



Artificial Intelligence and Start-Ups in Low- and Middle-Income Countries: Progress, Promises and Perils



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Executive summary

Around the world, artificial intelligence (AI) is automating functions and making new services possible with breakthroughs in cheap computing power, cloud computing services, growth in big data and advancements in machine learning (ML) and related processes. AI can radically alter and improve the way governments, organisations and individuals provide services, access information and improve their planning and operations.

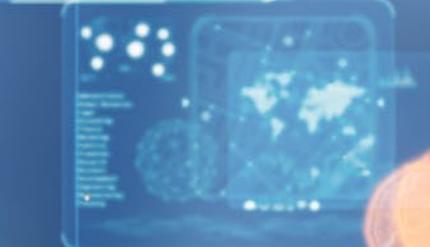
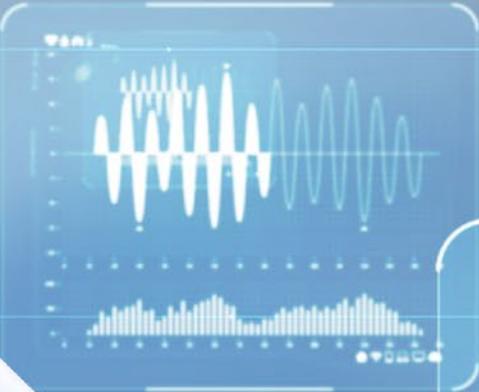
This study examines the current use of AI in low- and middle-income countries (LMICs) across Sub-Saharan Africa, North Africa and South and Southeast Asia. The report maps a sample of 450 start-ups by sector in alignment with the UN Sustainable Development Goals (SDGs) and, based on interviews with AI experts in LMICs, we explore trends and challenges in business models, barriers to innovation and the ethical and responsible use of AI.

Business intelligence and analytics emerged as a clear leader in the use of AI, as it captures a wide range of business services solutions, from accounting and decision making to customer service. Healthcare is also a leader and benefits from AI solutions in many ways, from sophisticated diagnosis and treatment options to hospital management systems, personalised lifestyle change recommendations and healthy eating habits. These sectors were followed by food and agriculture, financial services, education and retail and consumer goods.

The report concludes that while AI has the potential to achieve social good, positive outcomes are not guaranteed. There are many fundamental questions about data protection, ingrained bias as a result of poor data collection methods, social inclusion and the responsible use of AI. AI enables new technologies to improve efficiency and productivity, but it may also deepen inequalities, hindering the achievement of the UN SDGs. Since increased use of data introduces further privacy and ethical concerns, AI solutions should be guided by sound privacy and ethical principles.



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Research objectives and scope



This study aims to understand the current and potential use of AI by start-ups and small and medium enterprises (SMEs) in low- and middle-income countries (LMICs) in four regions: Sub-Saharan Africa, North Africa and South and Southeast Asia. We analyse the business models of companies using predominantly home-grown AI solutions and examine which sectors and countries are receiving the most funding.

The study answers the following research questions:

- What is the status of AI use in LMICs?
- Which sectors, geographies and business models are showing the most promise, and why?
- What are some of the barriers to implementing AI solutions in LMICs?
- How can AI be used ethically to accelerate the achievement of the SDGs?

Summary of methodology

Literature review

A range of sources were consulted to provide an up-to-date summary of the state of AI in LMICs, as well as opportunities and risks for sustainable development.



Key informant interviews

23 expert interviews were conducted with AI experts and practitioners, including entrepreneurs, donor organisations, project beneficiaries and technology users.



Mapping use cases in Africa and Asia

The study includes a sample of 450 AI start-up use cases in LMICs in African and South and Southeast Asian countries, most of which are early-stage, home-grown solutions with a focus on the SDGs.



Case studies

A range of case studies were selected to provide a more detailed picture of the business models being used by innovators, and the barriers they faced in implementing AI-based solutions in LMICs.



The Central Insights Unit mapped AI use cases to create a representative sample. The 450 use cases in the sample should not be considered an exhaustive list of AI applications currently active in the target countries. We are aware of over 3,000 use cases in these countries, but the focus was narrowed down to 450 use cases due to time and resource constraints.

The use cases were selected based on the extent to which they enabled progress on sustainable development in line with the SDGs. To explore home-grown innovation and local entrepreneurship, we focused on how start-ups and SMEs were using AI, rather than more established companies and mobile network operators (MNOs).



Overview of AI and its capabilities

AI is a rapidly growing field, with a vast range of processes and applications. Some of the underlying technology was first developed in the 1950s, but there has been a step-change in the range and effectiveness of AI in the last decade. AI applications have built on and enhanced many digital functions and can be developed with digital data that may have initially been gathered for other purposes.

AI is the ability of a machine or computer to emulate human tasks through learning and automation.¹ The UK Engineering and Physical Science Research Council explains it as: “Artificial Intelligence technologies aim to reproduce or surpass abilities (in computational systems) that would require ‘intelligence’ if humans were to perform them. These include learning and adaptation;

sensory understanding and interaction; reasoning and planning; optimisation of procedures and parameters; autonomy; creativity; and extracting knowledge and predictions from large, diverse digital data.”²

Solutions harnessing AI show promise in a variety of areas, as depicted in Figure 1.

Figure 1

Top AI use cases in LMICs



Source: GSMA

¹ GSMA (9 September 2019), Mobile Big Data Analytics and AI for a Better Future.
² EPSRC (no date), Framework for Responsible Innovation.

Machine learning

Machine learning (ML) is a process that enables a system to automatically and cumulatively learn and improve from experience, generally with more data. It is an important foundational concept of AI that enables applications such as deep learning, natural language processing (NLP), speech generation, computer vision, AI-optimised hardware, decision management (including categorisation and predictive analytics), biometrics, robotic process automation (RPA), virtual agents and more. There are three classes of ML algorithms:

- **Supervised algorithms** learn from data sets that have been labelled (e.g. pictures of animals) and then predict how to sort new data. Supervised ML requires those building models to specify correct answers from the training data, which the algorithm then learns to imitate. This is called a labelled data set. For example, a credit-scoring algorithm might analyse the repayment history of past borrowers to determine which future borrowers are likely to default, guided by data that indicates likely outcomes.³
- **Unsupervised algorithms** find their own patterns in data without labels. Clean and well-labelled

data sets are not easy to obtain, and sometimes researchers ask the algorithm questions they do not have answers to. In this instance, unsupervised learning is applied. A neural network is required to process a data set without explicit instructions for a specific outcome or correct answer. The neural network attempts to automatically find patterns in the data by extracting useful features and analysing structures. Data may be organised by clustering, anomaly detection, association or auto encoding. For example, an unsupervised credit algorithm might identify clusters of similar borrowers, but would not make individual predictions on their ability to repay the lender.

- **Semi-supervised algorithms** typically use some labelled data and more unlabelled data. Reinforcement ML algorithms are optimised with rewards, which nudge them towards progressively better performance. There are other approaches beyond this binary definition, such as reinforcement learning in which an objective is achieved through trial and error. Semi-supervised learning is also possible.

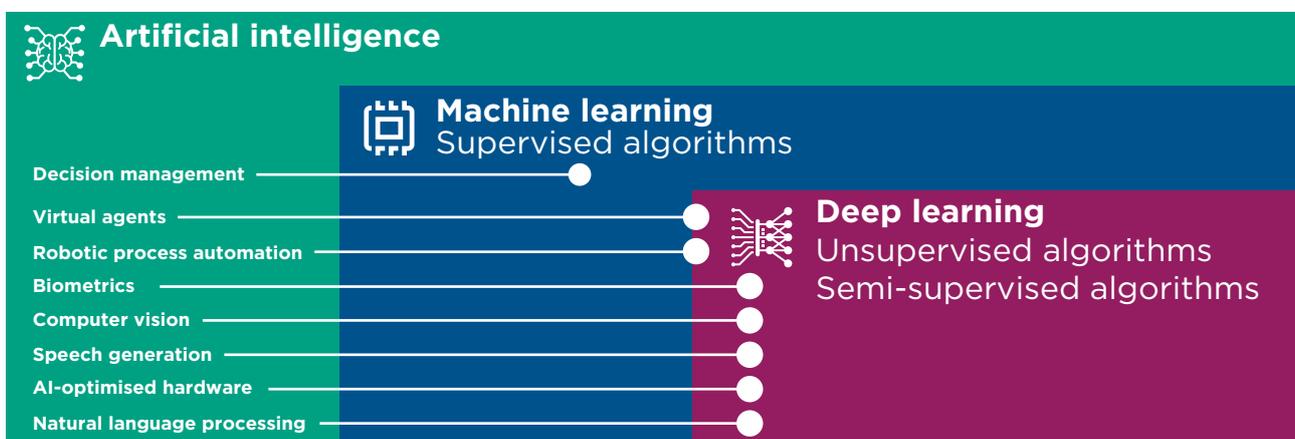
Types of AI capability

For this study, we have identified nine AI applications of machine learning (see Figure 2). Many of these

applications are complementary, and one service may use several of these techniques in combination.

Figure 2

Types of AI processes



Source: GSMA and UrbanEmerge

³ USAID (2018), Reflecting the Past, Shaping the Future: Making AI Work for International Development.

Computer vision

Computer vision focuses on replicating parts of the complex human vision system and enabling computers to identify and process objects in images and videos in the same way humans do.

Computer vision is used in medical diagnostics, face recognition, automated vehicles and a wide range of monitoring systems, from satellite monitoring of crops, livestock and environmental conditions to CCTV.

Natural language processing (NLP)

NLP enables computers to read a text, hear and interpret speech, gauge sentiment and prioritise and connect to appropriate subjects and resources.

The most familiar application is an automated call centre that sorts calls by category and directs the caller to recorded responses. NLP has become more widespread with voice assistants like Siri and Alexa. NLP uses machine learning to improve these voice assistants and deliver personalisation at scale.

Decision management (including predictive analytics)

Decision management refers to automated systems that accept inputs, perform analysis and deliver decisions based on those inputs. These systems provide decision making without human intervention, reducing the need for focused human labour. It can be particularly effective with detailed but repetitive decisions, for example, in financial services.

Decision management systems can convert big data (e.g. on customer behaviour) to predict trends. Combined with machine learning, decision management can help make business decisions more effective.

AI-optimised hardware

AI-optimised hardware refers to a class of microprocessors or microchips designed to enable faster processing of AI applications. This type of hardware is designed or adapted for AI workloads. One of the most common AI hardware architecture is graphic processing units (GPUs), originally designed to manage complex gaming visuals. GPUs have been particularly important in accelerating training and inference as they can be optimised for neural network operations.

Deep learning platforms

Deep learning platforms are a subset of machine learning developed to deliver solutions to complex problems. The 'deep' aspect refers to the structure of the system, which has multiple layers of ML processing called neural networks. There is an input layer, multiple 'hidden' layers and an output layer. The greater interconnection and sophistication of deep learning systems compared to simpler ML systems means that deep learning is particularly good at dealing with unlabelled and unstructured data, such as data coming in from multiple real-world sources like sensor systems or internet traffic.

Deep learning enables applications in complex environments, including autonomous movement, translation of spoken language, price forecasting and medical diagnosis from images.

Speech generation (or synthesis)

Speech generation is computer-generated human speech that combines recorded elements of speech to deliver language. Speech generation or synthesis is used in assistive technologies for people with a range of disabilities. Text-to-speech helps people with visual impairments and those with literacy and reading difficulties to read text. It can give people with speech disabilities a new voice. It is also used in automated translation.



