solutions [35]. The startup recently closed an $85 million Series B round.

Drone technology for precision agriculture—using targeted interventions that optimize the use of available resources to increase profitability and sustainability of agricultural operations [33]—is a potential game-changer for the African continent, albeit one that requires a skilled workforce with competencies ranging from planning flight itineraries, operating GIS and data analysis software, interpreting data, and providing agronomic advice [10]. Their use is growing quickly in situations where crops are grown as a monoculture on large holdings and local companies, e.g. [19] in Rwanda, [2, 42] in South Africa, are now addressing the challenges of deployment for small-scale, multi-crop farms. Significantly, this also opens up opportunities to develop systems that can automatically incorporate agronomic expertize to identify appropriate interventions based on real-time sensor data, e.g. soil moisture level, pH level, nitrate level, and temperature, exploiting IoT platforms [12]. Existing projects include the Third Eye project in Mozambique and Kenya using low-cost drones to provide advice to farmers on irrigation and when to apply fertilizer and sow seeds [83], resulting in an increase in crop production by 41%, a reduction of water use by 9%, and a 55% increase in water productivity [10]. Microsoft is working to apply its Farmbeats platform [86] in developing countries by lowering the high cost associated with dense deployment of sensors, exploiting sparsely distributed sensors and aerial imagery to generate precision maps, and using smart phones attached to hand-carried low-cost tethered helium balloons [81].

Drones are also used for surveying elephants in Burkina Faso [87], similarly as a tool to combat poaching of rhinos in South Africa [64], and for humanitarian aid, e.g. for detailed mapping and modelling flood risks in Dar es Salaam, Tanzania, Africa's fastest growing city where 70% of the people live in informal, unplanned settlements with inadequate infrastructure [80].

Evidently, the spirit of entrepreneurship and innovation in AI is flourishing in Africa. For example, Hepta Analytics, a startup by seven Carnegie Mellon University Africa graduates, specializes in helping local industry leverage the benefits of data science [37]. One of their products, Najua, focusses on using machine learning to make the web available in local African languages [65]. However, progress can be inhibited for so-called "low-resourced" languages, i.e. languages for which few digital or computational data resources exist [66], because of the lack of sufficient training data. This is symptomatic of a problem that is endemic to almost all applications of machine learning in Africa: the paucity of data. Another Carnegie Mellon University Africa graduate heads a team of entrepreneurs deploying IoT technology on tea plantations in Uganda [47]. Ubenwa is a mobile app developed by a start-up in Nigeria. It uses AI to analyse acoustic signatures in newborn babies to detect early signs on perinatal asphyxia, a leading cause of neonatal disability and death. Given that many developing countries in Africa have an agrarian economy driven primarily by smallholder farmers, agriculture, as we have noted already, is a popular target for African tech entrepreneurs. For example, uLima is a smartphone app for farmers, agro-dealers, and others in the sector. It provides access to crop and livestock management information, weather and market price information, as well as customized crop and livestock calendars, all focused on improving farm productivity and the livelihoods of farmers and their families [84]. Since most farmers in Africa are smallholders and don't have access to smartphone technology, other companies provide similar services using lower-tech feature phones [44].

4 Accelerating the Exploitation and Adoption of AI in Africa

Despite the positive outlook presented above, widespread benefits of AI won't materialize without appropriate investment, education, and a legal framework to safeguard ethical research, development, and innovation [20, 68] along with access to a deep pool of data that is relevant to Africa and initiatives to build trust [72]. The crucial importance of ensuring sufficient representative data is available cannot be overstated. One study targeting machine translation of over thirty African languages showed that participatory research offer a potential scalable solution to this problem [66].

Support from foreign agencies can help, particularly where it is collaborative and well-targeted. One example is the strategic partnership with the Smart Africa alliance [79] for a digital Africa, supported by the German Federal Ministry for Economic Cooperation and Development [23]. This program aims to advance Africa's development through digital innovations. The FAIR Forward—Artificial Intelligence for All program [29], also funded by the German government, seeks to strengthen local technical know-how on AI in Africa and Asia. To date, they have formed partnerships with five countries, four in Africa (Ghana, Rwanda, South Africa, and Uganda), and the fifth with India. Other programs target the promotion of tech start-ups, e.g. the Make-IT Initiative [58] and Google Startups Accelerator Africa [34].

