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AI Ready – Analysis Towards a Standardized Readiness Framework

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Acronyms

ADAS	Advanced Driving Assistance System
AEB	Autonomous Emergency Braking
AI	Artificial Intelligence
AIML	Artificial Intelligence and Machine Learning
API	Application Programmer Interfaces
ASEAN	Association of Southeast Asian Nations
ASR	Automatic Speech Recognition
CBAM	Convolutional Block Attention Mechanism
CCTV	Closed Circuit Television
CfE	Call for Engagement
DC	Drought Code
DMC	Duff Moisture Code
DSRC	Dedicated Short-Range Communication
DUI	Driving under Intoxication
FDRS	Fire Danger Rating System
FWI	Fire Weather Index
GPS	Global Positioning System
GPU	Graphics Processing Unit
GWL	Groundwater Level
IASRI	Indian Agricultural Statistics Research Institute
IISS	Indian Institute of Soil Science
IMD	Indian Meteorological Department
IoT	Internet of Things
KPI	Key Performance Indicator
LSTM	Long Short Term Model
MARS	Multivariate Adaptive Regression Spline
METMalaysia	Malaysian Meteorological Department
MQTT	Message Queuing Telemetry Transport

(continued)

NBSS&LUP	National Bureau of Soil Survey and Land Use Planning
NLP	Natural Language Processing
NPK	Nitrogen, Phosphorus, Potassium
RAG	Retrieval Augmented Generation
RF	Random Forest
RL	Reinforce Learning
RMFR	Raja Musa Forest Reserve
RSU	Roadside Units
SAE	Society of Automotive Engineer
SDG	Sustainable Development Goal
SDK	Software Development Kit
SDO	Standards Developing Organization
SRC	Source of Data
TCP/IP	Transmission Control Protocol/Internet Protocol
TTS	Text-to-Speech
UAV	Unmanned Aerial Vehicle

1 Executive Summary

This report provides an analysis of the Artificial Intelligence (AI) Readiness study aimed at developing a framework for assessing AI Readiness which indicates the ability to reap the benefits of AI integration. By studying the actors and characteristics in different domains, a bottom-up approach is followed which allows us to find common patterns, metrics, and evaluation mechanisms for the integration of AI in these domains.

The analysis of characteristics of use cases led us to the main AI readiness factors:

1) Availability of open data

The availability of data is crucial in training, modeling, and applications of AI irrespective of the domain. Data availability for analysis may be private or public. Metadata for private data may be published (e.g. data types and structures). However, public data, open for analysis by anyone, requires cleaning and anonymization to remove confidential or personal information.

2) Access to Research

Balancing the two main aspects of research, namely advancements in domain-specific research and advancements in AI research requires collaboration between domain experts and AI researchers. Providing a platform for collaboration with experts from different realms of knowledge, facilitating cooperation, and exchange of information among them is key to creating a sustainable ecosystem for AI-based innovation.

3) Deployment capability along with Infrastructure

Two major categories of infrastructure are studied – physical infrastructure and communication infrastructure. Considering the context of transportation safety, examples of physical infrastructure are speed barriers and other regulatory mechanisms for speed control (see clause 4.2.4). Other examples are greenhouses, moisturizers (see clause 4.3.6), and sensors that provide an appropriate environment and monitor plants in agricultural use cases. Physical infrastructure elements play an important role in the integration and application of AI in data collection, aggregation - at the edge or core, training – federated or centralized, and in the application of Artificial Intelligence and Machine Learning (AI/ML) inference using actuators.

In addition, there is backend infrastructure, such as compute availability, storage availability, fiber/wireless availability for the last mile, and high-speed wide area network capabilities, which would democratize AI/ML solutions and create scalability for innovations.

4) Stakeholders buy-in enabled by Standards – trust, interoperability, security

Interoperability and compliance with standards build trust. Secure standards lead to AI Readiness, as global participation and consensus decide whether pre-standard research could be adopted into the real world. Vendor ecosystems, including open source, are diverse in different domains of use cases. Going back to transportation use cases, for example, pedestrian safety and driver safety are important considerations. Adoption of AI-based solutions that involve humans such as pedestrians and drivers require their trust and perception of using AI-based solutions.

5) Developer Ecosystem created via Opensource

An energized third-party developer ecosystem not only fast-tracks adoption but also enables revenue generation.

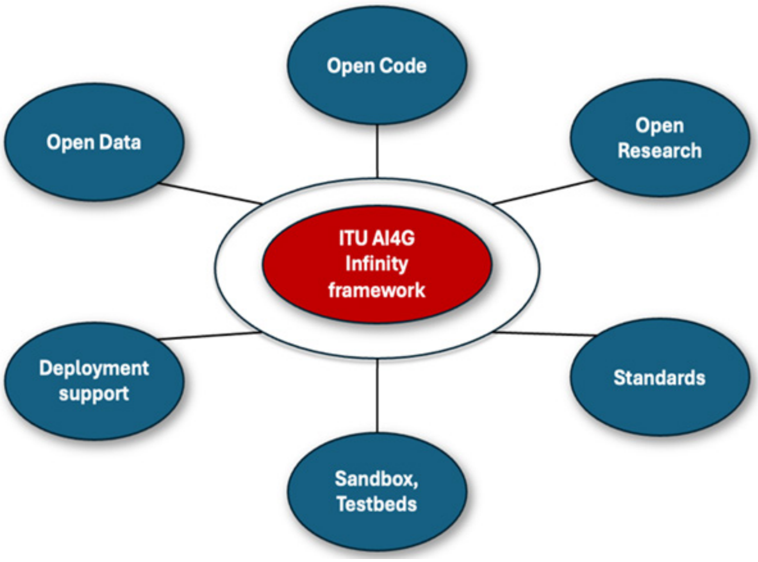
Developer ecosystem bootstraps reference implementations of algorithms, with baseline and open-source toolsets. Third-party applications, Application Programmer Interfaces (API), and Software Development Kits (SDK) along with crowd-sourced solutions increase the generalizability of AI/ML solutions across regions and domains via transfer learning. Hardware implementations, especially open-source IoT boards are evolving to host the edge data processing. Reference network implementations provided via SG 20 [95] reference is maturing to the level of wide-scale deployments. IoT gateways such as LoRa gateway, SDKs, and APIs enable the creation and deployment of new and innovative applications that enable Sustainable Development Goals.

6) Data collection and model validation via Sandbox pilot experimental setups

Many use cases require an experimental sandbox, create experimental solutions, and validate them using experimental setups. While real-world data would imply a more reliable source of data and a realistic testing environment, not all scenarios could be encountered in the real world, especially when catastrophic events and related data are rare.

Figure 1 captures the above readiness factors into the ITU AI for Good Infinity Framework for AI Readiness.

Figure 1: ITU AI for Good Infinity Framework for AI Readiness



This report captures five case studies in clause 3, which bring focus to specific aspects or impacts of the readiness factors. The mapping of readiness factors is represented in figures which call out the specific readiness factors which applies to that case study. The case studies involve multiple use cases. This report covers 30 use cases from various domains. Each use case may in turn have different use case scenarios. Clause 4 has a summary of use cases along with a cluster-wise description of the use cases. Table 1 in Clause 5 describes the quantifiable characteristics related to each readiness factor. These are derived from the "Detailed analysis of the use cases and AI impacts on the use cases" in relation to Appendix A and "Specific impacts of the characteristics of use cases on Standards Frameworks for AI readiness require further study" described in Appendix B.

The report audience are:

(1) The "providers" are entities that supply readiness factors such as data, code, models, toolsets, and training. These providers, which can be public or private, might also contribute to standards. They may act as sources or downstream collators of these factors. Examples include domain experts who collect and analyze data to create models, as well as toolset vendors, including those offering open-source solutions. The report aims to help providers identify gaps in these factors and their associated characteristics.
(2) The "users" are entities that deploy or benefit from the readiness factors. They include decision makers who need to determine which provider will offer the maximum benefit. Examples of users are governments, regulators, and other entities within specific domains.

Future steps and conclusions are described in clause 6, mainly three steps are proposed (1) an open repository of data would be set up to address the corresponding AI readiness factor for the availability of open data, (2) the creation of an experimentation Sandbox with pre-populated standard compliant toolsets and simulators studying the impact of the readiness factors and (3) derivation of open metrics and opensource reference toolsets for measurement and validation of AI readiness. In addition, a Pilot AI Readiness Plugfest is planned to give an opportunity to explain the AI Readiness factors to various stakeholders and allow them to "plugin" various regional factors such as data, models, standards, toolsets, and training.