Biometrics

Biometrics are the physical characteristics and behaviours of people used for analysis by AI. The premise of biometrics is that individuals can be accurately identified by intrinsic physical or behavioural traits, which are usually used for identification, assurance and controlling access.

Biometrics can support large-scale systems for identity assurance, which can be of great value in environments that lack other reliable identity systems. However, the personal nature of the data requires that effective data protection is in place. Ethical issues can also arise if a system performs unevenly across groups, for example, it does not perform equally for all skin tones. Biometrics can also be used to assist and monitor livestock and wildlife.



Robotic process automation (RPA)

RPA is a means of automating a business process. RPA tools are used to develop software, or a 'robot', that analyses and captures a process and then uses that process to deliver the same transaction. RPA can be used to deliver a simple response to a particular type of email or application process and can also be combined into complex systems.

RPA enables organisations to reduce labour costs and errors and can be lower cost and easier to implement than other AI applications. RPA can also be enhanced with higher level AI applications like NLP. Large-scale application of RPA carries social risks because it tends to directly replace functions (and even jobs) performed by people. An example is the production of suitable business forms or guidelines based on the needs of the user and the likely outcomes that someone of their profile would require.



Virtual agents/chatbots

A virtual agent is a dedicated software system that interacts with people and can be used in a team, service or information interface. The most familiar form of virtual agents is an automated representation of a customer service representative. Virtual agents identify appropriate responses and provide them in an informative conversation.

Chatbots tend to be oriented to a tightly defined set of processes for a business or public sector organisation. While virtual assistants like Siri and Alexa are oriented to individual users, and personalisation of individual needs and interests improves over time, virtual agents help deliver personalisation at scale, greatly reducing costs for healthcare and financial advice.

COVID-19 and the changing dynamics of AI

Over the course of our research in the second quarter of 2020, the world experienced unprecedented disruption due to the COVID-19 pandemic. As more traditional ways of working have ground to a halt, the digital economy has become vital to economic resilience and the ability to continue providing goods and services.

In light of the new normal, there is an urgent need to rethink data and predictions. Machine learning models trained on pre-COVID-19 events and movements of people and goods will no longer be accurate. However, the disruption from COVID-19 presents governments, companies and other organisations in LMICs with opportunities. It is clear that the digital economy is being accelerated, thanks to a shift to online communication and online provision of services to reduce physical contact and international travel. It is not yet clear if these shifts are positive or negative, including the greater use of AI and associated data privacy risks. It is also not clear whether increased uptake of technology and innovation will be sustained post-COVID-19.

In many cases, AI has had a positive impact. For example, the Government of Senegal automated part of its COVID-19 response to improve public access to healthcare information. The Ministry of Health partnered with a local lab to create a chatbot that can respond to people's questions on WhatsApp.

The need to deploy distance learning systems due to COVID-19 is becoming more urgent and there are many ways to create more responsive and bespoke services using ML processes and virtual agents. In Africa, global research partnership EdTech Hub has played an active role in supporting EdTech innovation and research. COVID-19 has also highlighted the importance of a secure local food supply and contingency planning. A shift towards more digital supply chains that connect producers to vendors and markets can improve food security and the reliability of food distribution. Twiga Foods in Kenya has been a leader in this area.

The COVID-19 crisis will likely stimulate faster changes in AI technology than previously envisaged. Governments in LMICs will need to work hard to ensure innovators have the best chance to participate in this rapid shift to the fourth industrial revolution. Technology companies and start-ups can take advantage of the increased attention on the digital economy and the potential of AI.



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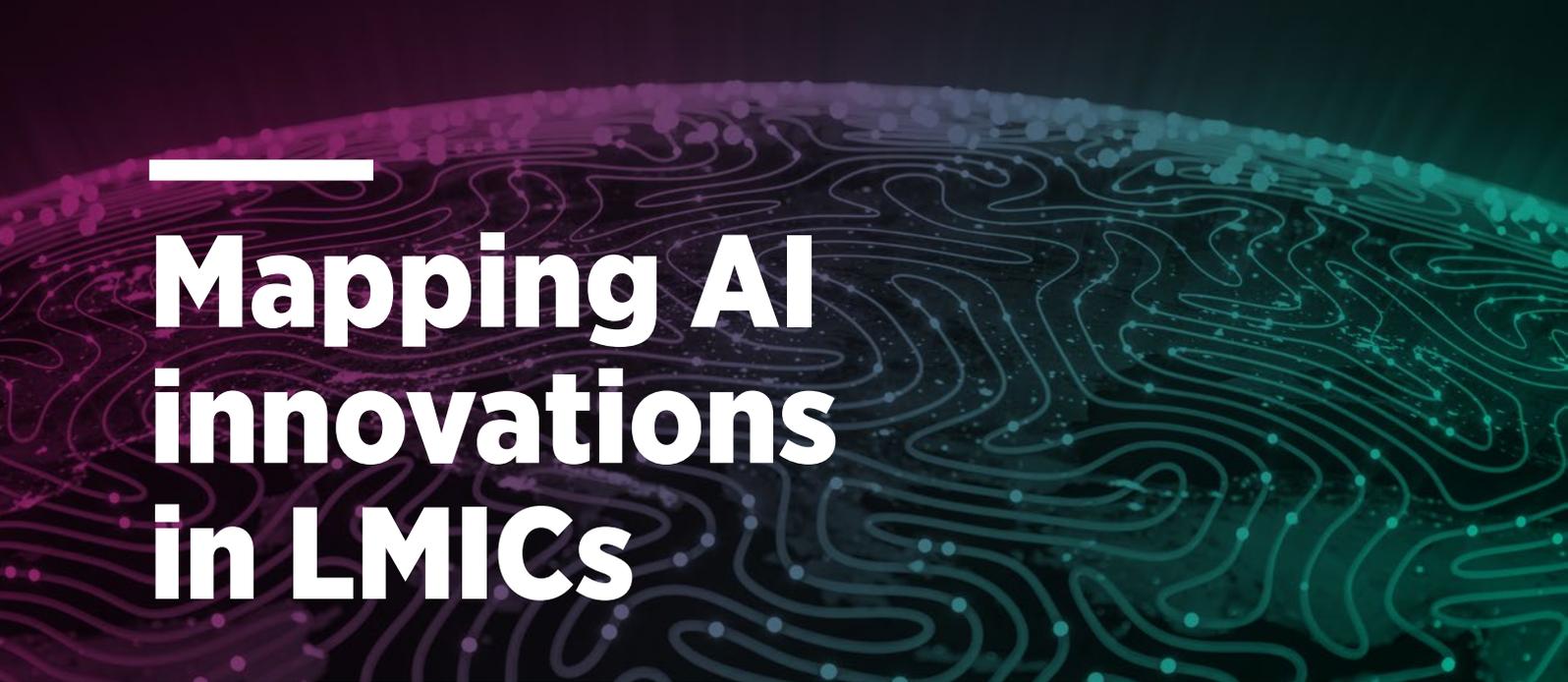
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Mapping AI innovations in LMICs

As part of this study, our team identified a sample of 450 AI use cases by start-ups and SMEs in our countries of interest. While over 3,000 separate entities were identified, we focused on those with a clear impact on sustainable development.

We then mapped the use cases against the following factors:

- Industry sectors in which AI is being used;
- Contributions to the SDGs;
- AI capabilities being used; and
- Whether a company had received funding and, where possible, the amount received.

Mobile network operators (MNOs) have not been included in the sample due to the focus on start-ups and SMEs rather than larger companies. However, MNOs such as Airtel, Vodafone, MTN and others, are leaders in the use of AI in many LMICs to enhance business services and provide a more inclusive service for more customers.

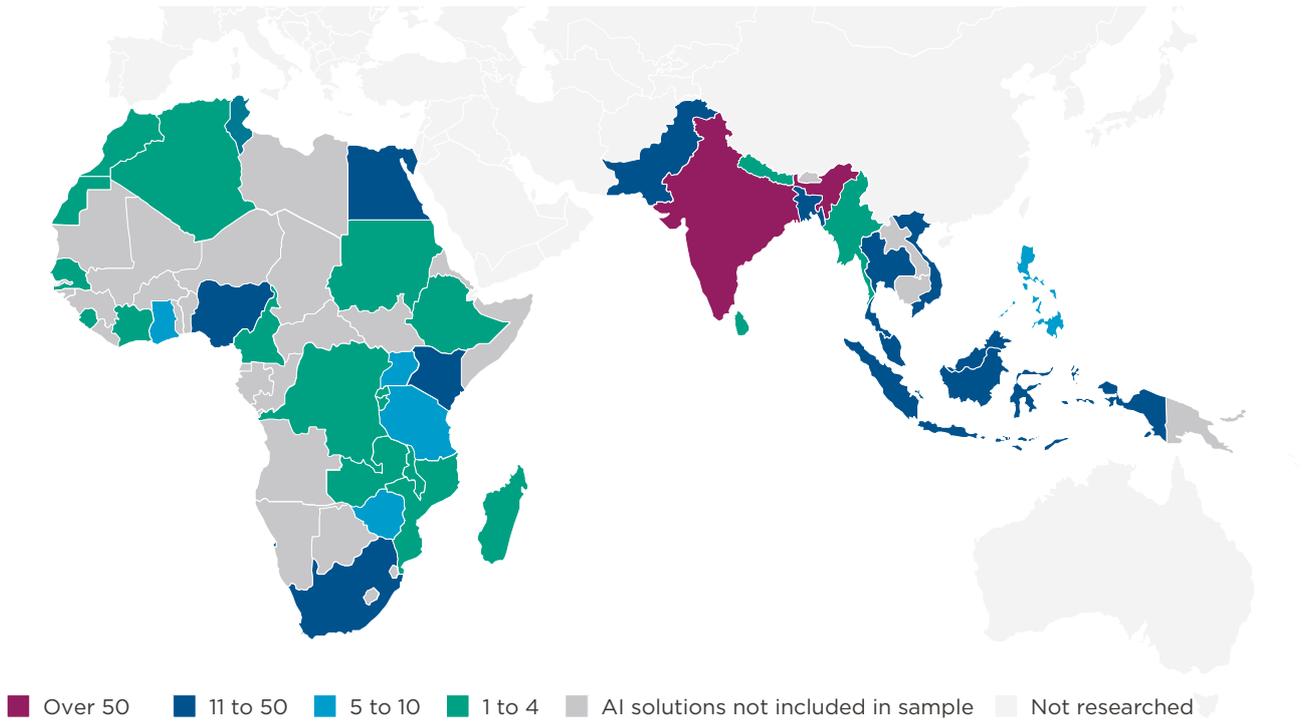
Use cases by country and region

The use cases revealed some interesting findings in AI innovation hotspots in LMICs in Sub-Saharan Africa, North Africa and South and Southeast Asia:

- India was the most represented country in our sample. The country accounted for over 40 per cent of the sample (180 use cases), indicating a high level of innovation and AI uptake in the country. Far more cases were identified in India, but were excluded due to limited alignment with development outcomes, apart from general economic development.
- Nigeria and South Africa were the next two most represented nations in the sample with 42 and 38 use cases, respectively.
- China was excluded from the study, along with the rest of East Asia, which are emerging as centres of AI innovation and investment. For example, in 2017, China submitted approximately 1,300 AI and deep learning-related patents, compared to 220 by the United States.

