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Bridging AI Literacy Skill Sets Gap: A Critical Priority Now and the Future in Developing Countries

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ABSTRACT

The leveraging of AI literacy in our world today has become expedient due to the growing demand AI plays in our daily lives. AI literacy is a set of competencies that enables individuals to critically evaluate AI technologies, communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace. The impact of AI technologies in critical infrastructures such as energy, education, technology, agriculture and healthcare has become crucial particularly in developing countries and as such demands public knowledge to hone their skills for greater efficiency and opportunities. The need to bridge the gap between AI literacy skills set has become imperative due to the rising demand for know-how and shortage of personnel in acquiring hard skills; technically, industry-specific skills, programming skills, IT systems knowledge and soft skills like problem-solving and effective communication skills, lifelong learning (willing to learn, unlearn and relearn), and so on. Finding a blend of these skills in individuals is grossly inadequate and difficult to come by. This study is aimed at an AI literacy paradigm shift to bridge skills with emphasis' on AI education, innovation with the help of case studies approach to showcase real-world applications as a corner-stone to close in this shortage in developing countries. It emphasizes the need for psychological readiness necessary to up-skill and re-skill, encouragement of diverse talent pipelines and collaboration with the government, public and private organizations and the academia to help address these skill gaps. This will inculcate confidence and know-how in developing countries necessary to build their AI capabilities to foster innovation, and create an enabling environment for a home-made AI adoption. This will make developing countries keep pace with technological advancement and a player in the global market.
Keywords: AI Literacy, Bridging, Skill set, Developing Countries, Hard skill, soft skill

INTRODUCTION

The vast majority of the public acknowledges the existence of AI services and devices, but seldom do they know about the concepts and technology behind, or aware of potential ethical issues related to AI [1]. This is more evident in developing countries where the adoption and implementation of these technologies seems to present challenges and opportunities as well. Developing countries, characterized by diverse socio-economic contexts, are at the crossroads of harnessing the potential benefits of AI to address existing challenges and propel economic development [2], [3], [4]. Many schools of thoughts have defined AI amongst them are some of the following: AI was first defined as "the science and engineering of making intelligent machines" in 1956 [5]. [6] broadened the definition as that which can perform cognitive tasks particularly learning and problem-solving with the exciting technological innovations such as machine learning, natural language processing and neural networks [7]. According to Columbia Engineering (n.d.) it defines AI as the development of computer programs that can imitate human thought and perform tasks in the real world, just like humans. The benefits AI poses for users, businesses and economies are enormous to lift productivity and economic growth. These can be seen spread across industries (e.g., business, science, art, education) to enhance user experience and improve efficiency, our everyday life (e.g., smart home appliances, smart-phones, Google, Siri) and so. This has created many job opportunities in various industries, as AI is believed to be the replacement for tomorrow's workplace. However, not all disciplines will be replaced by AI, only people with AI knowledge will replace those that do not in the future of work. This call for everyone to learn AI to gain competitive advantage as a new skill set in their workplaces in this new era of intelligence. Indeed, as AI is increasingly applied to non-labour-intensive tasks, including decision-making [8] and art creation [9], there is intensifying pressure on the current and future workforce to be adequately prepared for an AI future. While the transformative potential of AI is evident, its adoption and integration present a distinctive set of challenges and opportunities for developing countries [10]; [11]. Developing countries also grapple with a shortage of skilled talent proficient in AI technologies, hindering the effective deployment and maintenance of AI systems [12]. They struggle with a shortage of professionals trained with skills in machine learning, data science, and AI development. Thus, the bridging of these skills set gap requires concerted efforts in education and training programs making AI literacy emergence the new skill set for everyone to learn to respond to this new era of intelligence. AI literacy' refers to the elements that the workforce needs to harness AI and form a synergistic relationship with the technology. It is a multi-dimensional concept that relates to the preparation of educated citizens to contribute to their professions and to society in general [13] in the age of AI [14]. AI literacy means having the essential abilities that people need to live, learn and work in our digital world through AI-driven technologies [15]. Despite the importance of promoting AI literacy as universally as possible [16], most AI literacy education initiatives target computer science students in higher education and do not adequately emphasize the application of AI to diverse real-life problems [17]. This study bridging AI Literacy skill sets gap: a critical priority now and the future in developing countries is both an opportunity and necessity because there is a wide gap between the users; educators, trainers, expert and non-expert of AI technologies in the developing countries making the use of AI for research and development (R&D) still out of reach for most researchers in developing countries. Currently, most developing countries preparedness to harness the opportunities presented by AI technologies are not certain. The overall gap in capabilities between developed and developing countries is evident in the findings of the Government AI Readiness Index 2021, which measures the capabilities and enabling factors required for a country to implement AI solutions [18]. Europe, North America, and East and Central Asia have dominated the world's sources of AI conference publications. In 2020, East Asia and the Pacific accounted for 27% of all conference publications, North America 22%, and Europe and Central Asia 19%. By contrast, sub-Saharan Africa accounted for just 0.03% [19]. The curricula of educational institutions must adapt to include AI-related courses, ensuring that the workforce is equipped with the necessary expertise to harness AI effectively [20]. Furthermore, researchers from developing countries often play little if any role in key international conversations on AI, especially those held in the United States, Canada and Europe. Also, another major consideration for AI literacy is the psychological readiness of users to interact with AI. Psychological readiness is required for educated citizens to proactively use AI as a tool to solve real-life problems, and to fully harness AI technology to contribute to their professions and to society [21]; [22].