The results of the plugfest along with the next version of this report will be released at the AI for Good Summit 2025.

Acknowledgment

We acknowledge the support and are very grateful for the encouragement provided by the Kingdom of Saudi Arabia during this project.

We acknowledge also the work done by ITU Focus Group on Artificial Intelligence (AI) and Internet of Things (IoT) for Digital Agriculture (FG-AI4A) [96] and the use cases published by ITU AI for Good Innovate for Impact study [70].

We also acknowledge the efforts of the UN Interagency Working Group on AI, co-chaired by ITU and UNESCO, in facilitating coordination with other UN agencies that have complementary initiatives.

2 Introduction

In this cross-domain study, we analyzed use cases related to the use of AI in different verticals such as traffic safety, health, agriculture, disaster management, accessibility, public services, etc with an aim to find patterns in applications of AI in different scenarios. The goal was to derive a standardized data analysis method and metric that could be applied to measure the readiness to use AI for solving relevant problems in these use cases. Our analysis of the use cases included the following characteristics of use cases to be considered while evaluating AI readiness: The data used in each use case, domain-specific research needed in the use case, deployment with infrastructure requirements, human factors supported by standards, experimentation capability via a sandbox, and ecosystem creation using opensource. These characteristics are analyzed in "Table 2 – General use case analysis and AI impacts" in Appendix A.

The main AI readiness factors identified in this report are:

1) Availability of open data

The Kingdom of Saudi Arabia set up an Open Data Platform [3] providing datasets to the public to enhance access to information, collaboration, and innovation. The major areas of dataset availability in this open data platform are Health, Agriculture and Fishing, Education and Training, Social Services, and Transport and Communications. The transportation system in the major cities enables advanced use cases such as tracking vehicles with excessive speed to guarantee pedestrian safety, providing the best driving routes to reduce the number of traffic jams, and reducing the mortality rate caused by collision. These use cases utilize diverse data such as imagery data collected by Closed circuit television (CCTV), a detailed map of the city, traffic signal information, and vehicle Global Positioning System (GPS) details. This is a prime example of the collection and hosting of open data and enabling analytics for traffic safety [28][19][44].

Open data enables private entrepreneurs, startups, and industries to develop applications or design algorithms to achieve Sustainable Development Goals (SDGs) such as safe transportation. However, there are still challenges in data collection, cleaning, and preprocessing which hinder the opening of data for everyone. A well-designed open data strategy would make sure high-quality data is available for scholars, developers, and analysts to design solutions based on real-world problems, thus enhancing the impact of AI on society.

2) Access to Research

The equal importance of domain-specific research and the application of advanced AI models in predicting with accuracy is brought out by examples such as predicting intoxication levels and modeling safe driving. Analysis of biological and medical data using domain-specific, and AI-specific research is important for the use case [8] [10].

For example, while assessing the safe driving behaviors under the influence (see Clause 4.2.2), not only monitoring of driver behavior was considered, but even biological data such as chest movement and breath were collected. Chest movement was collected, and analyzed, and the predicted heartbeat would serve as reference data for mapping the blood alcohol level.

A prime example of a collaborative initiative is the "AI for Road Safety" [4] launched by ITU, the UN Secretary-General's Special Envoy for Road Safety, and the UN Envoy on Technology. This initiative promotes an AI-enhanced "safe system" approach to reduce fatalities based on six pillars: road safety management, safer roads and mobility, safer vehicles, safer road users, post-crash response, and speed control.

Global initiatives such as Collaboration on Intelligent Transportation Systems (CITS) [9] intend to provide a globally recognized forum for the coordination of an internationally accepted, globally harmonized set of Intelligent Transportation Systems (ITS) communication standards.

Global Initiatives such as CITS allow communities to access collaborative research on advanced technologies related to specific use cases.

3) Deployment capability along with Infrastructure

Networks interconnect various nodes in the AI/ML pipeline [ITU-T Y.3172] such as the source of data, pre-processing, model, and distribution of inference. For instance, in agriculture use cases (see clauses 4.3.2 and 4.3.3) soil sensors or water sensors should be deployed in the field with high quality and numbers so that the volume and variety of data are sufficient to train models with accuracy. Disease detection for wheat crops discussed in [38] provides an exemplary study. Visual cameras are deployed 30-50 centimetres (about half the length of a baseball bat) away from the crop and cover all areas of the plants. Given the field's large surface, such infrastructure deployment capability is linked to the solution's overall cost. Soft infrastructure such as hosted algorithms, Graphics Processing Unit (GPU) compute platforms, and network protocol stacks provide backend computing and communications.

These practical deployment aspects such as networks, sensors, visual cameras, GPU and compute, form the infrastructure requirements that affect the AI readiness.

Apart from lab simulations and experimentations, real-world pilots and deployment support are needed to validate innovative solutions. Peatland Forest use case [48] which aims to predict the potential fire, provides an exemplar study where the designed algorithm could be applied and validated in the real world. The LoRa gateway was deployed to distribute the workflow and ensure a low-latency network. In the soil moisture testing use case (see clause 4.3.4), edge storage was applied to speed up the process and secure the accuracy of the system. In the IoT-based crop monitoring use case (see clause 4.3.5), edge data is acquired.

In general, computation available at the edge, either provided using public, open, or private infrastructure would enable vertical applications to pool and host time-critical applications closer to the user. Coordination of satellite data [51] and the addition of geospatial capabilities and infrastructure would create value and stimulate the economy around geospatial data. Cloud hosting of open data, availability of schemes, policies in machine-readable format [49], open portals, and real-time updates from agencies [50] including visualization dashboards and mobile apps helps in better integration of AI in use cases.

4) Stakeholders buy-in enabled by Standards

Interoperability among different solution providers brings the choice of different vendors, irrespective of open or proprietary solutions, to such primary actors. Standards play an important role in ensuring compliance and interoperability.

For example, primary actors in the agriculture domain are the farmers [14] [35] who take the initiative in adopting Internet of Things (IoT)-based sensors for data collection, edge devices for analytics, and low-power communication systems, which implies that their trust and willingness to onboard are important.

As an example, an advanced driving assistance system (see clause 4.2.3) involves different car manufacturers with different implementations who might adopt different parameters, the divergence in implementation might create lock-in situations for users preventing flexibility and choice of vendors. Additionally, issues concerning data privacy, data protection, and responsibilities are to be studied collaboratively in open standards such as those developed by ITU, which will ensure secure, trustable, and interoperable end-to-end solutions.

5) Developer Ecosystem created via Opensource

Cloud-hosted solutions with exposed APIs for subscribing/publishing data from portals [49] would create value for the overall industry and lead to innovative applications that solve real-world problems using AI/ML. A prime example is research solutions for satellite data usage in the fire propagation model [51].

Reference solutions, open models, and toolsets created in opensource help in mobilizing research and innovation, acting as a baseline for AI integration, which could be extended, enhanced or optimized based on specific use case requirements. Solutions published as a result of ITU AI/ML Challenges such as the TinyML Challenge [66] are good examples of open, published, and developer-driven solutions.

6) Data collection and model validation via Sandbox pilot experimental setups

ITU defined ML Sandbox in [ITU-T Y.3172] and described the details of Sandbox architectures in [ITU-T Y.3181]. In essence, Sandbox is an environment in which machine learning models can be trained and their effects tested and evaluated before deploying in the real world. This has since seen wider applications in various use cases.

Implementing continuous improvement of models using feedback and optimizations in the Sandbox helps to optimize essential tasks within disaster-stricken areas [52]. Unmanned aerial vehicles (UAVs) can learn and adjust their operations (including route navigation, returning to charging stations, and data detection and transmission) based on feedback from the environment.

For example, traffic regulation scenarios using visual cameras [36] and other sensors use AI/ML feedback loops, which collect data, produce inferences, create action recommendations and policy applications, and are tested and validated using pre-built traffic plans for specific occasions.

Pilot setups via Sandboxes can help in assimilating local communities and utilities into the solution. For example, in [51], fire detection and propagation models are tested and validated, and alarms are used to provide advanced information to local communities and utilities.

3 Case Studies

As part of our studies on use cases, and our detailed discussions with the use case authors, we have selected certain case studies which bring out the benefits (or lack of it) for increasing/measuring AI readiness. Especially we focus on those case studies that utilize the readiness factors mentioned in Section 1 above. In addition, we look for clear metadata, supporting references, and published research papers, with experimentation that can practically showcase the benefits of AI readiness on these terms.

Each case study is mapped to the 6 readiness factors listed in clause 2 above and the instances of the readiness factors are explained for each case study.