Figure 3

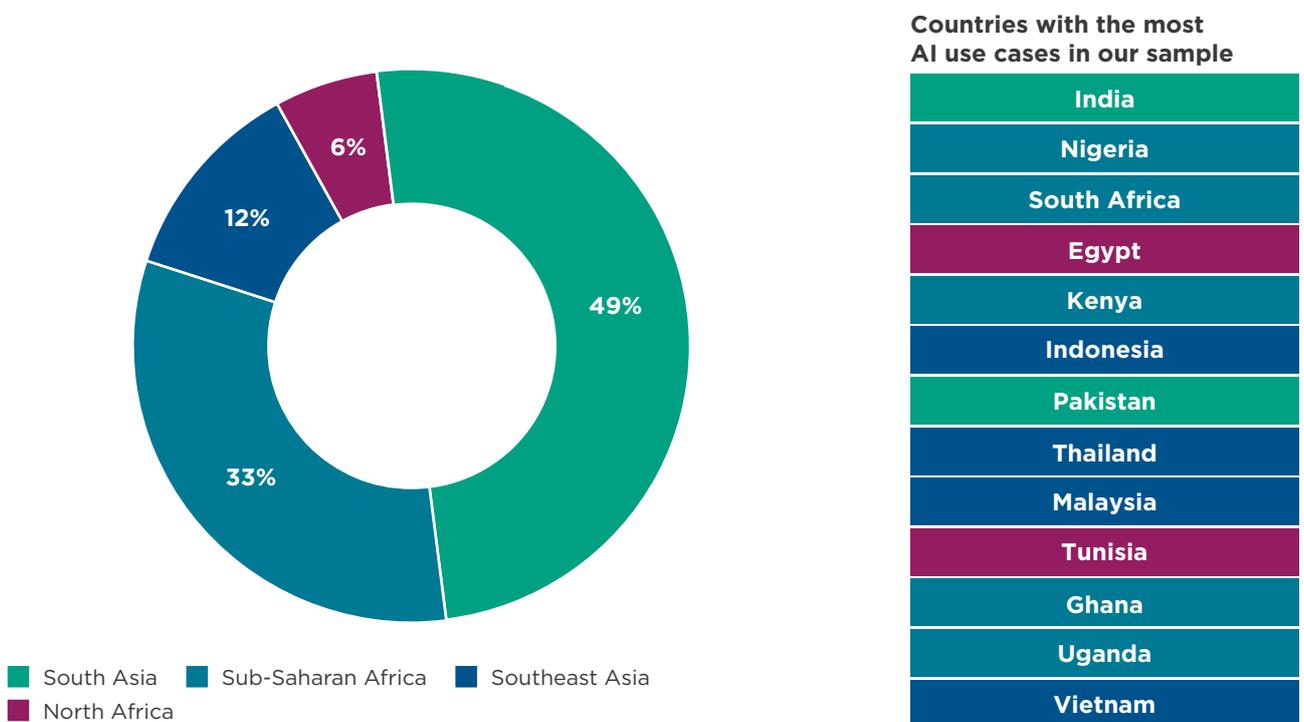
Geographic distribution of AI use cases in our start-up sample



Source: GSMA and UrbanEmerge

Figure 4

AI use cases by region



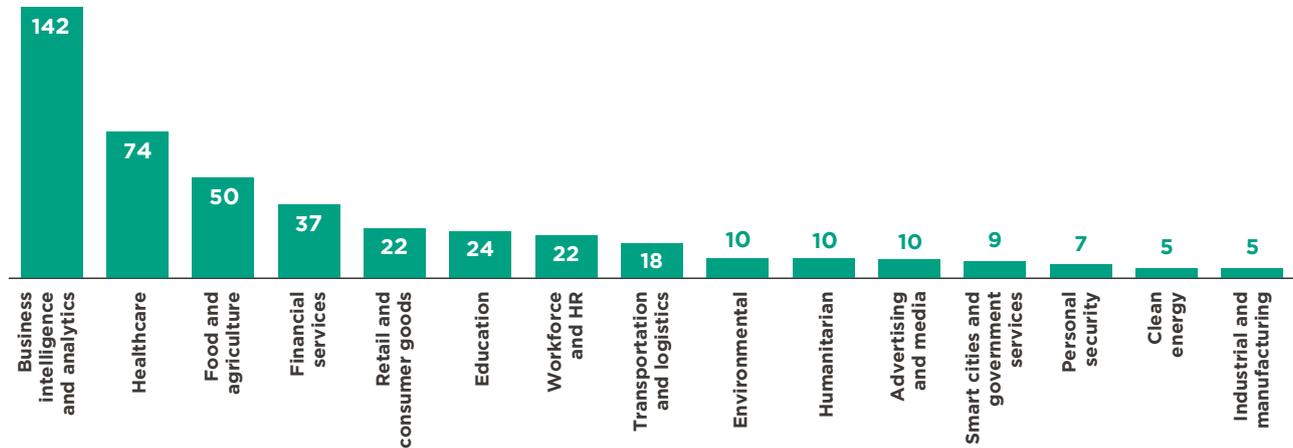
Note: Based on a sample of 450 start-up use cases selected to represent the geographic spread of AI innovations aligned with the SDGs in Africa and South and Southeast Asia
 Source: GSMA and UrbanEmerge

Use cases by sector verticals

- **Business intelligence and analytics** had the highest number of use cases as it captures a wide range of business-to-business (B2B) solutions, from enhanced retail market analysis and predictive decision making to customer service. Customer service chatbots, automated IT consulting, big data analytics and automated records are some examples of AI use cases.
- **Healthcare** had the second highest number of use cases and clearly benefits from AI solutions, including sophisticated diagnosis and treatment options, hospital management systems, lifestyle change recommendations and healthy eating habits.
- **Food and agriculture, financial services, education and retail and consumer goods** followed these sectors. Food and agriculture employs a range of AI-based services, including services for identifying and remedying crop diseases, linking producers more effectively to buyers and markets and helping farmers maximise crop yields based on climatic and soil conditions.

Figure 5

Distribution of AI use cases by sector in Africa and South and Southeast Asia



Note: Based on a sample of 450 start-up use cases selected to represent the geographic spread of AI innovations aligned with the SDGs in Africa and South and Southeast Asia.
Source: GSMA and UrbanEmerge

Table 1

Sector verticals using AI for social good, by region

Sector	North Africa	Sub-Saharan Africa	South Asia	Southeast Asia
Business intelligence and analytics	10	46	66	20
Healthcare	5	19	47	3
Food and agriculture	2	19	22	7
Financial services	1	19	8	9
Retail and consumer goods	5	12	7	2
Education	1	3	20	1
Workforce and human resources	1	5	10	6
Transportation and logistics	2	3	12	1
Advertising and media	1	2	6	1
Environmental	1	5	2	2
Humanitarian		3	5	2
Smart cities and government services		2	6	1
Personal security		4	3	
Clean energy		1	4	
Industrial and manufacturing	1	3	1	

Note: Based on a sample of 450 start-up use cases selected to represent the geographic spread of AI innovations aligned with the SDGs in Africa and South and Southeast Asia.
Source: GSMA and UrbanEmerge

When we break down our analysis by region, as shown in Table 1, some interesting trends emerge. Business intelligence and analytics is the dominant category across all four regions. The top two categories in Sub-Saharan Africa are healthcare and food and agriculture, while in North Africa they are

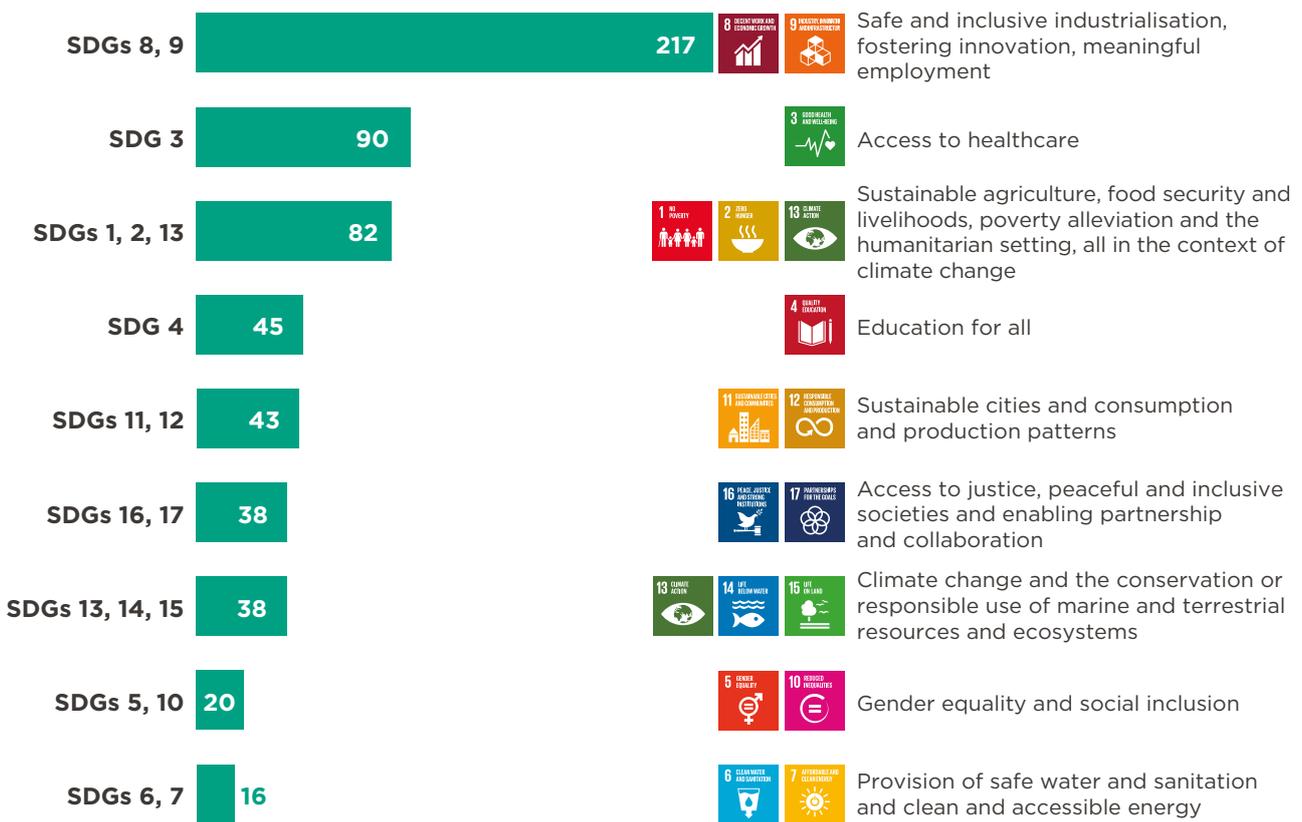
healthcare and retail and consumer goods. In South Asia, healthcare and food and agriculture are the dominant sectors followed closely by education. In Southeast Asia, the top two categories after business intelligence and analytics are financial services and food and agriculture.

Use cases by SDG

To capture all the areas covered by the 17 SDGs in broad categories, we combined several of them together. The use of AI is making a significant contribution to several of the SDGs.

Figure 6

Total number of use cases in the sample aligned with the SDGs



Note: Based on a sample of 450 start-up use cases selected to represent the geographic spread of AI innovations aligned with the SDGs in Africa and South and Southeast Asia.
Source: GSMA and UrbanEmerge

In Sub-Saharan Africa, sustainable economic growth and employment (SDG 8 and SDG 9) were the top category, covering a wide range of financial services, as well as general business services that improve business intelligence, operations and efficiency. There is also a strong focus on food and agriculture (SDG 1 and SDG 2), particularly in relation to poverty

reduction and climate-smart agriculture. For example, AI solutions can help farmers identify crop diseases, understand weather patterns and predict ideal times to sow and harvest crops to maximise yields and reduce waste, for example, CropIn in India.