Some Relevant Literature on Skills

The growing literature about skills is characterized by a lack of a clear definition or taxonomy of skills [23], and international skill strategies are constantly revised (e.g., Organisation for Economic Co-operation and Development (OECD) [24]. There are various examples of skills classification and frameworks, among them are such taxonomies as hard versus soft skills, cognitive versus non-cognitive skills, and portable versus unportable skills [25]; [26]; [27]; [28]; OECD, 2012). In this article, we have used the common hard versus soft skills division [28]and [29], have divided the examined skills into two main groups: technical knowledge and skills (hard skills) and organizational, managerial, social, and personal skills (or soft skills). Not minding the classification or definition used, the skill sets required must be comprehensive and multifaceted. Not taking cognizance of either it is hard or soft skills alone but their combinations. The complexity of tasks required, even at the lower end of the skills distribution, increases, and a "package" containing different types of skills is required from the employee [23]. Prospective careers of highly qualified labor also require complex skill sets, with competences acquired not only during university training but also during the lifelong learning process [30]. There is a growing demand for workers to obtain interdisciplinary and complex skill sets. This has been adopted in STEM (science, technology, engineering, and mathematics) related fields. Along with specialized skills, most STEM professionals nowadays need knowledge in areas that are not typically understood as STEM-related (e.g., humanities, social sciences, management, design) [31] [32]. The complexity of tasks required, even at the lower end of the skills distribution, increases, and a "package" containing different types of skills is required from the employee [23]. Prospective careers of highly qualified labor also require complex skill sets, with competences acquired not only during university training but also during the lifelong learning process [30]. Companies have gone ahead to needing employees not only with STEM but STEAM skills (where A stands for "arts"). This is to incorporate the artistic and design-related skills and thinking processes into STEM. The integration of STEM with arts is a response to the need to prepare young specialists for dealing productively with current global challenges [33];[34]; [35].

Case Studies: AI Implementation in Selected Developing Countries

Artificial Intelligence (AI) implementation in developing countries is marked by diverse initiatives that harness technology to address specific challenges and propel socio-economic development.

This section presents case studies highlighting notable AI implementations in selected developing countries, showcasing the transformative potential of these technologies.