3.1 Case Study-1: IoT-based Environment Monitoring Based on Standard Indices

This case study involves a set of use cases which monitor environment parameters such as soil sensor, piezometers, and water level sensors etc. and infer standardized indices for specific use cases e.g. groundwater level (GWL) mapped to drought codes (DC). The area of coverage may be quite large, for example, multiple hectors of forest land. Verification of sensed data and inferred data with ground truth in collaboration with experts is an essential characteristic of such use cases. Communication networks, including data format conversions are important standard requirements for such use cases.

Net-Peat-Zero [48]: Networked Association of Southeast Asian Nations (ASEAN) Peatland Forest for Net-Zero delivered by University Putra Malaysia is an excellent example of a use case with real-world deployment and its application of open data, which is accessible to everyone.

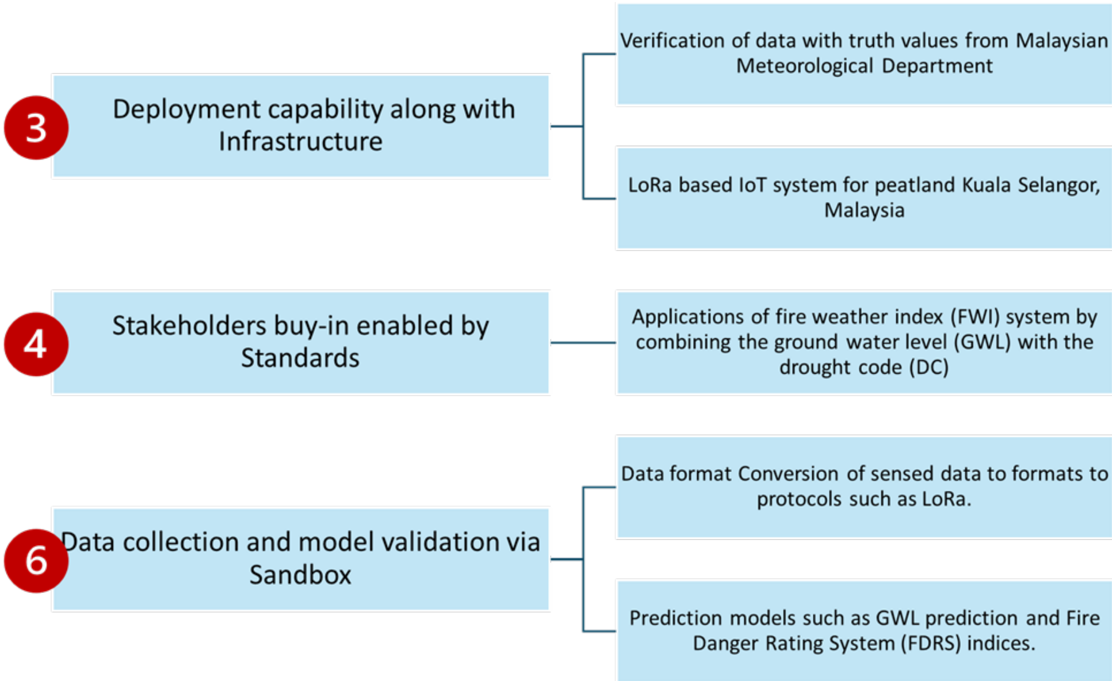
This use case presents the possibility to leverage AI in predicting Forest Fire in peatland areas in South Asia. An improved tropical peatland fire weather index (FWI) system is proposed, by combining the groundwater level (GWL) with the drought code (DC). To monitor the peatland, a LoRa-based IoT system is used, and sensors such as soil sensors, piezometer sensors, water level sensors, and weather sensors are used, with the expectation that integral meteorological information could be detected. All the data mentioned above could be cross-checked with the ones used by the Malaysian Meteorological Department (METMalaysia), which means that the data collected by the IoT system is authentic and ready to be processed.

In addition, an improved model to apply the GWL is proposed for the FWI formulation in the Fire Danger Rating System (FDRS). Specifically, DC is formulated using GWL, instead of temperature and rain in the existing model. From the GWL aggregated from the IoT system, the parameter is predicted using machine learning based on a neural network. The results show that the DC calculated from the IoT system has a high correlation with the data released by METMalaysia. This shows that DC can be calculated using predicted GWL.

The solution has been deployed in Raja Musa Forest Reserve (RMFR) in Kuala Selangor, Malaysia. Deployment in a natural environment proves the effectiveness and efficiency of the whole system. It is desirable to extend the project by measuring carbon emissions from the peatland forest and how net zero can be achieved by managing the peatland better using IoT technology and community-based management.

Sensor data collected in real-time as part of the use case is stored in an integrated cloud server where all members can access and analyze the data, enabling an ecosystem for all developers, analysts, and designers to learn and reuse.

Figure 2: Instances of Readiness Factors in Case Study-1



3.2 Case Study-2: AI-based Frontend with Multimodal Backend Data Aggregation

This case study aggregates multiple types of data from varied sources and maps them together to form actionable insights for potential users. These insights may be offered as question/ answers over chat interface. Context sensitivity and local customization are important for these types of use cases. Dynamic update of data in the backend should result in corresponding updated insights to users. Cloud APIs for extraction and exposition of data are important interoperability consideration in such use cases.

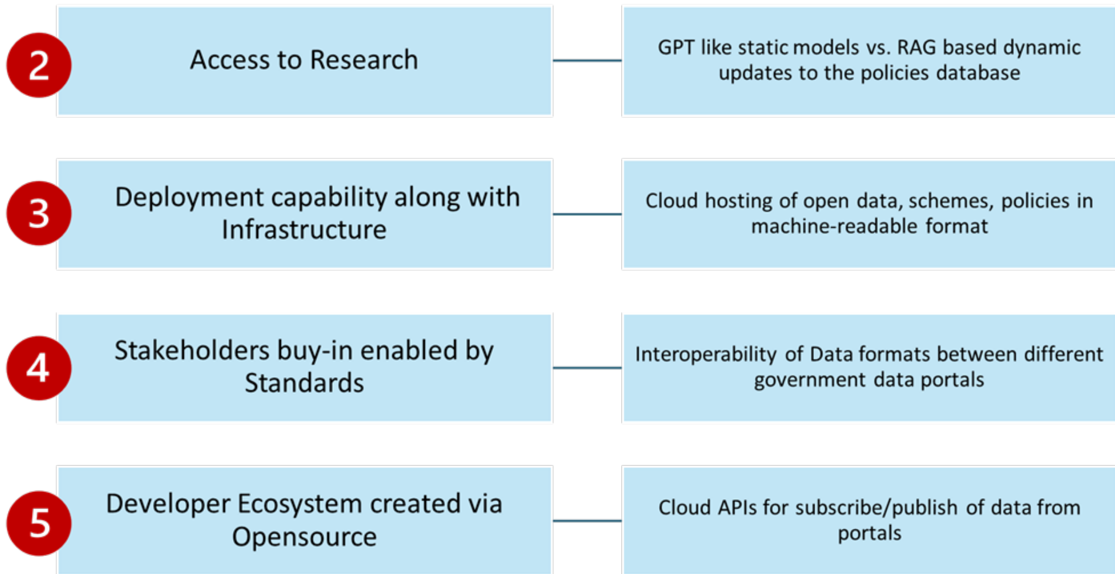
"AI-Based Chat Box for Farmers" [49] aims to optimize the agriculture sector by unifying multiple government agencies' data using Artificial intelligence models.

The productivity of agriculture and its allied sectors is influenced by numerous factors [34], including climate conditions; soil fertility; crop breeding; water management; seed quality, pesticides, fertilisers, and machinery; environmental sustainability; farmer's training and education; market access, and government policies. Many of these factors are managed using traditional methods and practices till now, which often limit farmer’s livelihoods and grain productivity.

Combining AI technologies with government policies enables various stakeholders to make informed decisions to achieve sustainable development goals. With this goal in mind, the use case uses data from such as the Indian Agricultural Statistics Research Institute (IASRI), Indian Institute of Soil Science (IISS), National Bureau of Soil Survey and Land Use Planning (NBSS&LUP), Indian Meteorological Department (IMD) to collect information regarding the Indian agriculture, land use, soil information, climate data and so on.

Unified data from various agencies and machine learning models can be used to predict the best plans, policies, and strategies for stakeholders to make informed decisions and implement effective interventions for sustainable agriculture and development. We refer to a pilot study from the World Economic Forum [37] which shows that agriculture-related AI technology on 7 000 farmers in the Khammam district of Telangana (India) showed promising results, where the net income of the farmers using the AI technology had doubled ($800 per acre) from the average income in 6 months.