The third most prevalent industry that aligned with the application of AI is healthcare (SDG 3). There are few educational innovations that rely on AI in Sub-Saharan Africa, although this may be due to the lack of high-quality and digitised data, combined with challenging internet infrastructure.

In North Africa, apart from sustainable economic growth and employment (SDG 8 and SDG 9), healthcare (SDG 3) is a clear leader. This is followed by a handful of examples that align with food security, education, gender and inclusion and sustainable cities.

Beyond business-related services, which are captured under SDG 8 and SDG 9, South Asia has a particularly strong focus on healthcare (SDG 3) and education

(SDG 4). There are also many use cases related to SDG 11 and SDG 12, which cover smart-city solutions, smart transportation and road safety and the circular economy.

In Southeast Asia, beyond sustainable economic growth and employment (SDG 8 and SDG 9), there is significant alignment with poverty reduction and food security (SDG 1 and SDG 2), followed by a handful of use cases that contribute to sustainable cities, environmental protection and enabling justice, collaboration and partnership. The Gringgo Indonesia Foundation, which has developed an image recognition tool to improve plastic recycling rates, reduce ocean plastic pollution and improve waste management in under-resourced communities, is a good example of an environmental services application of AI.

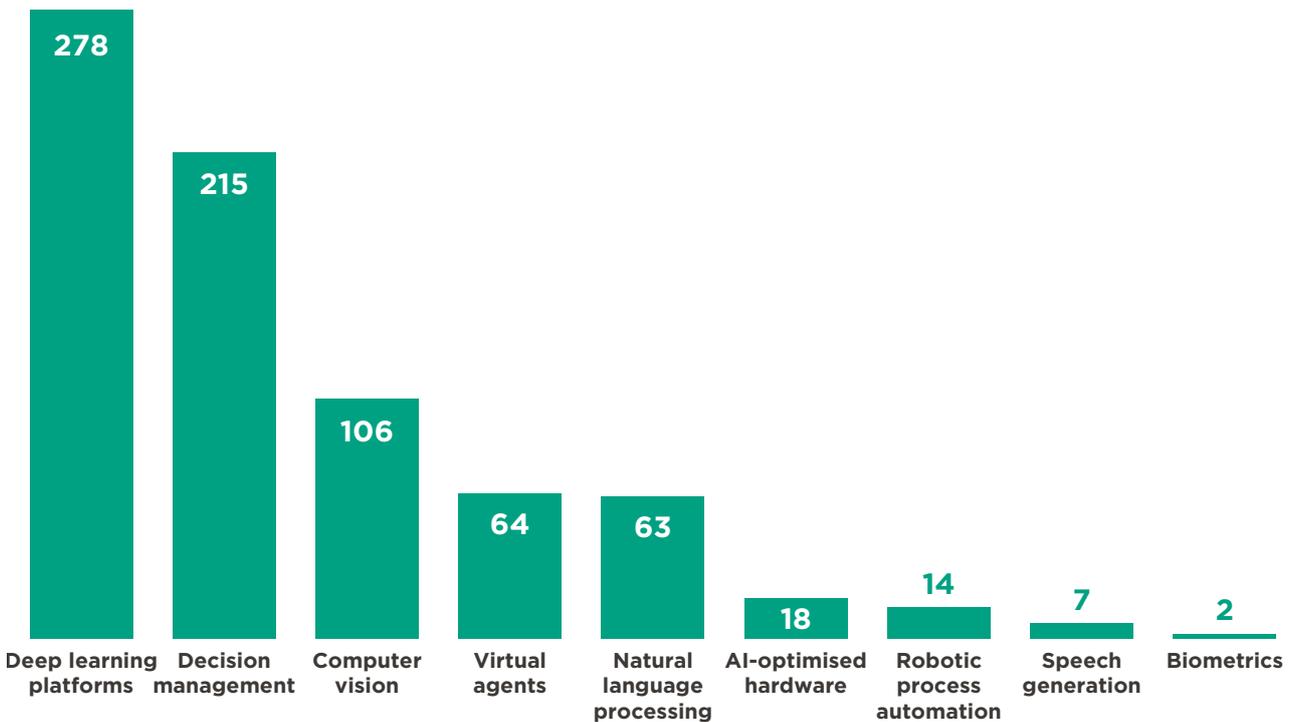
Use cases by AI capability

Segmenting use cases by AI capabilities is challenging given that there are significant variations in the definitions and descriptions of AI processes and

how they fit together, including within various sub-categories. Figure 7 shows the categories with the greatest overall distribution of AI capabilities.

Figure 7

AI capabilities within the sample of use capabilities



Note: Based on a sample of 450 start-up use cases selected to represent the geographic spread of AI innovations aligned with the SDGs in Africa and South and Southeast Asia.
Source: GSMA and UrbanEmerge

Deep learning platforms are the most commonly used, followed by AI decision management processes. Both are used by start-ups seeking to gain insights from big data and gain a greater edge in meeting the needs of customers and responding to customer feedback more effectively.

Computer vision is the third most used capability. Linked to deep learning, this is often involved in image recognition processes in diagnostics, such as in healthcare or agriculture. It is also important for tools that use a mobile phone to identify products or read text for persons with visual impairment. Virtual agents are also prevalent, such as chatbots that are used for a wide range of applications, from customer service to advice on health-related issues. Examples include the Foreign, Commonwealth and Development Office's (FCDO) Frontier Technology Livestreaming (FTL) pilot for reproductive healthcare and Springster by the organisation Girl Effect.

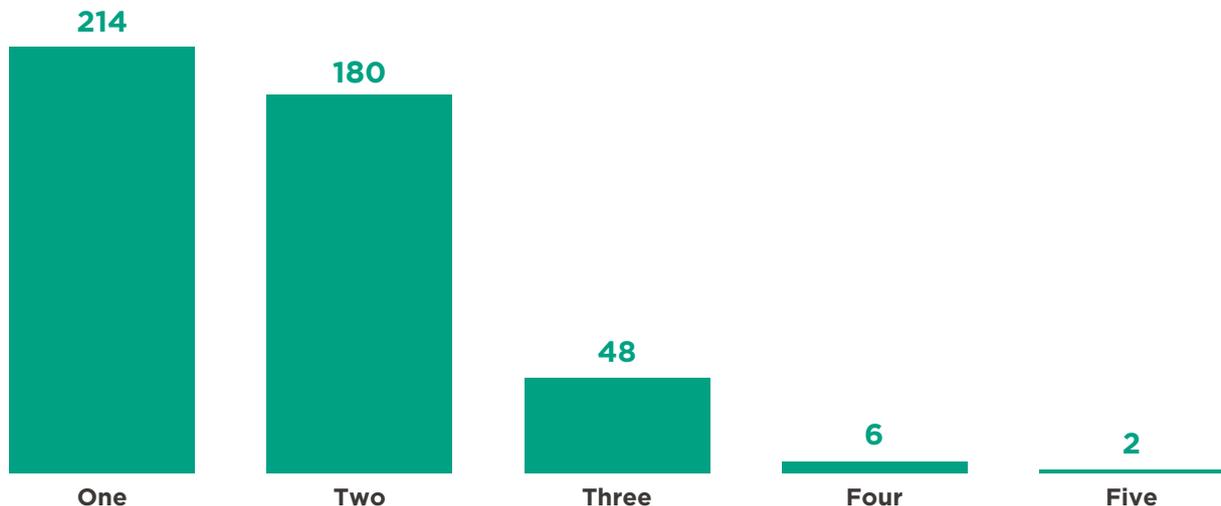
Natural language processing is another important AI use case in the sample. Only a handful of examples used AI-optimised hardware, RPA and

speech generation. There were very few examples of biometrics in the sample, but a notable one is M-PESA's secure personal identification process implemented by Vodafone. This allows persons with disabilities to use their voice as a biometric password, facilitating greater access to financial services and more autonomy in how they use the service.

It should also be noted that several use cases employ more than one AI process. Figure 8 shows that over half the use cases employed two or three AI processes and a small minority used four or five. These are often used in combination, for example, computer vision may be used for image processing combined with a deep learning platform to diagnose specific health issues. An example of this application is Skinzy in India a healthcare start-up that aims to provide affordable skincare solutions to people in rural and peri-urban India, where specialised dermatologists and doctors are scarce. AI-based machine learning and image processing algorithms help users detect skin diseases and connect them to a dermatologist to receive care quickly.

Figure 8

Number of AI processes used per solution (nominal value)



Source: GSMA and UrbanEmerge

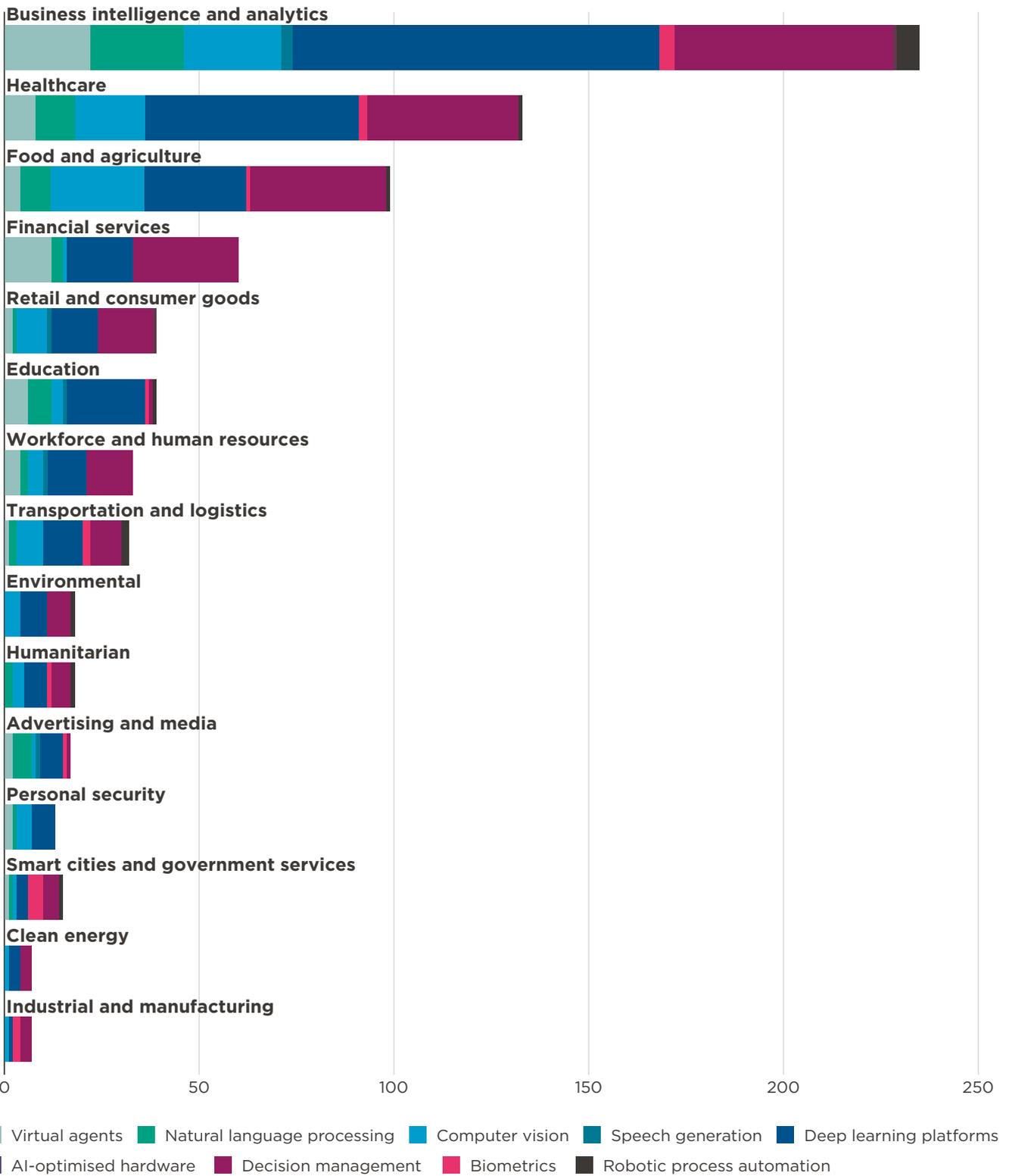
Our mapping analysis also provided insights into the use of AI by sector, as shown in Figure 9. Both healthcare and food and agriculture make extensive use of computer vision, deep learning and decision management. Virtual agents are used in the greatest proportion for business intelligence and analytics, healthcare and financial services, to provide an interface between users and the solution. However, many AI processes, such as NLP, computer vision

and virtual agents, are also used consistently across other industry verticals, suggesting a high degree of application in a range of sectors.