India:

Precision Agriculture for Smallholder Farmers: In India, where agriculture is a cornerstone of the economy, AI is being leveraged to enhance precision farming practices [36], [37]. Companies like CropIn are using AI algorithms to analyze satellite imagery, weather data, and soil conditions. Smallholder farmers receive personalized recommendations for crop management, irrigation, and pest control through mobile applications [38]. This AI-driven approach optimizes resource use, improves yields, and contributes to sustainable agriculture

Kenya:

AI-Powered Healthcare for Remote Communities: In Kenya, where access to healthcare is often limited, AI is making significant strides in improving medical services [39]. The company Ilara Health utilizes AI-driven diagnostic tools to enhance medical imaging analysis. This technology aids in the early detection of diseases, enabling timely intervention. Ilara Health's portable diagnostics also facilitate healthcare delivery in remote areas, addressing the challenges of distance and limited medical infrastructure. Also, Kenya's Kenindia Assurance plans to use AI to detect fraudulent motor insurance claims (https://www.kbc.co.ke/kenyan-insurers-utilizing-artificial-intelligence-to-curb-fraud-cases/). In addition to the industry's Integrated Motor Insurance Data System (IMIDS) through the Association of Kenya Insurers, it plans to establish a data center of customers' insurance history [40].

Brazil:

AI for Environmental Monitoring in the Amazon Rainforest: Brazil is deploying AI to address environmental challenges, particularly in the Amazon rainforest. The Instituto Nacional de Pesquisas Espaciais (INPE) utilizes AI algorithms to analyze satellite imagery and monitor deforestation in real-time. This AI-driven approach helps authorities detect illegal logging and enforce environmental regulations. By combining AI with geographic information systems (GIS), Brazil aims to preserve the biodiversity of the Amazon and combat deforestation.

Rwanda:

AI in Education for Enhanced Learning: Rwanda has embraced AI in the education sector to enhance learning experiences [41]. The Smart Africa initiative collaborates with companies like Zindi Africa to implement AI-driven platforms that provide personalized learning content. These platforms adapt to individual student needs, supporting educators in delivering tailored educational experiences. AI in education in Rwanda aims to bridge educational gaps and improve learning outcomes.

Vietnam:

AI-Driven Chatbots for Financial Inclusion: In Vietnam, AI is being utilized to promote financial inclusion. The National Payment Corporation of Vietnam (NAPAS) employs AI-driven chatbots to provide financial information and services to individuals without access to traditional banking [42], [43]. These chatbots enable secure and convenient financial transactions, fostering financial inclusion in regions with limited banking infrastructure.

Nigeria:

Healthcare and Medical: Nigeria's RxAll's handheld scanner fights fake drugs. It assesses a drug's compound by connecting the device to cloud-based databases, which contain information related to what the drugs should contain. The information is sent back to the phone. The database is updated using AI. The app also shows which other neighborhoods tested the drug. This gives information related to bad suppliers [44].

Skill Gaps:

Since skill gaps can be defined in various ways, it makes it difficult to measure them [44]. For instance, skills can refer to general cognitive and noncognitive abilities or the skill characteristic of a particular job, profession, or sector [45]. These can thus be technical, cognitive, or soft skills. Thus, various stakeholders have different interests, which leads to disagreements about the exact skills that are needed and how skills issues should be addressed [46]. Researchers, in turn, have struggled with the nuances of skill gaps, skill mismatches, and skill shortages, since they are broadly and commonly referred to in policy debates and documentation [47]. Gaps, in turn, have been described and captured in three commonly used terms: skill gaps, mismatches, and shortages. Skill gaps occur when employees do not have adequate skills to perform their tasks [48]. They are also closely related to skill shortage—the mismatch between the demand for and supply of specific skills—which is often used to describe the lack of available and suitably skilled candidates for vacant job positions [48]; [49]. Skills mismatch, in turn, reflects the imbalance between an employee's skill level and the skill level demanded by the work [49]; [45]. Evidently, no clear definition of skill gaps exists. Skill gap analysis is an important part of competency-based management. Project managers find it challenging to assign members to project teams, especially for projects that require expertise rather than for projects that are labor-intensive and need to deal with skill-related project risks [50]. The support of many already existing systems, ranging from infrastructure to information technology, can become much more difficult due to the loss of critical human skills and the lack of workers with the required skill set [51]. Industries are confronted with the lack of right-skilled workers, which contributes to a slowdown in adopting key technologies and reaching key goals [52]; [53]; [54]. This mismatch between the skills required by employers and those possessed by employees is often called a skill gap or skills gap [55]; [56]; [47]; [48]. Skill gap is an issue: The lack of workers with required skill sets is practically omnipresent, when the type or level of employee's skills is different from that required to adequately perform the job [57]. There are several causes for skill gaps. In a world gripped by severe environmental, economic, and social challenges and changes [58]; [59]; [60]; [61]; Organisation for Economic Co-operation and Development [45], workers in the industry sector are especially facing higher skill demands [3]. Due to constant changes, industry sectors must make disruptive changes to their operating environments and workflows. These changes modify employees' tasks, which demand new skills at all value chain stages of Industry 4.0 [53]; [62]. Hence, owing to the increased complexity of work environments and new operational structures, successfully implementing Industry 4.0 demands a wide range of skills [63]. Despite the attention paid to these phenomena and all the proposed solutions, this gap resists all efforts for closure [64]. Not only technical skills but also workers' transferable soft skills are insufficient (soft skill gap) [65]; [66]. Concerns about growing skill gaps have thus been raised worldwide [58] [67]; [45]; [48]. Consequently, individuals must be prepared to continuously update their skills to meet evolving skill requirements [33]. Fostering a work environment in which employees can continuously develop their potential is thus vital [68]. Moreover, workforce training/re-training should be considered a continuous process rather than an on-off activity [59]. This situation is challenging for engineering and information and communication technology (ICT) also: Gaps between industry expectations and perceptions of graduates' skill sets are taking place [69]; [70];[71]; [72]. Graduating students do not always possess the necessary skills required by employers, and they often lack not only professional knowledge or abilities but also soft skills such as communication, decision-making, problem-solving, leadership, self-motivation, creativity, emotional intelligence, and social ethics skills, as well as the ability to work with people of different backgrounds [73]; [74]; [75]. Young engineers often do not fully realize how important their soft and managerial skills will become in a professional career [76] and show a low level of motivation and satisfaction with soft skill courses [77]. The existing notable soft skill gap between ICT and engineering students' preparation and industry requirement is a challenge for the whole education system [78].

Bridging Skill gaps from educational change

Researchers have pointed out that fundamental conceptions of learning and teaching remain relatively static. Traditional curricula sometimes reflect what teachers regard as important, rather than what skills are actually required [79]. Nevertheless, there are good examples—in terms of high-quality teaching, effective school improvement programs, or valuable research evidence—of how and in what direction educational practice should be changed [80]. Unfortunately, these examples too often remain isolated islands unattached to the broader educational landscape [81] [82]. Therefore, it is often not a problem of the supply of good examples but of deficiencies in how this knowledge is transferred or adapted to the school's context [81]; [83]. To Bridging the skills gap in the educational system, there should be alignment to providing students with basic digital and ICT skills comprising the knowledge of algorithms, coding simple programs and logical reasoning. The early integration of digital skills in the curriculum will play a decisive role for the maintenance of a competitive labour force in the future. However, the acquisition of digital skills alone is not enough because technology is never static its always changing and so the digital skills we have today are likely to be obsolete tomorrow than we may imagine. Educational efforts should aim at providing its participants with integrated skill-sets of technical, creative and social skills. We are aware that innovations of tremendous heights have been achieved from successful combination of technical know-how with creativity suggesting that bridging technology which is the hard skills and the social and arts which represents the soft skills will be vital for future competitiveness. In a case study, [84] analyzed questionnaires and found that bridging the gap between universities and industry brings about full learning and it is no longer just about theories but also having industrial experience [84]. In the U.S., intense work is being carried out on the integration of AI in schools and among these schemes, AI4K12 stands out [85]. This scheme is especially interesting since it defines the national guidelines for future curricula, highlighting the essential collaborative work between developers, teachers and students [86]. In the U.S. we can also mention the proposal made by the Massachusetts Institute of Technology, which is an AI curriculum that aims to engage students with its social and ethical implications [86]. In China, the Ministry of Education has integrated AI into the compulsory secondary school curriculum [87]; [88]. Among their schemes we can reference the AI4Future initiative of the Chinese University of Hong Kong (CUHK), which promotes the co-creation process to implement AI education [89]. In Singapore, a program for AI learning in schools has also been developed, where K-12 children learn AI interactively. However, the program is hindered by a lack of professionals (teachers) with adequate training [85]. In Germany, there are also several initiatives to pilot AI-related projects and studies [90], including the launch of a national initiative to teach a holistic view of AI. This initiative consists of a 6-module course aimed at explaining how AI works, stimulating a social discourse on AI and clarifying the abundant existing mis-conceptions [90]. Canada has also designed an AI course for high schools. The course is intended to empower students with knowledge about AI, covering both its philosophical and conceptual underpinnings as well as its practical aspects. The latter are achieved by building AI projects that solve real-life problems [91].