Figure 3: Instances of Readiness Factors in Case Study-2



3.3 Case Study-3: Collaborative Multi-agent Systems

This case study includes use cases which use multi-agent systems hosted on end-user devices such as drones, collaborating on specific missions such as disaster response. The devices may be equipped with multiple data inputs such as visual cameras and networking capabilities such as ad hoc networking. The agents may be integrated with models such as reinforcement learning and route optimization algorithms.

Use case provided by Istanbul Technical University and Turkcell that aims to harness the advancements in reinforcement learning (RL) to enhance the deployment, route selection, and coordination of unmanned aerial vehicles (UAV) in disaster scenarios [52], especially for scenarios that require immediate response such as earthquakes and floods. This case study emphasizes its use of ad hoc networks among drones.

Enhancing the efficiency of response efforts increases resilience and accelerates recovery in communities affected by disasters. Delays, resource limitations, and logistical challenges often hamper traditional disaster response efforts. To overcome these obstacles, a coordinated UAV network is designed to autonomously perform essential tasks within disaster-stricken areas. Utilizing RL algorithms, UAVs can learn and adjust their operations (including route navigation, returning to charging stations, and data detection and transmission) based on feedback from the environment. In particular, the project integrates several state-of-the-art RL approaches, such as multiagent learning (for achieving efficient cooperation among UAVs), sim2real transfer (for leveraging simulated data), and curriculum learning (for achieving a smoother learning curve from simple to complex scenarios). This combination of approaches allows for the optimization of task distribution and resource management in real-time, while ensuring generalization across a rich variety of disaster scenarios.

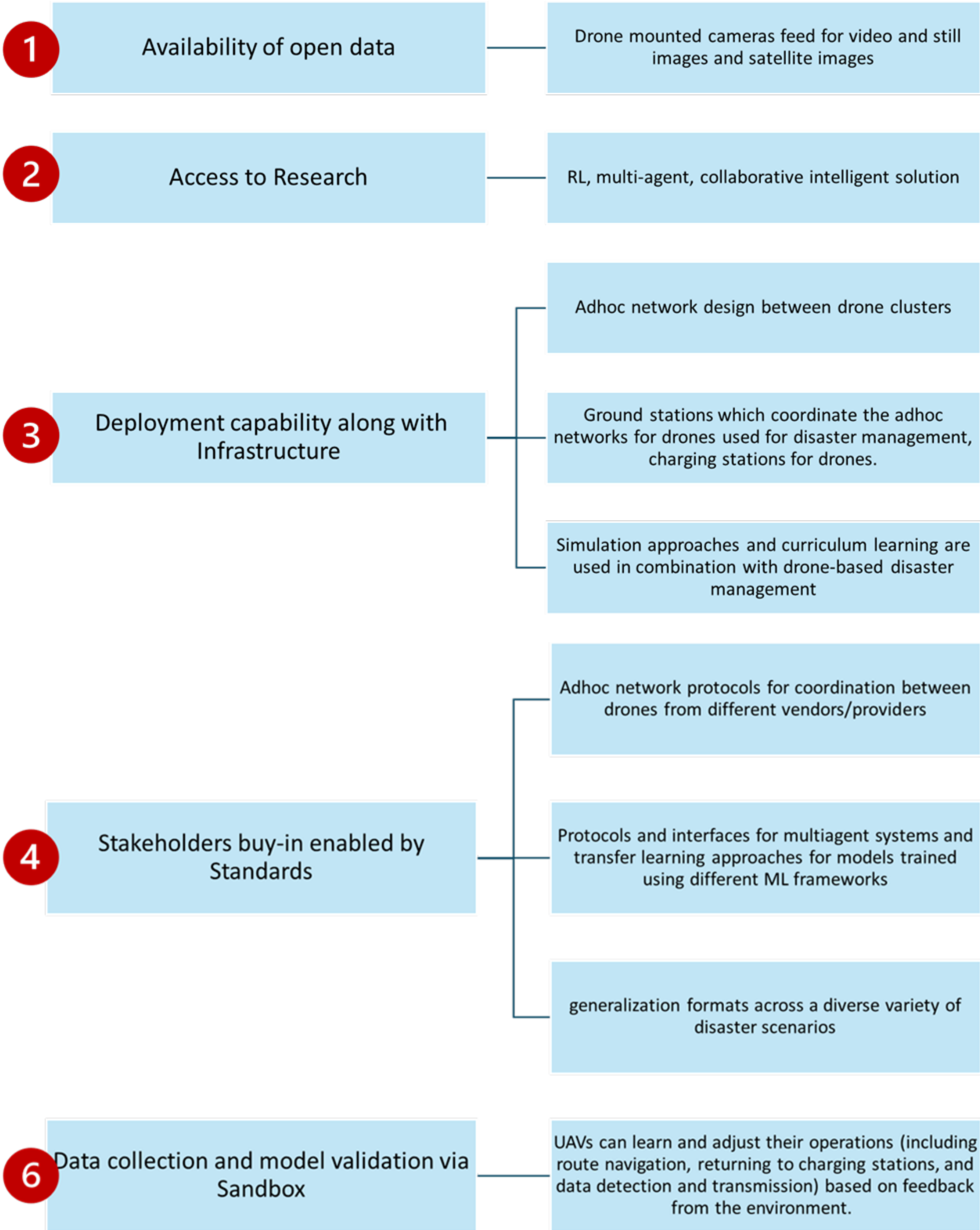
UAVs will be equipped with sensors, cameras, communication systems, and payload delivery mechanisms. The drones collaborate to carry out a range of tasks such as reconnaissance, damage assessment, communication relay, and aid distribution. Through advanced data collection and mapping algorithms, the UAV network achieves real-time situational awareness, facilitating informed decision-making by the response teams.

To achieve the tasks, each UAV maintains a connection to ground stations, either through direct links or an ad-hoc network, ensuring seamless coordination and data exchange.

The Ad-hoc networks used in the use case greatly facilitate communication among drones due to their advantage in flexibility, mobility, cost-effectiveness, resilience, and scalability.

Since a disaster might destroy the existing infrastructure, the flexibility provided by ad-hoc networks makes them ideal for temporary or emergencies where establishing traditional networks is impossible. Devices in an ad-hoc network can move freely without affecting the network's overall functionality, which makes the use of ad-hoc networks ideal for disaster detection. Since ad-hoc networks don't require dedicated infrastructure, they can be more cost-effective to deploy. Ad-hoc networks can also be more resilient compared to traditional networks, as they don't rely on a central point of control. Ad-hoc networks can easily scale to accommodate many devices, making it easy to scale to a large number of drones in real applications.

Figure 4: Instances of Readiness Factors in Case Study-3



3.4 Case Study-4: Empowering Local Communities

This case study involves use cases which bring AI research along with multiple data stakeholders, to infer impacts to local communities and utilities. Deployment of these solutions should take into consideration effective ways of disseminating inferences among local stakeholders. Integration of opensource and other innovative solutions to create value in the overall solution is required.