Smart cities and government services use AI-optimised hardware the most, particularly for Internet of Things (IoT) and interconnected devices, data and hardware.

Figure 9

Use of AI by industry vertical



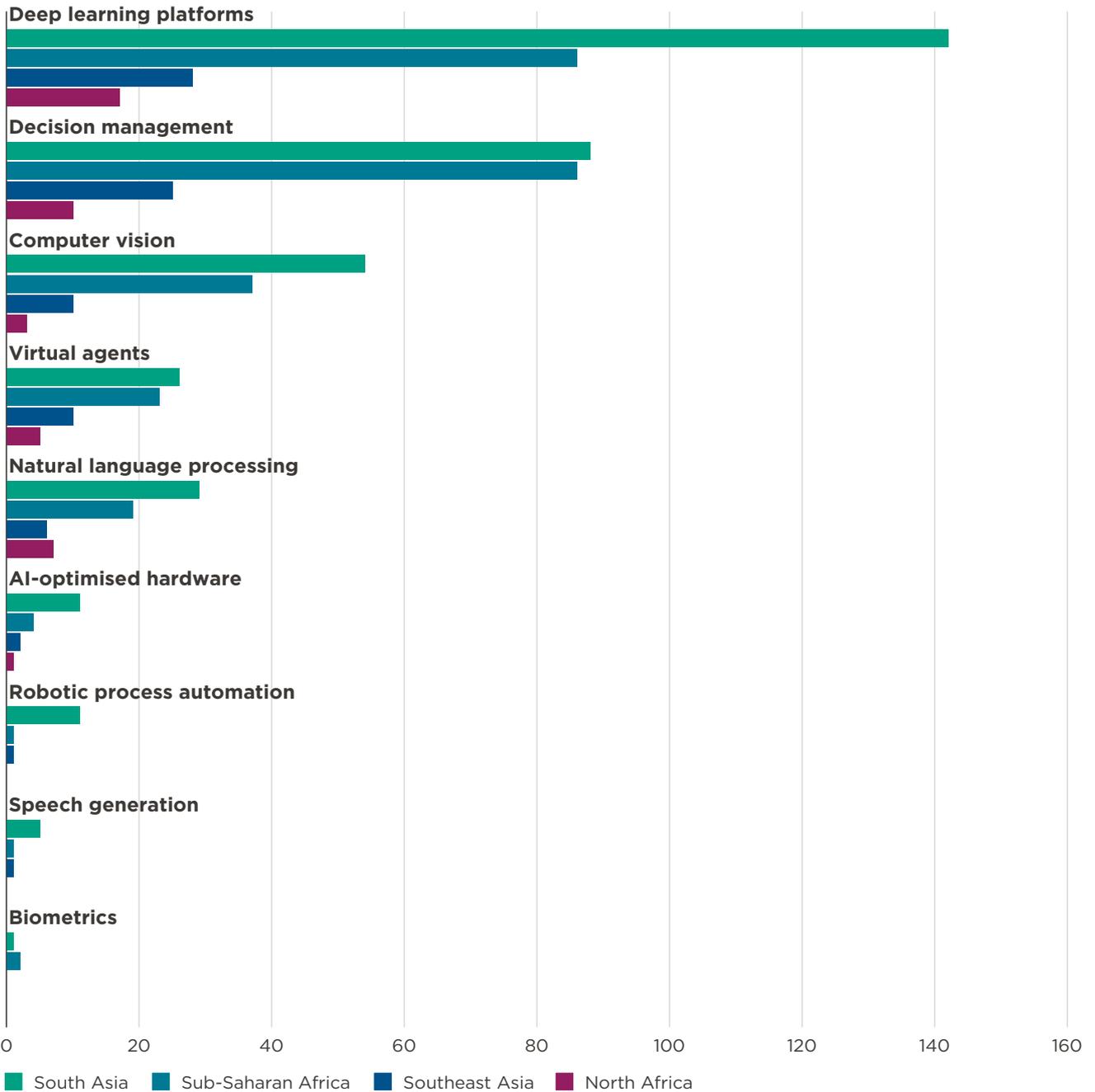
Source: GSMA and UrbanEmerge

The use of AI capabilities by region generally aligns with the geographic distribution of use cases, which suggests that no AI process is used to a greater or lesser extent in a particular region (Figure 10). However, start-ups in South Asia use RPA and speech

generation more than those in other regions. Use of AI decision management tools also seems to be disproportionately higher in Sub-Saharan Africa than in South Asia.

Figure 10

Use of AI by region



Note: Based on a sample of 450 start-up use cases selected to represent the geographic spread of AI innovations aligned with the SDGs in Africa and South and Southeast Asia.
 Source: GSMA and UrbanEmerge

Funding for AI use cases

Mapping AI use cases also allowed us to analyse funding to AI start-ups in Africa and South and Southeast Asia. In our indicative sample, most of the funding is directed at financial services, followed closely by food and agriculture, healthcare and business intelligence and analytics. It is worth noting that this is a high-level analysis based on limited, publicly available data.

Some notable start-ups that have received large amounts of funding in the food and agriculture sector are Twiga in Kenya (\$30 million), Cropln in India (\$13.5 million) and Dahmakan in Malaysia (\$27 million). In the financial services sector, some notable funding recipients are OneFi in Nigeria (\$6 million), SME Corner in India (\$50 million) and Happy in India (\$17 million).

Our analysis of start-up funding from venture capital partners, accelerators, foundations and international donors revealed that India was the clear leader. Kenya, Malaysia, Thailand and South Africa were next in terms of funding volume, followed by Tunisia, Nigeria and Indonesia. However, these results are only indicative as the availability of funding data is extremely limited.

Many of the use cases have benefited from funding from multiple partners. For example, Cropln in India has received a grant from the Bill & Melinda Gates Foundation and a mix of venture capital partners. Dahmakan in Malaysia has received funding from Y Combinator and a mix of venture capital firms. Technology companies like Google are also involved in financing innovative start-ups in LMICs. For example, Instadeep in Tunisia has received \$7 million in funding from Google Launchpad.

Examples of AI use cases across the SDGs

Apollo Agriculture, Kenya

Apollo Agriculture⁴ helps farmers in emerging markets improve yields and efficiency and maximise profits. Its solution uses agronomic ML, remote sensing and mobile phones to deliver financing, farm products and customised advice to smallholder farmers. Apollo uses ML algorithms on satellite data, soil data, farmer behaviour and crop yield models to deliver customised packages of seeds and fertiliser, as well as advice on how to grow better crops. Apollo bundles many services a farmer is likely to need: financing, farm inputs, advice, insurance and market access.

Mindspark, India

Mindspark,⁵ built by Educational Initiatives (EI), is an adaptive learning software that improves educational outcomes. The solution progressively introduces more challenging concepts using text, video, games and interactive tutorials that students can access on multiple devices. At £35 (\$45) for one student licence, the initiative is cost effective. Based on a robust evaluation of the effectiveness of the software, Mindspark is now being scaled across India. RISE is also researching how Mindspark could be integrated into schools most effectively. A randomised study of 619 government school students in Delhi by MIT found that students in grades one to eight made significant progress in mathematics and Hindi after using the Mindspark software.

⁴ Apollo Agriculture is funded by Shell Foundation and FCDO.

⁵ Mindspark is an EdTech Hub and FCDO-funded grantee.

Gringgo Indonesia Foundation, Indonesia

Gringgo is creating an image recognition tool to help informal waste collectors and independent waste management companies in Indonesia increase recycling rates and better integrate with city sanitation crews.⁶ By improving and expanding community trash collection, the start-up is addressing Indonesia's plastic waste problem and reducing ocean plastic pollution. With 50,000 kilometres of coastline and low public awareness of waste management, much of Indonesia's trash ends up in the ocean. To add to the complexity, waste workers often have irregular routes and schedules, leaving many parts of the country unserved. Workers also do not always have the knowledge and expertise to accurately identify what can be recycled and what recycled items are worth. Together, these factors have had a devastating impact on recycling rates and the livelihoods of waste workers.

Synapsica, India

Synapsica is a HealthTech and teleradiology firm that provides AI-enabled automation of diagnostic radiology workflow and reporting. The company uses NLP, computer vision and deep learning software products to assist with diagnosis in x-ray, CT and MRI scans. ML automation supports workflow management at diagnostic centres, improving the efficiency of stakeholder coordination, disease diagnosis and report production. Synapsica's goal is to make reporting more efficient in terms of quality, time and cost.

Digi Smart Solutions, Tunisia

Digi Smart Solutions provides smart water management solutions using IoT and AI, offering an intelligent system for managing and controlling water consumption in real time. By collecting data from multiple devices, sensors and systems, it can provide actionable reports for management and decision-making processes. By managing and saving water resources, Digi Smart Solutions is helping to meet future water demands, deal with urgent challenges and forge a pathway to sustainability and resilience in arid climates.

Eyedentify, India

Eyedentify is an end-to-end automotive IoT solutions company that strives to alleviate the safety and security concerns of vehicle occupants, drivers and fleet owners. The system alerts drivers to be attentive and drive safely. Eyedentify's solution has three main components: vehicle tracking (GPS), camera and edge video analytics platform, which identifies and monitors the driver based on vehicle location and speed combined with edge-based video analytics. It incorporates all AI-related processes, including convolutional neural networks (CNNs), GPU optimisations, feature point extractions and a trained 128-D feature vector embedded for analysis.

Twiga Foods, Kenya

Twiga Foods⁷ is a mobile-based supply platform for Africa's retail outlets, kiosks and market stalls. It's cashless business-to-business (B2B) supply platform enables urban grocers to order produce from smallholder farmers across Kenya and have it delivered at competitive prices. This eliminates the inefficiencies of sourcing perishable foods daily while also guaranteeing farmers consistent income and timely payments. Twiga has been sourcing from over 17,000 producers and delivering three times a week on average to over 8,000 retailers.

Twiga's digital platform and logistics network links retailers with farmers and food manufacturers, providing a convenient and reliable alternative to the current inefficient and expensive farm factory-to-market processes. To optimise delivery for large numbers of customers, Twiga maps its vendors using a Geographic Information System (GIS) and its AI-enabled distribution platform to see who is ordering, where they are located, the road conditions and how to plan deliveries most efficiently.