Strategies for Bridging the Gap

The gap in AI implementation, particularly in developing countries, can be bridged through strategic and concerted efforts. This section outlines key strategies to address challenges and promote the inclusive deployment of AI technologies. To bridge the gap, significant investments in digital infrastructure are crucial. Governments and private entities should collaborate to improve broadband connectivity, ensure reliable power supply, and establish data centers. Accessible and robust infrastructure forms the foundation for effective AI implementation.

Addressing skill gaps is paramount

This is because of the emergence of newer skills together with new and modern technologies, while some have been in existence and relevant but are needed in particular combinations ("skill sets"). Initiatives for capacity building and education in AI-related fields should be prioritized. This includes incorporating AI courses into educational curricula, providing training programs for professionals, and fostering a culture of continuous learning.

AI literacy curriculum design

Approaches to curriculum development differ widely, ranging from the product-centered model (technical-scientific perspective) to the process-centered model (learner perspective). It is necessary to define the core competencies for AI literacy according to three dimensions: AI concepts, AI applications and AI ethics and security [16]. This can be applied to all the strata of education; primary, secondary and the tertiary levels. According to [89] curricular design must include different elements such as content, product, process and praxis. The curricula of educational institutions must adapt to include AI-related courses, ensuring that the workforce is equipped with the necessary expertise to harness AI effectively [92]. It is also convenient for learning in AI to follow the computational thinking model [18], contextualizing the proposed curriculum and providing it with the necessary resources for teachers [21].

Partnership and Synergizing

Partnerships between educational institutions, industry, and government bodies can facilitate knowledge transfer. This can help to establish a fora for development cooperation, shared challenges and technological innovations to synergize either regionally or internationally. For example, the partnership existing between Canada's International Development Research Centre with Sweden's International Development Cooperation Agency resulted to the Artificial Intelligence for Development in Africa (AI4D) with an investment of CAD 20 million over four years, plans to support African- led research on using AI to meet local needs. This partnership with the Human Sciences Research Council ZA in South Africa, also supports the African Observatory on Responsible AI (AORAI). In addition, AI4D works with the African Union Development Agency to develop a model African AI policy. The Observatory aims to position the African continent in global debates and policy making on responsible AI [93]. Also, in 2021, France's Agence Nationale de la Recherche, in partnership with the AFD, launched the IA-Biodiv Challenge, aimed at supporting AI-driven research in biodiversity (AFD, n.d.). This research initiative provides a space for scientists working on AI and biodiversity in France and Africa to mutually learn, share and engage. Developing countries can benefit from partnerships with tech companies, research institutions, and international organizations. Knowledge exchange, joint research projects, and sharing best practices contribute to a collective effort in bridging the AI gap.

Technology Hub for Research and Development

The encouragement of research and innovation in AI is key to be informed about current advancements. Stakeholders in developing countries could also consider formulating research questions relevant to local priorities and amenable to analysis using AI. The 100 Questions Initiative, launched by the GovLab, could provide inspiration (The 100 Questions, n.d.). The selection of such questions could be informed by a dialogue between civil society, the private and public sectors, and academic and research institutions. Knowing priority questions could lead to new forms of data collaboration with the private sector to help advance the necessary science. Research efforts tailored to the locality will ensure that AI solutions confines to the specific needs and challenges of that place. For example, in the quest for stakeholders in Bangladesh to analyse and respond to climate extremes, a leading telecommunications provider, Grameenphone, shared its anonymous mobile call data records with three partners. Grameenphone, the United Nations University Institute for Environment and Human Security, the International Centre for Climate Change and Development, and the Telenor Group examined population movements before and after cyclone Mahasen struck Bangladesh in May 2013, an extreme climate event that affected 1.3 million people [93]. In addition, grants could support investments in AI R&D in developing countries. This could include the creation and support for centres of research excellence like the African Research Centre on Artificial Intelligence (ARCAI) in the Democratic Republic of Congo (DRC) [93-95]. ARCAI will assist in AI research, collaborate with universities in Africa, participate in the creation of a network of researchers and contribute to training to help citizens actively participate in the digital transition.