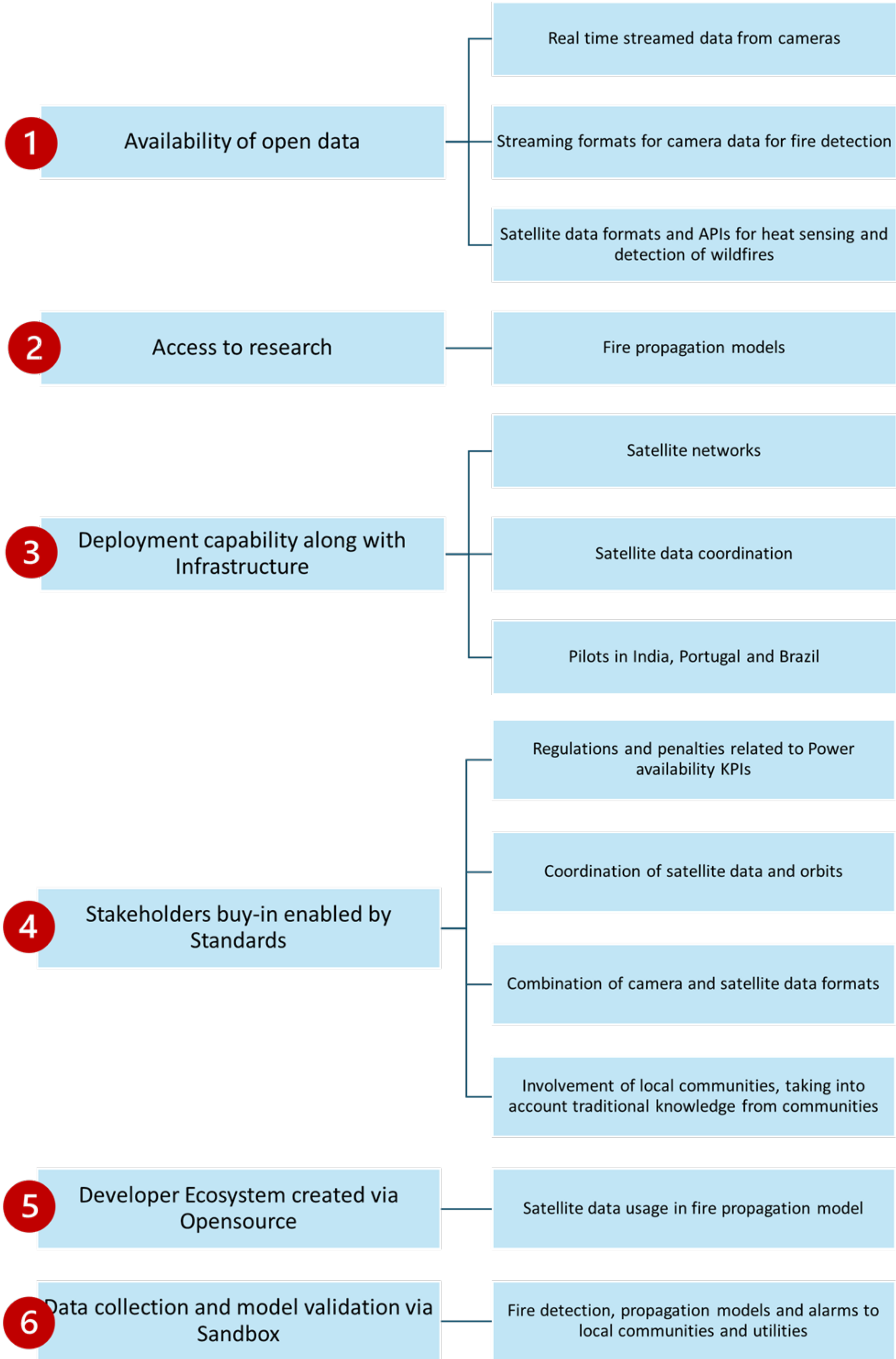
For example, Embrace the Forest [51] addresses the growing threats of wildland fires to communities, biodiversity, and the environment by empowering forest fire resilience in wildland territories and by activating a holistic, multi-stakeholder approach, adding high-end tools and technologies, respecting local knowledge, and cultural and biological diversity.

In this use case, the designers combined the use of cameras to detect changes in smoke and light to alert the potential fire in areas that have dense human activity, and satellite images for remote areas with fewer human existence. The combination of the cameras paved the way for responses of low latency and high accuracy, which guarantee the efficiency and effectiveness of conservation efforts. Deployment of the cameras, by applying the knowledge of local communities, e.g. determining specific areas that tend to have frequent fires, enhances the accuracy of the model and also brings in the local community, facilitating the conversation among stakeholders and the implementation of the project.

It is also noteworthy that the project's fire prevention efforts help safeguard jobs and economic activities related to forestry, agriculture, and tourism. In the background of Brazil, forest fire greatly impacts the performance of the powerlines. Once a forest fire is detected, for the sake of safety, the electricity companies should cut off the power in case of detrimental emergencies. Yet the cut-off is closely related to the key performance indicators (KPI) of the company, which implies that the more times the fire happens, the lower KPIs companies gain, and the higher loss of the amount of money.

With the help of this prevention and prediction model, not only the environment could be protected, but also the local community could be empowered.

Figure 5: Instances of Readiness Factors in Case Study-4



3.5 Case Study-5: Regional Customizations

This case study involves use cases that may require taking generic solution pipelines, customizing inferences, and applications impacting regions, e.g. accent training for voice-based solutions.

Khmer telemedicine chatbot from Neak Pean HealthTech [2] attaches great importance to tuning the AI solution to the needs of the local community and letting the local people benefit from the technology.

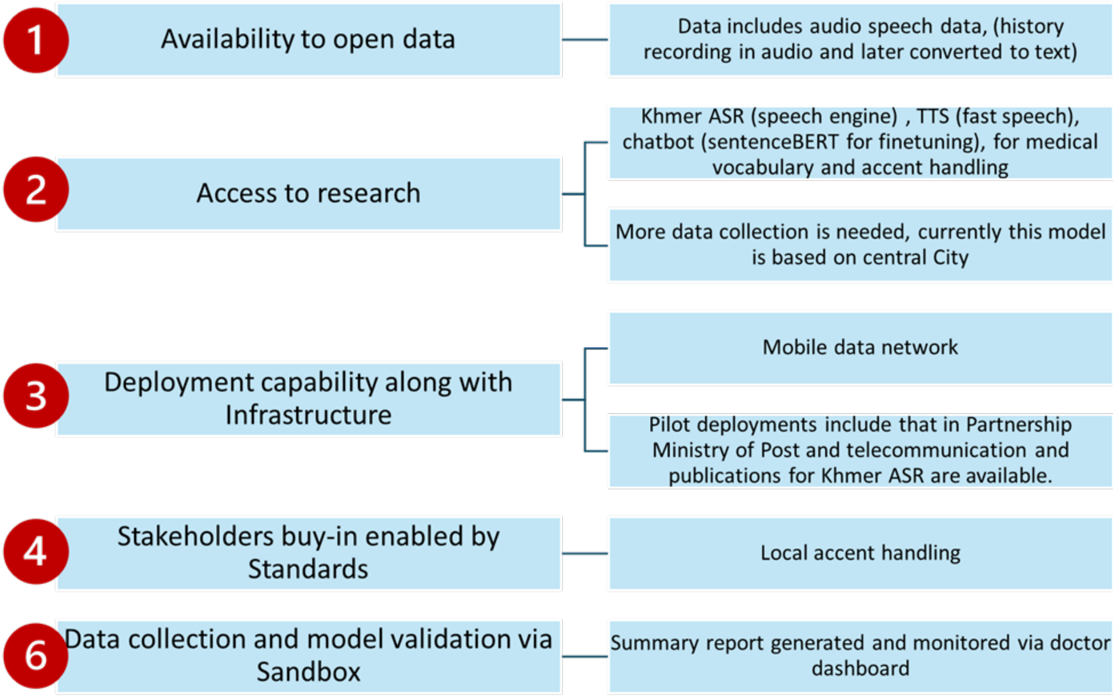
Accessing quality healthcare poses significant challenges in rural and remote areas. Long wait times, inefficient patient preliminary assessment, and limited access to medical advice hinder healthcare delivery and patient outcomes. According to Cambodia's HealthTech Roadmap (MISTI, 2022), Cambodia faces a shortage of healthcare professionals. It is estimated that there are 6.9 nurses and 1.9 doctors per 10,000 patients, which is the lowest rate in the region. With the innovative application of AI, Neak Pean HealthTech, the Khmer telemedicine chatbot is to revolutionize healthcare accessibility in Cambodia.

Neak Pean HealthTech integrates advanced technologies like natural language processing (NLP) and Khmer automatic speech recognition (ASR) to facilitate efficient communication between patients and healthcare providers. This bridges the gap between patients and healthcare providers, especially in remote and rural areas by reporting symptoms remotely, detecting keywords, generating summary reports, scheduling appointments, storing medical records, and accessing medical advice in Khmer.

The challenging part of this use case lies in processing audio data in the local language with various accents. Khmer has a complex script, making typing difficult for many Cambodians. As a result, voice input is more commonly used. Patients can talk or text in Khmer with the chatbot of the Neak Pean platform to report their symptom or their health concerns as a preliminary assessment before meeting doctors, which is believed to be patient-friendly. In some cases, as the local community does not speak the language the model or the algorithm is using, the indigenous people cannot benefit from the technology. By using the local language, this platform bridges the pervasive gap in education level or socioeconomic status, reducing the inequalities in the distribution of medical resources.

To successfully facilitate the use of local languages with different accents, this platform employs keyword detection algorithms to extract crucial information from patient inputs. Then it will automatically generate a comprehensive summary report for health for healthcare providers' review. Patients can then schedule appointments seamlessly, with the platform facilitating efficient communication between patients and healthcare providers. Importantly, patients have access to medical data in Khmer, empowering them to make informed decisions about their health and well-being.

Figure 6: Instances of Readiness Factors in Case Study-5



4 Use Case Analysis

For each use case, there are several sub-scenarios investigated.