6 Javerbaum, M. (10 July 2019), "To reduce plastic waste in Indonesia, one startup turns to AI", *Google.org*.

7 Twiga Foods is a GSMA and FCDO-funded grantee.

GSMA AI initiatives

Telco-X Collider Lab

Telco-X Collider Lab is part of the GSMA's on-going AI partnership with the University of California, Berkeley and the Sutardja Center for Innovation and Entrepreneurship. Launched in September 2020, the lab is open to GSMA members from around the world, who, as participant sponsors, will be matched with UC Berkeley student teams. Bridging the gap between academia and industry, the lab offers an advanced project course that will create new applications for AI in telecom operations, new opportunities for different verticals and ML applications in the 5G era. The course builds on the spring 2020 course, 'Innovating 5G Mobile Networks with AI', and employs a mix of online and in-person formats, which are interactive, dynamic and collaborative.

GSMA members can leverage the course as an open-ended project, and continual and close interaction with UC Berkeley will maximise its potential. The first half of the course is devoted to generating a story and low-tech demo for a real-world project, while the second half is an agile sprint that culminates in the demonstration of working project code.

Telco-X Collider Lab commences in January 2021. More information on the course and how to apply can be found [here](#).

Global AI Challenge

The GSMA Global AI Challenge is a GSMA initiative open to members to solve challenging and complex real-world business problems by accessing the best AI talent and state-of-the-art machine learning techniques.

In partnership with The Alan Turing Institute and the UK National Institute for Data Science and Artificial Intelligence, the Global AI Challenge brings together stakeholders from the mobile industry and data scientists from various backgrounds to explore new approaches and expand current efforts in AI.

The Global AI Challenge is a week-long hackathon followed by a longer-term collaborative research project. During the hackathon, dedicated teams of PhDs and researchers work closely with participating companies to explore what does and does not work and identify new ways of solving complex problems in the telecommunications industry.

The Global AI challenge is open to all organisations across the mobile industry. More information about the Global AI Challenge, how to participate and previous projects, can be found [here](#).



```
group_info->small_block) {  
info->nblocks; i++)  
long)groupinfo->nblocks[i];  
er-space array */  
user *groupList,  
info *group_info)  
nblocks; i++) {  
min(NGROUPSPERBLOCK, count);  
nblocks*sizeof(gid_t *), GFPUSER);
```

```
mirror_mod.use_x = False  
mirror_mod.use_y = True  
mirror_mod.use_z = False  
elif_operation == "MIRROR_Z":  
mirror_mod.use_x = False  
mirror_mod.use_y = False  
mirror_mod.use_z = True
```

```
#selection at the end add back the de  
mirror_ob.select= 1  
modifier_ob.select=1  
bpy.context.scene.objects.active = modifier  
print("Selected" + str(modifier_ob)) # mod  
mirror_ob.select = 0
```

```
EXPORTSYMBOL(  
return NULL;  
/* export the s  
static int gro  
EXPORTSYMBOL(groupalloc);  
void group_free(struct group  
{  
int i;  
if (groupinfo->nblocks[0] >  
int i; unsigned in  
for (i = 0; i < group  
freepage((unsigned  
for (i = 0;  
kfree(groupinfo) unsigned  
unsigned  
EXPORTSYMBOL(groupfree);  
if (cop  
/* export the groupinfo to a  
static int groups (unsigned  
const struct group  
groupinfo  
unsigned int len = ep  
groupinfo->nblocks = (gidsetsize + NG  
nblocks = nblocks * a * group  
groupinfo = malloc(sizeof  
if (groupinfo)  
free_page((unsigned long)group_info->nblocks[i]);  
return NULL;  
kfree(group_info);groupinfo->ngroups = gidse  
return NULL;  
groupinfo->nblocks = nblocks  
atomic_set(&group_info->usa  
d groups_free(struct group_info *groupinfo)  
if (gidsetsize <= NGROUPSP  
groupinfo->nblocks[0] =  
small_block  
else {  
for (i = 0; i < nblock  
freepage((unsigned long)groupinfo->nblocks[i]  
gid_t *ob;  
if (!ob)  
goto outundo_p  
groupinfo->nblocks[0]  
return group_info;  
outundo_partial_alloc:  
while (--i >= 0) {  
free_page((unsigned lo
```



Understanding AI business models in LMICs

Given that AI use is still nascent in LMICs, most businesses are still learning how best to monetise their solutions and attract users. While attention has been focused primarily on the effect of AI on consumers and businesses, there has been a shift towards understanding how existing technology business models can be transformed to account for the more complex aspects of AI.

To fully grasp the opportunities, limitations and outlook of AI business models for a company's growth, and the wider economic and societal implications of AI, technology start-ups must conduct a substantive analysis that evaluates critical business factors at the intersection of financials, technology and future growth. One common approach to evaluating and

designing a business model is the Strategyzer Business Model Canvas developed by Alexander Osterwalder.⁸ However, this study used a more concise assessment that looked at three factors: consumer segments, monetisation and outlook. The following sections present the findings, observations and insights gathered from our interviews and case studies.

Monetisation

Monetisation is a critical component of any business model. The results of the use case mapping, along with existing industry analysis and interviews, show that the majority of AI companies globally remain AI-enabled, although there are a growing number of AI-first companies. This distinction determines the core competency and unique value proposition of all AI

companies. To better understand the business models, we have divided AI companies into two groups:

- **AI-enabled companies:** AI is used to enhance their offerings; and
- **AI-first companies:** AI is the core product.

⁸ [The Business Model Canvas](#).

AI-enabled companies

The revenue streams of most AI-enabled companies resemble traditional software companies, such as subscriptions, commissions, revenue sharing and a project-based approach. These companies often strive for multiple revenue streams to make the most of their digital platform and to reduce the risk of one revenue stream becoming unviable. Besides acquiring a diverse range of clients and customers, multiple revenue streams can be generated through a combination of the following approaches:

- **Software-as-a-Service (SaaS):** This is a delivery and licensing model in which software is accessed on the web via a subscription rather than installed on local computers. SaaS typically incorporates a freemium model⁹ with tiered levels of pricing based on the features and benefits offered.
- **Transaction fees:** These are fees charged as a percentage of sales for processing a user transaction, such as a payment processing company. Fees can be incurred as a percentage of sales or a flat fee per sale.
- **Commissions and referral fees:** These are usually commission and referral fees received by companies when they partner with a third-party

business to sell products and services or help acquire customers.

- **Hardware fees:** Companies may charge for the purchase of related hardware while software and subsequent updates are free.
- **Consulting fees:** Companies can charge for consulting services that may be supported by AI-powered tools.
- **Set-up and maintenance fees:** Companies may be able to provide a service that is essentially free apart from an initial set-up cost and on-going maintenance.
- **Advertising revenue:** Rather than charging a fee to users or customers, revenue is generated from advertising.
- **Selling data:** Companies selling data to third parties is also a potential revenue stream. Many AI companies whose solutions and services are based on processing customer data have data volume at the centre of their monetisation strategy, rather than just charging for a finished product or service. However, privacy and ethical considerations are important to maintain customer confidence.

AI-first companies

Whereas the quality of a AI-enabled company is defined by the functionality of the end solution, the quality of AI-first companies is much more open to subjective benchmarking as the solution or output is the data interpretation itself, such as the accuracy of speech recognition and language processing.

The threshold for quality can vary widely among customers, who commonly, but unrealistically, expect that the AI should be a panacea. Moreover, the data interpretation and training also depends on the quality, complexity and volume of data the client provides to the company, which often require more customer education and persuasion and customised on-boarding to improve the integrity and quality of the inputs. As a result, the sales cycles of AI-first companies are often slower and optimal outputs may be delayed given the initial learning curve. AI-first companies often have an

AI-as-a-Service platform as its unique value proposition because the solution is the service. Accordingly, the value of the solutions and the pricing of the technology are implicitly connected.

While AI business models are still trial and error and will continue to evolve, AI-first companies resemble more of a service than traditional software, especially with their back-end human support for maintenance and custom inputs for clients.

Given that the AI-first sector is in early stages of development, there is still a lag in technology investors' understanding and expectations of the business models. According to Forbes,¹⁰ "One of the major drivers of the slow rate of adoption is the disconnect between venture capital norms and the realities of building an AI-first company. Specifically, AI companies require

⁹ A freemium business model offers a basic service for free. Additional premium functions or services are available for a fee.

¹⁰ [AI Can Change the World...If Only Investors Catch Up](#), *Forbes*.

three to six times greater upfront investment as compared to traditional SaaS companies but in return have three to six times market opportunity. Therefore, the time horizon to realise meaningful commercial traction is much longer; typically between five to six years and a minimum of \$10 million investment to progress from concept to working prototype and approximately 10 years to get to meaningful commercial traction. This timeline does not align with

the predilections of most venture capital funds that typically look for a seven-year time horizon.”

Therefore, while displaying distinctive characteristics that can be qualified as a new category of business, combining a traditional SaaS company with a service business, it is still critical for AI-first companies to focus on building a sustainable, long-term foundation.

Consumer segments

AI companies primarily serve businesses (B2B), consumers (B2C) or both, depending on the product and industry. Each customer segment has its own advantages and disadvantages. For example, B2B businesses tend to have longer sales cycles and more relationship management but offer greater upfront revenue, which many AI-start-ups prefer. While the B2C sales cycle is shorter, the customer acquisition

process is different and requires more investment in marketing and promotion.

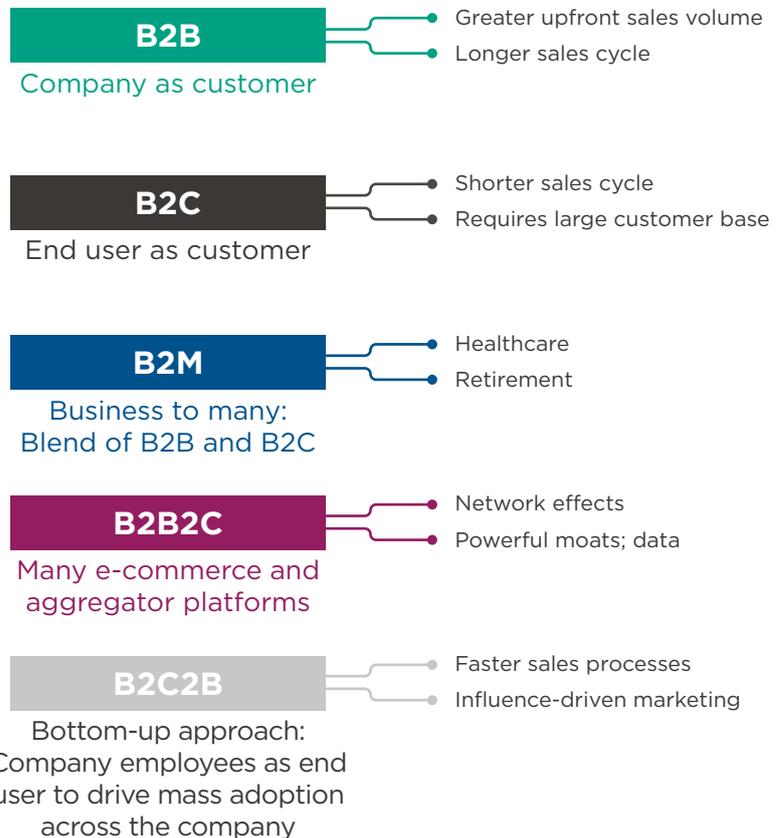
For AI-enabled companies, B2C is more common than in AI-first companies. Due to the higher upfront investment in AI resources, AI-first companies are focused primarily on B2B customers, which provide better opportunities for initial cash flow.

Figure 11

Customer segments of different AI business models

AI business models are relatively aligned with standard business models in the IT/software industry.