5 The Downsides of AI

It's not all good news, though. The deployment of AI in developed countries can have a severe negative impact on developing countries due to the phenomenon known as premature deindustrialization [53, 75] which sees low-wage developing countries having fewer opportunities for industrialization before achieving income levels comparable to those in developed countries. Kenya, Nigeria, and South Africa, for example, are projected to have approximately 5.5%, 8.5%, and 12.5%, respectively, of their workforce displaced by automation [59]. A report by the Oxford Martin School at the University of Oxford and Citi summarizes the situation in Africa in stark terms [31]:

> In most of sub-Saharan Africa, the manufacturing share of output has persistently declined over the past 25 years. The share of jobs in manufacturing is even smaller: just over 6% of

all jobs. This figure barely changed over the course of the three decades leading up to 2008, while manufacturing employment in Asia grew from 11% to 16% over the same period.

Developing countries lose their competitive advantage in manufacturing due to the lower cost automation in developed countries and therefore miss out on the economic benefits that developed countries enjoyed as their workforces moved from low-value work to manufacturing before progressing to a post-industrial service economy. Consequently, developing countries are increasingly likely not to have the opportunity for rapid economic growth by shifting workers from farms to factory jobs because (a) automation undermines the labour cost advantage and (b) developments in robotics and additive manufacturing allow companies in advanced economies to locate production closer to domestic markets in automated factories, allowing this work to be moved closer to home in the developed countries.

AI and robotics can help offset this trend, at least to some extent [53]. This growing concern about premature deindustrialization in emerging and developing countries will require new growth models: "because skilled jobs are substantially less susceptible to automation, the best hope for developing and emerging economies alike is to upskill their workforce" [31].

It is also important to keep in mind that AI can be used for negative purposes, either intentionally or unintentionally, e.g., by fomenting religious, ethnic, social, and political divisions through deep fake misinformation [15], the lack of democratization in AI, including implicit and explicit bias in the data that are used to train the AI models.

For concrete examples of this danger, consider the following. Buolamwini et al.'s [18] evaluation of bias in automated facial analysis algorithms and datasets with respect to phenotypic subgroups showed an uneven distribution of skin colors in datasets. The datasets were overwhelmingly composed of lighter-skinned subjects with 79.6% for IJB-A and 86.2% for Adience. Upon the evaluation of three commercial gender classification systems (Microsoft, IBM, and Face++) using a corrected and representative dataset, results showed that darker-skinned females are the most mis-classified group with error rates of up to 34.7%. The maximum error rate for lighter-skinned males was 0.8%.

Wilson et al. [89] showed that object detection systems like those used in autonomous vehicles had uniformly poorer accuracy (5% less accurate) when detecting pedestrians with darker skin types. This is a serious issue for autonomous driving in Africa. Unfair decisions have also been experienced in search engines. Search algorithms (e.g. Google) have also been noted in [67] for reproducing and reinforcing social stereotyping and racism among the minority groups.

COMPAS is a proprietary tool used to assess the probability of recidivism [17]. However, there are concerns about COMPAS being discriminatory [36]. Larson et al. [54] disclosed that the COMPAS algorithm produces recidivism risk assessments that are attributed with higher false positive rate and much lower false negative rates for darker-skinned defendants compared to light-skinned defendants.

These instances have negative impact on the perception of trust and confidence of Africans, which in turn, affect the adoption of such technologies especially when they are not developed locally.

Despite all these potential downsides, AI still comes with promising advantages. In the guise of digital forensics and cybersecurity, it assists in identifying misinformation. It also assists in healthcare administration, business, and education. As we saw in Sect. 3, and as we will see in the next section, Africa can harness the many upsides of AI, especially through education.

6 AI Education in Africa Is the Key to Progress

In Sect. 2, we argued that Africa must participate in building and deploying its own AI if there is to be trust, adoption, and consequent benefits. In turn, this meaningful exploitation of AI requires a skilled workforce and the demand for AI engineers will increase significantly [72]. The challenge for the education system in Africa—at every level, from primary to third level and beyond—is to adapt to the new needs for Industry 4.0 by focusing in primary and secondary education on science, technology, engineering, and mathematics (STEM) subjects [13, 14], and in third- and fourth-level education on imparting the requisite skills that will allow graduates to adapt quickly to the evolving AI landscape [12].

There is evidence that this is happening. For example, with sponsorship from Google and Facebook, the African Institute of Mathematical Sciences [9] launched a Master of Machine Intelligence in Kigali, Rwanda, in 2018 [8, 20]. With the backing of the Government of Rwanda, Carnegie Mellon University Africa offers two Masters programs, one in in Electrical and Computer Engineering and one in Information Technology, both targeting key skills in AI, machine learning, data science, software engineering, cyber-security, telecommunications, and energy systems [21], with a dedicated Master program in Engineering AI in the pipeline. With the support of over US$10 million from the African Development Bank, the Rwandan Development Board completed the construction of a new campus for CMU-Africa in 2019 as part of Kigali Innovation City (KIC) [12]. Google opened an AI Research Lab in Accra, Ghana, in 2018; and the Deep Learning Indaba summer schools [45] attract more applicants than they can accept from almost half the countries in Africa [20]. When the constraints of the Covid-19 pandemic meant that they could not hold these summer schools, the organizers, still committed to their mission to "strengthen African machine learning and artificial intelligence", launched instead a program of AI4D innovation grants [46]. The successful annual IBRO-SIMONS Computational Neuroscience Imbizo[4] also had to be suspended during the pandemic but will be held again in 2022 [43].