For example, driver distraction detection [5] [18][26] under the topic of traffic safety is an umbrella use case, under which there are several scenarios such as – drowsiness detection [25], texting while driving, and detecting lane infractions. Similar to this transportation parent use case, in the "accessibility" use case [2] [77], there are also different scenarios, each of which has a specific focus for hearing-impaired groups and visually impaired users.

For each of these sub-scenarios, the actors could be specific to the scenario, for example, the major type of sensor may be different in each scenario.

The classification of the source of data (SRC) [ITU-T Y.3172] into external and internal (to the vehicle or system) can be used to derive additional metadata about the source. Roadside units (RSU) can tell whether the lane discipline is correctly followed, and v2v sensors can tell if the distance is maintained. The SINK [ITU-T Y.3172] could be integral (built-in) controls e.g. braking systems [45] and accelerating systems in a vehicle, however, there could be vendor-provided differentiated signal processing which is applied on such controls that are used to find if the driver is distracted. Apart from these integral controls, another type of controls could be add-ons provided by 3rd parties. For example, Add-ons such as driver observation cameras [6] or sensors may be purchased from 3rd parties and installed in the vehicles by owners. In such cases, Interoperability and integration aspects are critical for the overall use case.

Simulation of use case-specific scenarios is important to validate and certify the compliance of various actors to local and global standards and regulations [30]. To make sure the end-user has a common understanding, simulation setups, parameters, and boundary values may be studied in Standards Developing Organizations (SDO).

Thus, standards and regulations studies related to the quantification of the specific actors and behaviours including various simulation and validation scenarios along with compliance thresholds are needed.

The application of AI in various scenarios brings the question of trust, explainability, traceability, and accountability for decisions. Models and algorithms used in the use cases are required to be trusted, explainable, and accountable. Deployment and hosting conditions may meet specific requirements such as low latency in the vehicle, low memory footprint, and low power consumption.

Mitigation of privacy concerns such as data handling of systems where there is personal data involved, needs further study. E.g. The distraction detection system may use a camera, but the system is designed to purge the visual data permanently within a regulated time period. The non-visual data may still be stored (e.g. alarms and timestamps). However, there are regulations such as sharing raw data with law enforcement agencies.

4.1 Use Case Summaries

The use case summaries below give specific details of the use case that are relevant for the AI readiness study. The details of the use cases with notes on characteristics are in Appendix A: "Detailed analysis of the use cases and AI impacts on the use cases". In addition, Appendix B: "Specific impacts of these characteristics on Standards Frameworks for AI readiness require further study" covers the analysis of use case scenarios. We cluster the use cases based on the domain they involve.

4.2 Traffic Safety

In this section, several use cases related to traffic safety are studied. AI technologies are integrated into autonomous and remote-driven vehicles with the aim to improve both drivers and pedestrians' safety on the road.

4.2.1 Platooning

This use case [24] [23] involves autonomous or remote-driven vehicles such as enterprise vehicles, in-campus vehicles, carts, and mover trucks in stores, factories, or maritime ports. To control the optimal distance vehicles, proximity and distance sensors using ultrasound are applied. Due to the strict requirements of latency and bandwidth, a 5G network is needed. Private 5G such as campus networks managed and operated by the enterprise, may be used. Bluetooth might be used for communications between each unit. To facilitate communication, standards such as Dedicated Short-Range Communication (DSRC) [47] and IEEE 802.11p [42] are considered. Human supervision is still needed to minimize the risks in deployment. In addition, roaming cases across borders should be planned in advance [29].

4.2.2 Driving under Intoxication (DUI) Detection

Driving under intoxication [8] [10] has different standards in different countries, so it is essential to obtain the test parameters and thresholds such as blood alcohol level accordingly for standard field tests. In terms of in-vehicle measurement, various inertia, response times, and signal processing on the controls should be considered. Based on the chest movement, medical data such as heartbeat, breathing, and even blood alcohol level might be inferred.

4.2.3 Autonomous Emergency Braking-based (AEB) Collision Avoidance

This use case used [7] algorithms to predict and avoid collisions by collecting data from a sensor fusion and multi-modal for commercial vehicles. Specifically, blind spots, lane merging, and direction of movement are noted to complement the angle detection data. In case of collision, safety accessories such as seat belts and airbags are to protect the drivers and passengers. To test the AEB system [32][33], an international standard issued by the Society of Automotive Engineers (SAE) is referred to. In addition, driver preferences and parameters for the level of alert should be considered according to the different driving habits of drivers.

4.2.4 Pedestrian Safety

Smart vehicles, sensors such as Lidar and cameras, networks with low latency and high throughput, AI/ML feedback loops, and roadside units (RSUs) like smart traffic signals play an important role in this use case. The level of impact of the use case, its potential influence, and predictive human intervention (preventive and post-facto interventions) are studied. Decision-making aspects, such as sensor deployment responsibilities, subsidies, and goal setting for deployment timelines, are critical.

Data analyzed includes various types, such as open data, and authorized data. The location of data such as data processed at the core cloud and edge cloud will have different implications for the use case. Data handling involves a pipeline from source, collection, preprocessor, model, policy, and distributor to action application, considering ownership and readiness evaluation of data across various stakeholders.

Infrastructure including triggers, speed bumps, barricades, banners, advertisements, and route planning should be considered. Additional considerations include fiber to the RSU, computation available in the edge, wireless capabilities in the vehicle, between the vehicle and RSU, etc.

Technologies used encompass collision avoidance, driver attention, and human detection systems, with local innovations such as the number of patents, publications, local research, and maturity levels manifested by validation, standards compliance, certifications, and labs being significant.

Interoperability and human factors like awareness and training, trust, and security are vital for successful implementation. Mapping technology use cases to regulations and policies is essential for achieving specific safety goals, such as reducing pedestrian mortality.

4.3 Smart Agriculture

The use cases described in this section cover smart irrigation, soil moisture monitoring, agricultural policy chatbot, disease detection, and other scenarios and their applications in different regions in the world, providing diversity in the utilization of similar technologies, leading to requirements for the readiness factors.

4.3.1 AI-based Chatbot for Farmers

This is an agricultural use case [49] that collates data from open data portals maintained and updated by government actors. Time series and government data related to agriculture, including crop production, land use, water use, market prices, weather patterns, and government schemes are used for training models. GPT-like static models vs. Retrieval augmented generation (RAG)-based dynamic updates to the policies database [49] are to be studied to bring maximum benefits to farmers who use this solution. Satellite images to locate the stakeholders and farmers along with time series market data on crop prices are other factors to consider in this use case. The pilot study of agriculture-related AI technology on 7000 farmers in the Khammam district of Telangana (India) showed promising results, where the net income of the farmers using the AI technology had been doubled ($800 per acre) from the average income in 6 months [33]. The solution readiness may include cloud APIs for subscribing/publishing of data from portals [46].

4.3.2 Disease Identification in Wheat Crops

This use case [38] uses multiple drones and High-definition cameras to obtain high-quality pictures to identify wheat crops and detect disease. To ensure the coverage surface and the quality of image content, cameras are deployed 30-50 centimetres (about half the length of a baseball bat) away from the crops without any objects or humans being captured. In addition, because some diseases can be detected only at a certain growing stage, images are captured during all growing periods, ensuring a high frequency. Regulations related to the drones regarding height and geo-restrictions, however, should be noted. The use case used convolutional block attention mechanism (CBAM) as the model and applied IoT gateway.

4.3.3 Smart Shrimp Farm Aquaculture

This use case [39] applied cameras with night vision and sensors with underwater capabilities to capture shrimps and other water parameters such as pH value, turbidity, and oxygen concentration. Since the images are captured underwater, pre-processing tools such as robotflow [55] are used to enhance the quality. A special model YOLO is deployed for unique object counting. In addition, to predict the length of the shrimps, the ArUco marker [54] is used for measurements. This use case referred to available standards such as BAP 1000, ASC shrimp standard, Global GAP Aquaculture standards, ISO 9001: 2015, and ISO 22000: 2018.

4.3.4 Soil Moisture Testing

This use case [40] used soil sensors with a limited measurement range to detect soil parameters and water usage. The data collected undergoes the process of conversion with the protocol of Message Queuing Telemetry Transport (MQTT) [56], quantization/aggregation/range-checking, network, and model, and finally reaches users. Random Forest (RF) and Multivariate Adaptive Regression Splines (MARS) as classification models are applied. Transmission Control Protocol/Internet Protocol (TCP/IP) with error handling capabilities are used. The analysis is achieved using edge data, edge board and sensors, and edge storage. Given that the sensors and facilities are deployed outside, ruggedness is considered under the standard of IP65. The edge data processing board is open-sourced.