In terms of monetisation, the majority of AI companies use some type of SaaS model with freemium subscriptions and offsetting of additional products/services. For many B2B2C companies, monetisation commonly includes commissions and transaction fees on products sold.



Source: GSMA and UrbanEmerge

Outlook

AI companies, particularly in LMICs, must anticipate opportunities and prepare for risks in a rapidly evolving industry. Business models must withstand the impact of these risks and reach scale with new markets and customers. Specifically, resilient AI business models must consider the two following factors:

A dynamic regulatory environment

The industry must address a variety of questions from users and customers about how they use their data. Our research revealed that many companies in LMICs are being asked questions such as:

- Who will own the IP on my data?
- Will my data be sold without my authorisation?
- How will my data be collected? What degree of anonymity do you provide?
- How is my data stored? What are your security measures to prevent and deal with hacking?

With respect to regulations, a number of AI companies interviewed indicated that bureaucratic red tape, varying levels of government readiness for AI-related policymaking and wariness of AI technology create measurable delays in product launches, approvals and expansion. In highly regulated industries, such as financial services and healthcare, the extent to which

AI guidelines were in place or created value rather than harm, differed significantly between countries. Countries with a robust start-up scene and active investor community, such as India, already have more regulatory frameworks in place. In less-developed AI markets, such as Myanmar, interviewees indicated they could converse with the government on how such regulations should take shape.

Another consideration for AI companies is the monetisation of data itself, given the magnitude of data needed for algorithmic computations. Many AI companies whose solutions and services are based on processing customer data have data volume at the centre of their monetisation strategy. While many AI companies sell data to third parties, whether as raw user information databases or packaged reports and analytics, ownership of client and customer data is a major concern.

Industry trends and outlook

AI-related companies in LMICs should anticipate the following AI technology and business model trends, which will shape their outlook:

- **More advancement in data analytics**, from diagnostic and predictive to prescriptive. This will be a game changer in terms of enhancing business operations and processes.
- **Significant advances in AI research**. Applied AI innovation is still a burgeoning space for exploration, and implementation and research should be aligned with sustainability and social innovation for effective deployment, from the lab to the market.
- **AI will continue to be shaped by and paired with other frontier technologies**, such as IoT and blockchain. IoT is proving to be a transformative technology for start-ups that use connectivity to streamline resource-consuming functions and responsibilities.
- **More careful assessment of company operations and sustainability**, in both LMICs and high-income countries (HICs). In terms of investment, there has been much hype surrounding AI and machine learning, leading to saturation in funding and less than favourable results for many bandwagon investors.
- **FinTech, HealthTech, EdTech, AgriTech, InsurTech, GovTech and ClimateTech** are all growing sectors for AI innovation and deployment in LMICs, especially for COVID-19 and post-COVID-19 solutions.



Qlue

Indonesia



Problem

Government services face huge challenges with monitoring, data collection and service management, especially in cities like Jakarta. They need better solutions to monitor and manage social problems

effectively and efficiently, including flooding, traffic congestion, crime and waste management. Fieldwork can be inefficient and costly, with poor reporting due to the manual collection of data.

Solution

Qlue is a platform that provides a comprehensive solution for government services. Features include visual ID, facial recognition and vehicle recognition, and it uses predictive data analytics to provide reporting for the government to act and make

better decisions. Consumers also use the Qlue app to report issues, such as potholes and crime, and can communicate with police and other government responders depending on the issue.

Business model

Qlue is based on a B2B SaaS model. Customers pay for subscriptions and are charged per account or engine/function. For governments that cannot pay

for the solution, a one-time fee is charged along with maintenance fees. Hardware is also a one-time purchase. Citizens can use the app for free.

Impact and traction

Qlue was established in 2014 in Jakarta, working side by side with the city government to implement the first smart city concept in Indonesia. Between 2014 and 2020, the province and its citizens reduced potential

flood points by 94 per cent, improved government performance by 61.4 per cent and increased public trust in the government by 47 per cent.



Optimetriks

Retail, East Africa



Problem

Distribution companies often struggle to manage the vast amounts of data collected on the ground by their sales force and field representatives. A lack of visibility

into delivery routes and real-time inventory stock have negative effects on decision making and planning.

Solution

Optimetriks is an end-to-end software solution that connects companies, primarily fast-moving consumer goods (FMCG) to their field sales and distribution network. Data reporting via predictive analytics helps companies better manage and apply the information derived from their data. Specific functionalities include:

- Data collection, image recognition, route optimisation and inventory management;

- Ensuring field users complete the route as planned;
- Following activities performed and helping them achieve their targets;
- Digitising sales orders, retail audits and outlet visits; and
- Automating real-time visualisations on dashboards as data is collected.

Business model analysis

Optimetriks uses a SaaS model based on pricing per user for tiered access to features and benefits. It also offers a customised enterprise project solution with

custom pricing. A one-time set-up fee is charged for new customers and is determined by the complexity of the implementation.

Impact

Since launching in 2017, Optimetriks has worked in 20 countries across Africa.



Curacel



Health, Nigeria and Uganda

Problem

Only around two per cent of the entire population of Africa currently benefit from any form of insurance. While a growing number of underwriting firms are

providing increased cover in sectors ranging from health to travel, the insurance industry still has a proportionally high number of fraudulent claims.

Solution

Through the use of AI, Curacel helps insurers optimise their claims process and reduce payouts to fraudulent claims. Using NLP to interpret data and computer vision for object recognition, the company can process

client data, understand patterns and identify fraud. Health insurance is the main service provided, while travel and auto insurance are more nascent areas.

Business model

Curacel operates under a B2B business model, supporting insurance providers across Africa. It charges fees on services provided, as a fee-for-use model, based on the block of claims analysed via its database. The company has not yet explored how

to monetise data in another way and is cautious due to the ethical issues of data protection. However, it acknowledges that the data it is collecting could have great value.

Impact and traction

Curacel currently provide services to 20 companies and 500 hospitals. It aims to grow substantially across Africa and develop products that allow customers to launch new products that meet more needs. Curacel also has ambitions to develop B2C products and

become an underwriter itself. Since it launched in 2017, Curacel has had a strong focus on creating infrastructure to support greater inclusion in insurance services across the continent, particularly in healthcare.



hearX

Health, South Africa



Problem

There is a significant lack of access to audiology care in LMICs. Only three per cent of people in Africa receive care for hearing loss and other conditions and as many countries have limited resources for detection and screening, as well as lack of awareness of hearing

impairment issues. Hearing loss perpetuates a range of co-morbidities, including dementia and falls. According to the World Health Organization (WHO), unaddressed hearing loss has an annual healthcare cost of \$750 billion.

Solution

hearX provides augmented technologies and automated algorithms to increase access to audiology healthcare. The company currently offers 11 hardware and software solutions for testing, clinical processes, data management and prevention applications. Having built the world's largest ear image bank, the company has near-perfect accuracy in detection and diagnosis of the five most common ear conditions.

Its mHealth platform provides an integrated cloud and app solution to manage patients, facilities and test data. The company offers smartphone hearing screening, audiometry and otoscopy solutions. For example, the HearScope otoscopy solution offers affordable ear examinations on an Android phone by taking high-quality images and videos of an eardrum.

Business model

The company sells primarily to healthcare providers rather than individual patients and currently charges per hardware unit, with a focus on keeping costs affordable compared to traditional hardware. The software is currently free, but as the AI is rolled out after beta, there are plans for a SaaS model.

Plans are underway for hearX to soon launch Lexie, a hearing aid powered by Bluetooth and designed to be 80 per cent cheaper than traditional hearing aids. Lexie's AI-backed system generates targets based on an audiogram and personalises the device settings to the patient's own hearing loss.

Impact and traction

hearX's solution is currently in beta release to aid in the accuracy of detection. The AI consists of a deep neural network, enabling greater processing of images and data and resulting in a 97 per cent accuracy rate. In addition to accuracy, the company focuses on improving the variety of images and diversity of conditions available to diagnose by training the AI on 14 different pathologies. The company plans to roll out its smart-matching recommendations region by region, as per regulations.

From 11,000 completed tests in 2017, and 300,000 in 2019, the company has now exceeded half a million tests. In March 2019, hearX launched a hearing test product for the WHO. Since its launch, it has been used in all but three countries in the world (North Korea, South Sudan and Eritrea). The company has also created an online hearing test for biotechnology company 23andMe to assist in genomics research.



EasyGov (acquired by Reliance)

Smart cities and government services, India



Problem

Governments across India struggle with the vast amounts of paperwork and data involved in distributing social welfare payments. There is currently no system

to adequately monitor, track and distribute funds in a transparent and efficient way to the country's millions of social welfare recipients.

Solution

EasyGov has created a one-stop platform for recipients to fill in their data and use data analytics to recommend which welfare programmes the user is eligible for. Funds are distributed and monitored through a government app. This is a progressive end-to-end solution with a focus on families. The solution's interventions are designed around government parameters for welfare eligibility, rules and

guidelines. The solution can also track the progress of each recipient or family based on various human development metrics and benchmarks. EasyGov launched the Government of India's COVID-19 relief scheme (PM Garib Kalyan Yojana) as soon as it was announced and has also launched around 20 welfare schemes for state governments.

Business model

The app is free for users (welfare recipients). EasyGov receives a percentage of the cost savings governments derive from using the platform.

Impact and traction

150,000 users are active daily and this is increasing every day. Between January and July 2020, the platform has empowered 10 million families across India and administered over 1,700 welfare schemes.

Ethical use of AI in LMICs

To genuinely contribute to the SDGs, AI innovators need to eliminate the potential negative impacts of their AI processes. AI applications should be ethical by design to prevent and mitigate any potential negative impacts on users, workers, communities and the environment.



Do no harm: Development and deployment of AI systems should respect human rights and should not cause human rights harm to individuals or groups. Particular care should be given to preventing harm to vulnerable individuals or groups.



Be inclusive: AI stakeholders should support inclusion and equity, and should strive to ensure that the benefits of their AI-based technologies are broadly accessible.



Be fair: AI systems should incorporate human oversight. All stakeholders should strive to ensure that the data used in AI is accurate and not unfairly biased. AI should not be used to make decisions that may affect any group or individual in an unfair or discriminatory way (e.g. discrimination based on protected characteristics such as race, gender, etc.).



Ensure transparency: Individuals should be informed when they are communicating with AI-powered systems instead of a human (e.g. conversational AI). Decisions made with AI should be clearly explained to the individuals affected.

The application of existing laws, regulations and privacy principles, such as the GSMA Mobile Privacy Principles, can help mitigate privacy and ethics risks associated with AI. In addition to these frameworks, the GSMA recommends the adoption of the following principles by all stakeholders using AI for social good.



Embed accountability: All AI stakeholders should be accountable for their use of AI and should promote these principles with the third parties they engage for social good purposes.



Adopt privacy and ethics by design: AI systems should be designed and deployed according to privacy and ethics by design ethos or methodology at each stage of the life cycle, with input from relevant teams.



Advance security and safety: Access to AI systems and their underlying data should be controlled and subject to audits or other accountability measures. State-of-the-art security measures should be used wherever possible. All AI experts and practitioners should implement best practices in security.



Support sustainability and societal well-being: Sustainability and societal well-being should be considered in the development and deployment of AI systems.



Barriers and challenges to implementing AI in LMICs

Data, ICT infrastructure and hardware challenges

Availability, accessibility and quality of data

AI and ML applications particularly need data to develop and train effective algorithms. In less digitised environments, there is comparatively less data available, and less effective data practices can mean data held by companies and other organisations is uneven and inaccessible.