Government Policies

It is essential for government in developing countries to develop a comprehensive AI policy framework that will ensure ethical practices and inclusivity. Although, policy- makers all over the world are facing the challenge of improving skill provision systems and upgrading education policies aimed at rapidly increasing the skill levels of individuals of all ages, particularly with regard to both STEM (science, technology, engineering, and mathematics) and non-cognitive soft skills [94]. Governments should establish frameworks that address concerns related to bias, transparency, and privacy. Engaging stakeholders, including AI developers, civil society, and marginalized communities, in the policy-making process ensures diverse perspectives are considered. The community input in the decision-making processes serve to address the local needs making the AI solutions culturally sensitive to them. Governments can give incentives to businesses to encourage and support them to invest in AI to foster a system that can spur innovation. The promotion of an inclusive A.I development by government necessitates adequate funding and support targeted at AI-driven startups and entrepreneurs. Accessibility to funds, mentorship programs, and incubators can bring about empowerment to local innovators who now fashion out localized solutions that address specific challenges in their communities. The goal is for creation of an enabling environment where AI technologies contribution is an inclusive development that ensures that the benefits of these innovations spreads to all segments of society in developing countries.

Public Private Collaboration

Collaboration between the public and private sectors is vital for successful AI literacy implementation. A good example is the collaboration between The GovLab (an action research centre based at New York University's Tandon School of Engineering) and the Agence Française de Développement (French Development Agency, or AFD). Together, they launched the recent #Data4COVID19 Africa Challenge. This supported Africa-based organisations to use innovative data sources to respond to the COVID-19 pandemic [22]. The collaboration between the public and private facilitates the sharing of resources, expertise, and data. An example is the Africa Regional Data Cube, an initiative brought about by collaboration among many actors. These include the Committee on Earth Observation Satellites, Strathmore University in Kenya and the Global Partnership for Sustainable Development Data. Directly supporting activities in Ghana, Kenya, Senegal, Sierra Leone and Tanzania, the Data Cube has helped harness the latest Earth observation and satellite technology and data to address issues related to food security, urbanization, deforestation and more [95]. With the global nature of AI challenges, it is important for developing countries to also seek international collaboration.

CONCLUSION

This study stem from the fact that the proliferation of A.I and its attendant benefits across all sectors of the economy is unfathomable all over the world and the developing countries are not left out. But there are skills gap that are important to be understood due to the astronomical rate of our industrial changes in recent times which have mostly affected developing countries whereby workers' learning speed is hampered, causing delays and failures in adopting technology and sustainable development. So, the need for A.I literacy to bridge the gap in the skill sets as emphasized in this study. This is particularly necessary for developing countries of the world who still grapple with the technology not to be solely consumers and dependent on the advanced countries for A.I technologies which further heighten and entrench economic disparities but to fashion out a niche for themselves to grow and build their AI capabilities, foster innovation, and create an enabling environment for AI adoption to thrive. Also, to understand the skills workers should have, to be in demand in the labor market and encourage education and training organizations to go beyond the normal by providing a foundation for extending the acquired skill set in the future, adding what may be required in the "Lego mode" (modular education). The study considered some strategies that can be used to bridge these skills gap using education and training institutes by broadening A.I participation for everyone, government policies encouraging the principle of inclusivity, provision of equitable access, and collaboration and synergizing with all stakeholders and users using technology hubs and research and development. The emergence of A.I literacy as a new skill set for everyone to learn in this new era of intelligence provides a competitive advantage at work which compares to classic literacy that includes reading/writing and mathematical abilities.

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