4.3.5 IoT-based Crop Monitoring

In this use case [31], edge data such as pH value, Nitrogen, Phosphorus, Potassium (NPK) levels, electric conductivity of the soil, weather parameters, and leaf wetness are captured. Sensors use solar panels to harvest energy. By combining the data, it is possible to not only manage pests and diseases but also plan pesticide usage and irrigation schedules.

4.3.6 Agriculture: Crop Monitoring and Planning

In this use case, all sensors are connected to IoT to collect temperature, moisture, crop health, yield, minerals, soil health, and carbon level data. Based on the information from the greenhouse station, camera, and weather station, the actuators controlled remotely such as sprinklers could be used to manage irrigation and potentially crop planning mapping between crop, fertilization, and pesticide usage. Storage security is an important consideration in this use case. OneM2M [22] standard is applied in the use case.

4.3.7 Smart Irrigation

In modern agriculture, the integration of advanced technologies involves a diverse array of actors and systems working together to enhance efficiency and yield optimization. Agricultural farmers use both traditional methods and modern technology for irrigation, pesticide usage, and farm management. Sensors are used to monitor temperature, humidity, soil moisture, fluid levels, and mineral content in the roots, feeding data into low latency, high throughput networks such as edge networks. AI and ML systems collect this data and infer actionable insights aligning with policies, which are then executed by actuators such as automated irrigation systems, tractors, and dispensers for pesticides and fertilizers. Backend cloud storage supports this ecosystem, while dashboards provide farmers with information. Local conditions, such as water and air quality and soil fertility, are also considered. Technologies like LoRa, LoRa-WAN, RFM69, Bluetooth, and narrow-band IoT facilitate robust communication and low-power operations, while AI, ML, and emerging technologies like 6G enhance data analysis and decision-making capabilities. Ensuring interoperability between different sensors and communication systems is crucial, as is incorporating farmers' experiences and practices to refine and adopt these technologies effectively.

4.3.8 Intelligent UAV-Assisted Plant Disease Detection in Rock Melon Greenhouses

This use case [60] addresses the problem of plant disease detection and optimal resource allocation in melon greenhouses through a UAV-assisted model. The data used in this use case consists of plant leaf images, collected by unmanned aerial vehicles equipped with cameras.

Data collection involves drones capturing images of leaves from different angles and heights, enhancing detail, and improving model robustness through data augmentation. The images are then pre-processed, labelled, and categorized using the YOLOv9 model according to various disease categories.

Model training is based on the processed data, with ongoing feedback from farmers to test and evaluate the model's performance. The real-world deployment in a Melon Greenhouse ensures the collection of high-quality data and effective disease classification.

4.3.9 Digital Twins for AI-based xApps in Open RAN for Smart Agriculture in 5G

This use case [61] using digital twins for validation of xApps and encapsulates vertical applications in the form of xApps in Open RAN in sandbox in the context of 5G and 6G. The data used in this use case is publicly available. Architectures compliant with ITU-T-Y.3172 [63], ITU-T Y.3179 [62], and ITU-T Y.3181 [64] frameworks are used to route data to the digital twin for validation.

Initially, a training pipeline is set up involving model selection, hosting the model in an xApp, and validation within a sandbox using digital twins and simulators. Subsequently, configuration and deployment in the digital twin occur, involving intent-based selection of xApps, data models, model selection, and sandbox configuration. Once the verification is completed in the sandbox, an inference pipeline is established where data is collected and sent to the Distributed Unit (DU), and inference is performed within an Open RAN xApp that hosts the real-time model.

4.3.10 AI-enabled Soil Analysis and Weather Station for Local Farmers in Ghana

This use case [66] analyses inaccurate weather and soil condition predictions for local farmlands in Ghana. National meteorological data is typically not specific to local areas and hence usually not helpful in reducing economic losses. The use case supplements global with real-time data collection using AI-enabled weather stations and soil analysis sensors. This data provided by CESM [65] is used to train a tinyML model [21] in the weather station challenge [67] 2024. The sound of rain and wind collected by microphones could be analysed thus enabling the prediction of rain intensity, precipitation, wind speed, and wind direction.

This model is deployed in affordable weather stations located directly on local farmlands. These stations would enable precise and localized forecasting of environmental conditions essential for optimizing agricultural practices and minimizing risk. These weather stations operate without mechanical parts, capturing real-time data on rainfall intensity, wind direction and intensity, temperature, humidity, pressure, and air quality. Simultaneously, they conduct real-time soil analyses to measure temperature, humidity, pH levels, NPK content, and conductivity. The collected data is then visualized through intuitive dashboards accessible via smartphone apps and web browsers.

The inference from the model could be used to maximize the precision of the irrigation and reduce energy consumption by controlling actuators such as sprinklers or other types of dispensers. The process is visualized via mobile and web applications; thus, experts and farmers can monitor the model in real-time.

4.3.11 Water Conservation using AI-enabled Smart Irrigation Systems in Agriculture

This use case [71] aims to utilize AI-driven smart irrigation systems to optimize water usage. The traditional irrigation methods in Tanzania face the problem of efficiency and water wastage [76]. By leveraging the power of real-time monitoring and adjustment of irrigation schedules realized by integrating AI, sustainable agricultural practices [72] could be achieved. The use case utilizes public data including weather data, soil data, and environmental data from the Ministry of Agriculture in Tanzania, and incorporates private data from local regions [73].

The use case applies the Long Short Term Model (LSTM) model that is trained based on local data and can be fine-tuned for a good performance designed to conserve water during irrigation. This model is also capable of providing predictive analysis of crop status, soil moisture level, and future water needs using historical data and real-time sensor inputs [75]. The model also allows feedback collected from experts, can be integrated into agricultural practices via communication networks.

This use cases utilizes opensource toolsets such as TensorFlow, NumPy, Keras, Pandas and scikit-Learn and the jupyter notebooks and PyCham as the software tools for developing solutions. Simulation environments such as Matlab/Simulink and SimPy are used to experiment and simulate various conditions.

The use case has been deployed in testbeds in the Dodoma region due to its representative soil type, crop varieties, and climate conditions prevalent in Tanzania [74].

4.4 Health Care

Healthcare use cases studied in this section focus on the combination of portable application of AI technology and localization, with an aim to enhance affordable access to basic healthcare services. These use cases utilize generalizable models and data and retrain the model with the local context. Specific requirements on personal data protection in the healthcare domain make it essential to establish international standards.

4.4.1 Neak Pean HealthTech - Khmer Telemedicine Chatbot

This use case [2] solves the problem of access to medical care, inefficient management of waiting times, and long queues. Key solutions include speech-speech local language Chatbot, medical records, pre-health assessment, summary report generation, doctor dashboard, using a mobile-based solution. Data includes audio speech data, (history recording in audio and later converted to text). The Models include Khmer ASR (speech engine), Text-to-speech (TTS) (fast speech), and chatbot (sentenceBERT for finetuning), for accent handling more data collection is needed, currently, this model is based in the central City. Pilot deployments include deployment in the Partnership Ministry of Post and telecommunication and publications for Khmer ASR are available.

4.4.2 Improving Early Detection of Neonatal Asphyxia with Smartphone-based AI Technologies

This use case [68] [69] aims to develop more robust and reliable AI-based solutions for neonatal asphyxia detection on smartphones. This medical condition is critical for newborns who experience oxygen deprivation during birth. The use case uses data from more than 1000 one-second-cry voice samples from existing datasets. The regression and ensemble model applied in this use case makes it amenable to retraining these models based on the regional-specific data so that the machine learning result is adaptable to regional problems.

The model is deployed in smartphones that are affordable and ubiquitous for most of the population, making the solution deployable in resource-limited settings. So far, 4 pilots in 4 hospitals from different divisions have been set up for a year.

Collaboration with hospitals to collect data on a larger and more diverse population of newborns, including data from different ethnicities, gestational ages, and birth complications can further make the models generalizable. Comprehensive data collection would also include collecting data from pre-birth stages (fetal heart rate, maternal health data) to identify potential risk factors. Simulating variations in crying sounds due to background noise, microphone quality, and different recording environments would make the models more reliable and robust.

4.5 Public Services

AI technologies could be integrated into different public services to address critical requirements such as access to precise policy information, complex societal issues, the need for contextualized local engagement. Technologies such as large language model, generative AI, text detection and other AI technologies are applied in these use cases, demonstrating the power of AI technology in the domain of public services.