The signs are positive at secondary and primary level too. For example, 42 teams from 18 countries in Africa attended the fourth edition of the Pan-African

[4] *Imbizo* is a Xhosa word meaning "a gathering to share knowledge" [43].

Robotics Competition (PARC) in Ghana in 2019 [71]. In 2018, senior students at the Massachusetts Institute of Technology helped organize a three-week robotics camp focusing on agriculture, bringing together more than 40 students aged between 14 and 17 years (18 boys and 22 girls) drawn from 20 schools in Rwanda [62]. Fundi Bots [32] in Uganda provides classes in robotics, and has already reached 10,000 children in an effort to encourage them to learn STEM subjects in a fun, interactive, and practical manner. In addition to that, they launched a special program, Fundi Girls to increase the significant under-representation of girls and young women in STEM education. Start-up companies such as the Children's Creativity Lab [22] in Rwanda are also looking to cater for younger children.

The plenary talk by Ayorkor Korsah, Ashesi University, Ghana, at ICRA 2015 on robotics in education in Africa [52] highlighted the relevance of robotics to Africa. She surveyed the various activities in promoting robotics in, e.g., Ghana, Kenya, South Africa, and Egypt, and emphasized the need to find ways to empower young Africans to provide robotics solutions to African problems.

The availability of a good education is not enough, however: that education must also be accessible. Regrettably, most young Africans cannot afford the high cost of education and it falls to governments to put in place free or reasonable-cost education and scholarships. Again, there is growing evidence that this is beginning to happen. For example, the Government of Rwanda provides the financial backing to reduce the costs of the CMU-Africa Masters programs to place them within the reach of students across Africa, with additional scholarships provided by, for example, Mastercard [60], Smart Africa Smart Africa [79], and the Mandela Institute for Development Studies [61], helping to bridge the remaining shortfall in required funding. With the backing of Google and Facebook, the AIMS African Master of Machine Intelligence is fully funded [8].

In a testimony to the drive and motivation to engage with AI in Africa, young Africans are taking matters of education in AI into their own hands. For example, young women and men meet every week to teach each other the latest techniques in AI, machine learning, and data science under the guise of AI Saturdays Lagos in Nigeria [6]. Some of these young people are students, others are budding entrepreneurs, while others are waiting (usually successfully) to be admitted to a Ph.D. program abroad, with the clear intention of returning to take up where they left off after they have gained the extra knowledge and know-how that will enable them to help transform the educational and technological landscape in Africa. This will foster the design and deployment of trustworthy AI technologies by Africans for Africans.

7 Conclusions

There are many factors that need to be addressed to achieve the benefits of AI in Africa, but success hinges not on enabling Africa, but on facilitating Africa's nascent efforts to enable itself. As Moustapha Cissé, head of the Google AI Centre in Ghana, states, "Fewer African AI researchers and engineers means fewer opportunities to use AI to improve the lives of Africans" [20].

In that context, it is important to keep in mind that the relevance of AI to Africa is not just to exploit it for social and economic development. There are several reasons why Africa can also play an important role in advancing the discipline of AI. For example, the elimination of bias and implicit discrimination in AI algorithms can be addressed in many ways. One of these is to increase the diversity of AI developers by growing the number of AI researchers and innovators in Africa.

So, how can the global AI community play its part in facilitating Africa's effort to enable itself? Greater attention can be paid to ensuring training sets for machine learning algorithms are available and that they are not biased and reflect the social, cultural, and ethnographic reality of African people, including the wide diversity of local languages. National and international research programs can allow African researchers to participate in collaborative research projects and provide funding for marginal costs. Educators can take sabbatical leave to teach in African universities. Researchers can do the same. Authors and instructors linked with online courses, such as the ones that AI Saturdays Lagos use to bootstrap their education, can give targeted guest lectures, either in person or remotely. GPU cloud providers can make their platforms accessible free of charge. Universities can greatly increase the opportunities for young aspiring researchers and developers to pursue fully-funded Masters and Ph.D. degrees in AI, machine learning, robotics, data science, and cybersecurity. All of this will help bright, ambitious, innovative African people to play their pivotal role in Africa's continuing efforts to embrace trustworthy AI, leading to the creation and adoption of African solutions to African problems.

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