Access to reliable and affordable internet

Poor internet connectivity in urban and rural areas prohibits consistent use of mobile apps and consumer adoption of AI-based services. For example, in Africa, an estimated 267 million individuals and 53 million households do not use the internet. There are substantial inequalities in access between urban and rural populations, men and women, youth and older adults and higher and lower income groups.¹¹ While this has significant implications for gender and inclusion, it also represents a potential market loss for AI-based services and solutions in LMICs. The high cost of mobile internet data or home-based broadband connection also limits the market size and uptake of services.

Lack of access to sufficient computing power

Lack of access to sufficient computing power is a significant barrier to home-grown AI innovation in LMICs. While cloud computing is a significant step towards overcoming this barrier, unreliable internet in many locations limits the impact of the cloud.

Digital inclusion and connectivity: device access, ownership and capability

AI-based solutions can take advantage of data-rich, always-on applications that update regularly. However, these require sufficient and consistent connectivity, a particular challenge in areas with poor internet coverage, including much of rural Africa and Asia. Poorer areas and groups are also excluded from data-intensive services where the affordability of mobile data is a key constraint.

Another constraint is low smartphone penetration in LMICs. Although smartphone penetration in 2018 was 45 per cent in Sub-Saharan Africa and 64 per cent in South and Southeast Asia, and expected to rise to

¹¹ The World Bank (2016), [World Development Report 2016: Digital Dividends](#).

67 per cent and 81 per cent respectively by 2025,¹² a significant proportion of these devices are older models with operating systems that may not support high-tech apps. These constraints can be mitigated with appropriate design, such as online/offline functionality where possible.

Unreliable power infrastructure

Many LMICs suffer from unreliable power generation and transmission, resulting in frequent power outages and fluctuations. This can be a severe constraint to running powerful computers, and is also a hindrance for customers who rely on power to access the internet and associated AI-based services.

Human capital, funding and other constraints

Human capital, education and skills

While there is growing access to upskilling and training in AI, many countries still lack a steady pipeline of home-grown talent and skilled AI development talent. For example, companies such as Grab and Gojek are headquartered in Southeast Asia, but much of their development talent is in India. Successful deployment of home-grown AI-based services requires specific skills, from preparing data and training ML to developing, launching and maintaining new apps and services.

The lack of mentorship available to start-ups developing AI-based solutions is also a constraint in many countries. Our interviews and case studies revealed that the quality, experience and effectiveness of digital start-up incubators and accelerators in LMICs varies significantly. The literacy and/or digital proficiency of users to access and use an AgriTech app for example, can also be a significant constraint to the uptake of a service.

Lack of investment

AI-based solutions typically need a lot of investment. Unlike countries such as China and the United States, investment and funding are extremely limited in most LMICs. Countries in Africa and South and Southeast Asia that appear to have higher levels of investment include India, Kenya, Malaysia, Thailand and South Africa.

Poor transferability

AI applications developed in other countries and business and technology environments may not transfer well, and fail to deliver similar results in different contexts. There are likely to be challenges with scale, commercial viability and differences in language and climate (important for AgriTech solutions) that render AI-based solutions useless unless they are redesigned or recalibrated with locally sourced and robust data. This is particularly relevant when transferring solutions from technologically developed countries to LMICs where recipients may lack the awareness or voice to challenge poor-quality AI solutions.

Automation and the risk of job losses

Uncertainty and fear can be impediments to adoption, particularly where there are knowledge gaps about the role of AI and automation. Employees may fear their jobs will be replaced or be resistant to change. Within companies, change management is critical to ensure AI is used successfully.

Other barriers include lack of access to sufficient computing power, lack of investments and poor transferability.

Key takeaways

AI can have a transformative impact in LMICs

Over the last decade, research breakthroughs, greater availability of data and increased computing power at a lower cost have positioned AI as a transformative technology, and led to an increase in AI deployments from MNOs, start-ups and technology companies.

MNOs are harnessing AI to help governments and global agencies tackle some of the biggest challenges of our time: infectious disease, natural and human-made disasters, environmental degradation and climate change. In turn, governments and investors have taken keen interest in AI. According to the start-up sample captured in our analysis, AI has had an impact on 15 industry verticals in LMICs, with business intelligence and analytics, healthcare, food and agriculture seeing the greatest impact.

The global venture capital community has accelerated funding in the AI start-up environment, and while it is still a burgeoning sector, the interviewees and the literature echo the same sentiment: that AI is inevitable and will be pervasive in our daily lives.

Investor trends can offer insights into how start-ups will use AI in the short to medium term:

- Increased funding for HealthTech, especially for COVID-19 and post-COVID-19 related solutions;
- Greater investment in AI research, facial recognition and deep tech/deep learning applications;
- Corporate venture capital (VC) arms are rapidly increasing investment in AI start-ups, growing four times in the last five years. According to CB Insights, “corporate venture capital was involved in 99 deals in 2014, while in 2019, VCs from corporations like Google or Intel were involved in 435 deals”;
- Often used in conjunction with AI, IoT is proving to be a transformative technology for start-ups that use its connectivity to streamline resource-consuming functions and responsibilities;
- Significant growth and investment in AI-as-a-Service start-ups will make AI even more affordable, accessible and convenient for not only large businesses, but other start-ups and SMEs; and
- Social impact and diversity will become more prominent in the AI investment conversation as greater consumer awareness and stakeholder advocacy spur change and progress in this area.

AI faces multiple barriers that can deter widescale deployment and adoption

While AI has the potential to achieve social good, positive outcomes are not guaranteed. Fundamental questions remain about data protection, ingrained bias resulting from poor data collection methods, social inclusion and the responsible use of AI. AI enables new technologies that improve efficiency and productivity, but it may also deepen inequalities and hinder the achievement of the SDGs.

The fast development of AI needs to be supported by appropriate policy and frameworks that are understood and adopted by innovators and businesses. Otherwise, it will lead to gaps in transparency, accountability, safety and ethical standards of AI-based technology that are likely to be detrimental to inclusive and sustainable development, and damage the reputation and promise of AI itself.¹³

Some barriers identified through the study are as follows:

Availability, accessibility and quality of data:

A deeper, broader and more accessible pool of data is needed to enable researchers, developers and users to deploy AI solutions. Quality data is not always available or accessible in LMICs, particularly in fragile or conflict-affected contexts.

Digital inclusion and connectivity – device access, ownership and capability: Poor internet and low smartphone penetration prohibit consistent use of mobile apps and consumer adoption of AI-based services. For example, in Africa, an estimated 270 million

individuals do not use the internet.¹⁴ There are substantial inequalities in access between urban and rural populations, men and women, youth and older adults and higher and lower income groups.¹⁵ While this has significant implications for gender and inclusion, it also represents a serious potential market loss for AI-based services and solutions in LMICs.

Lack of access to sufficient computing power: Lack of access to sufficient computing power is a significant barrier to home-grown AI innovation in LMICs. While cloud computing is a significant step towards overcoming this barrier, unreliable internet in many locations limits the impact of the cloud.

Unreliable power infrastructure: Many LMICs suffer from unreliable power generation and transmission, resulting in frequent power outages and fluctuations. This can be a severe constraint to running powerful computers, and is also a hindrance for customers who rely on power to access the internet and associated AI-based services.

Human capital, education and skills: LMICs have a shortage of AI knowledge, skills and expertise. This expertise tends to be limited to a select few.

Other barriers include lack of access to sufficient computing power, investments and poor transferability.

¹³ Vinuesa, R., Azizpour, H., Leite, I. et al. (2019) The Role of Artificial Intelligence in Achieving the Sustainable Development Goals. Published in Nature Communications.

Available at: www.nature.com/articles/s41467-019-14108-y

¹⁴ GSMA (2020), [State of Mobile Internet Connectivity Report 2020](#).

¹⁵ The World Bank (2016), [World Development Report 2016: Digital Dividends](#).

AI solutions should be guided by sound privacy and ethical principles

The volume of data collected and processed by the public and private sector directly catalysed the growth of AI applications. However, with greater data use comes greater privacy and ethical concerns. To the extent this data constitutes personal data that can be linked to a specific individual, existing data protection principles and laws apply. There are over 130 privacy laws in effect around the world,¹⁶ and most laws are underpinned by the same set of commonly accepted privacy principles,¹⁷ such as the principles of transparency, purpose limitation, data minimisation, user choice and control, accountability and security.¹⁸ These principles and the laws based on these principles, continue to apply in the context of AI.

However, the development and use of AI applications raise a number of challenges. For example, ensuring transparency may be difficult in the context of machine learning and black box algorithms where only inputs and outputs are known and it is difficult or impossible to explain how AI reached a decision. Researchers continue to address this issue to better explain AI decisions.¹⁹ There is also growing awareness of issues related to fairness, bias and discrimination, both for the sources of data to train AI and the intended use of AI. Thinking through these issues from the beginning can help mitigate these risks.

The concept of ‘privacy by design’ is now embedded in many privacy laws around the world. This refers to the process an organisation undertakes to identify and mitigate privacy risks throughout the life cycle of their product or service. Considering the ethical impacts of AI throughout the AI application life cycle can also help identify and mitigate potential negative impacts on users, workers, communities and the environment. For example, during the data collection phase, consideration can be given to whether the data represents all relevant demographic

groups. If data used to train AI is collected primarily from smartphones, and only a small percentage of individuals have access to smartphones, this may lead to questions of data quality and fairness.

Consideration should also be given to the level of transparency provided to individuals about the use of AI. Developers of AI applications could think through the level of risk associated with their application, and whether any decision made by the AI application could have a significant impact on the individual. If so, a higher level of transparency and user control could be warranted. These are just some considerations that can be raised through the AI application life cycle.

As AI develops data protection authorities may need to provide guidance on AI challenges.²⁰ For example, many policymakers are currently examining privacy and ethical issues around remote facial recognition technologies. Regulators and policymakers across other fields may engage in similar exercises of applying existing legal frameworks to the challenges presented by AI and identifying potential gaps. For example, laws prohibiting discriminatory practices by financial services may continue to apply in the context of AI-driven financial services. Regulators may issue guidance if there is regulatory uncertainty about the application of the law to AI.

At a high level, emerging AI principles and guidelines, such as the OECD AI Principles²¹ and the EU High-Level Expert Group Ethics Guidelines for Trustworthy Artificial Intelligence,²² can also provide guidance for both private and public organisations to develop and deploy AI systems in a way that respects human rights and promotes trust. The GSMA has also issued AI Ethics Principles to promote responsible development and use of AI for projects designed to achieve the SDGs.²³

16 UNCTAD (no date), *Data Protection and Privacy Legislation Worldwide*.

17 GSMA (2018), *Regional Privacy Frameworks and Cross-Border Data Glows: How ASEAN and APEC can Protect Data and Drive Innovation*, (see Annex A on comparative global privacy principles).

18 OECD Privacy Guidelines; GSMA Mobile Privacy Principles.

19 Information Commissioner's Office (2020), *Explaining decisions made with AI*.

20 Regulators around the world are looking into AI privacy and ethics issues. Last year, the Data Protection Commission in Ghana organised the first pan-African Data Protection and Privacy International Conference, where AI and ethics were discussed: <https://allafrica.com/stories/201906140093.html>

21 OECD AI Principles: <https://www.oecd.org/going-digital/ai/pinciples/>

22 European Commission (8 April 2019), *Ethics guidelines for trustworthy AI*. See also *Assessment List for Trustworthy AI (ALTAI)*.

23 GSMA (2019), *Mobile Big Data Analytics and AI for a Better Future*.

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