4.5.1 Enhancing Transparency and Accountability in Public Procurement and Project Monitoring

This use case [57][58] solves the problem of flagging corruption and irregularities in the procurement process with the help of an AI model trained on tender documents. The consumer of inference is the Prevention and Combating of Corruption Bureau (PCCB), a government oversight body. The data used in this use case is text data, coming from historical records of procurement-related text documents, mostly in the local language. A natural language processing model is applied to detect anomalies and flag irregularities in the tender process.

Data collection and model training are based on historical records and data, with expert insight, from the tender process. After the model is built, anomaly detection is done on the ongoing procurement process with the help of expert insight, which ensures the verification of the model. The real-world deployment of a verified model makes sure of the quality of output. The model will be updated periodically to train on new data such as the latest tender docs so that new regulations will be included in the training data.

4.5.2 U-Ask

This use case [59] addresses the challenge of finding policy regulations on various government portals using an AI model trained on United Arab Emirates (UAE) government portal content and other public sources. Providing a single window of information to the citizens about the various public service schemes is an important governance initiative. The end users of this solution are public users accessing the chatbot. The data utilized in this use case comprises contents from all UAE government portals and other publicly available government sources. A generative model is employed to produce answers based on personalized requests, while a prediction and recommendation model is applied to offer precise follow-up questions that might benefit users. Additionally, a voice-to-text model is implemented to streamline the inquiry process.

The large language model is trained on UAE government portal content and other government public sources. The chatbot is trained on queries/responses from the public and citizens. Upon query from the public, the chatbot generates accurate responses based on the trained model and context. The operation efficiency and performance of the chatbot is enhanced by the feedback from users.

4.5.3 Computer Network Fusion Video Brain

This use case [1] combines large models and small models to monitor video content with high accuracy and flexibility. The large models are used to extract features and infer image events and behaviours based on colour, texture, shape, and motion; while the small target detection models then take the task to analyse and predict the content. Cloud-edge collaboration is required in the process.

The platform offloads the video decoding frame extraction and AI inference service computing power to the cloud node, realizing the optimal and intelligent scheduling of video analysis computing resources at the edge side, effectively saving 60% of bandwidth resources and optimizing the delay by 30%. Expert verification of recognition results is carried out to improve the accuracy of video intelligent recognition.

Facing the problem of insufficient sample size and data skew in the traditional visual AI training process, this use case applied artificial intelligence-generated content (AIGC) technology so that researchers could use large models to produce small samples to improve AI recognition ability.

The deployment of the use case is only available within China Mobile's internal network due to the use of data from CCTV cameras.

The annotation results are saved in Visual Object Challenge (VOC) or Common Objects in Context (COCO) formats [82][83][84].

4.5.4 Using AI to Reduce the 6G Standards Barrier for African Contributors

This use case [27] addresses the standards gap between developed and emerging nations in Africa especially in 6G. This use case uses a text-to-text chatbot that predicts the new use cases and their architectures, classifies material, including multimedia material from ITU into context-specific useful classes which can be easily consumed, generates captions in regional languages, and provides answers to queries from students and scholars. The text data collected is publicly available.

Technologies used are NLP parsing on the standards documents, creating annotated datasets as a step to preparing the data for fine-tuning/ training, expert validation of responses for the fine-tuning, and using inferred knowledge to generate responses on 6G innovations.

Knowledge base creation using generated output in combination with expert validation helps in assisting potential contributors from developing regions to make relevant and potentially substantial contributions while taking the assistance of AI. Code generation is used in the sequence diagram [70] to create model training notebooks. Question answer dataset is used to create query responses for potential contributors.

4.6 Disaster Prevention

Disaster prevention is essential to save lives and the environment, especially with the focus on climate change. Data acquisition for disaster prevention is challenging due to rare conditions. Use of AI technologies such as generative AI, simulation and experimentation techniques in Sandboxes as well as shared open data and models along with standardized methods to interoperate these solutions, would make societies ready to tackle disasters.

4.6.1 Smart UAV Networks for Efficient Disaster Response

This use case [52] uses drones with object detection and satellite-based coordination for rescue operations in case of disaster responses and drone-2-drone or drone-base station communication. The trade-offs in this use case include minimizing battery usage while maximizing the area coverage for drone-based disaster response. Ad hoc network design between drones helps in using multiple drones for surveillance and rescue. Models used include Reinforcement Learning models, multi-agent systems and systems, and collaborative intelligent solutions. Data collected include video and still images along with satellite images. Simulations including sim2real [53] approaches help curriculum learning (for achieving a smoother learning curve from simple to complex scenarios. UAV network design is used to autonomously perform essential tasks within disaster-stricken areas.

4.6.2 Management of Wildfires

This use case [51] uses predictive wildfire prevention and early detection of wildfire, in addition, it adds value to local knowledge and aids in community empowerment. The output from the use case is consumed by powerline utilities with KPIs on availability. A combination of cameras (private) and satellite heat sensors (could be public) are used for prediction in this use case.

Datasets include streamed data from cameras and smoke and light detection. Post-fire analysis using proprietary algorithms for fire prediction, detection, and fire propagation models. Pilot deployments in India (2 reserves), Brazil, and Portugal are used to test the models.

4.6.3 Disaster Risk Management in Complex Geography

The use case [50] actors in this case are transporters, and other systemic actors such as businesses, insurers, disaster management entities such as government agencies, and the general public. Data analysed includes open data from disaster management agencies (risk data, real-time), and private data for creating context country-region specific advisories (satellite images). This data is used for training models such as generation (advisory generation) and prediction (forecasting), including continuous improvement models. Interoperability and compatibility of cross-region data (e.g. early warning) and generated advisories are major reasons for standards and metrics for AI readiness in this use case.

4.6.4 Networked ASEAN Peatland Forest for Net-Zero

This use case [48] proposes a tropical peatland fire weather index (FWI) system by combining the GWL with the DC. Pilot deployments include a LoRa-based IoT system for peatland management and detection in RMFR in Kuala Selangor, Malaysia. Verification of data with truth values from the Malaysian Meteorological Department (METMalaysia) are significant in this use case. GWL is predicted and FDRS indices such as DC, Duff Moisture Code (DMC), and FWI are predicted based on the GWL. Gateways such as weather stations, water level sensors, and soil sensors in combination with LoRa nodes and LoRa Gateways make it an end-to-end solution.

4.7 Climate, Clean Energy

While we transition to cleaner sources of energy, AI technology can provide suggestions on optimizing energy sources and enable a smooth transition from conventional energy sources. AI-based forecasts are crucial for real-time power distribution and load balancing, as they help integrate green energy into electric grids and overcome the challenges of intermittent availability.

4.7.1 AI Boosted Interpretable Renewable Energy Forecasting

This use case [80] [81] uses AI-based methods to deliver accurate and interpretable renewable energy forecasting, which covers all the wind plants and the rooftop photovoltaics within the area, alongside an attribution analysis and error analysis. The predictions are used to decide power distribution and real-time power load balancing. AI based predictions help the integration of economic green energy to the electric grids despite the intermittent availability of alternate sources of energy.

The use case applied convolutional neural networks and conventional tree-based models with large-scale automatic feature augmentation to produce reliable wind power and solar power forecasts and shapely value-based explainable AI to interpret the underlying reason for such interpretations. Ray Tune is used for hyper-parameter tuning. Data including measured power from turbines, solar panels, and weather predictions are privately available.

The use case has been deployed in Zhejiang China.

4.8 Future Networks and Telecommunications

As future network technologies such as IMT-2030 [97] evolve in parallel to evolutions in the AI domain, integration of AI in future networks is shaping the nature of 6G and leading to new applications and services. Topics of AI for Networks and Networks for AI have been discussed which looks at the application of AI in networks as well as connectivity as an enabler for new AI-based services. This section describes a typical use case where the application of the latest advances in the field of Natural Language Processing (NLP), generative AI, and digital twins could be used to enable self-optimization and integration of intelligent applications in networks.

4.8.1 Easing Operations Using AI/ML Solution for 6G and Beyond Network Orchestration and Secure Network Operations

This use case [93] proposes to use Natural Language Processing (NLP), Digital Twins, and Extended Reality (XR) to improve the network operations and orchestration in 5G/6G networks. The solution simplifies the deployment and configuration of network functions (NFs). Operators can input commands in natural language, transcending language barriers and reducing the need for specialized technical knowledge. There are 3 aspects to the solution

A) A digital twin of the Kubernetes cluster simulates and predicts resource utilization, helping operators manage infrastructure efficiently. This reduces the need for overprovisioning, thereby saving costs and minimizing carbon emissions.
B) XR provides responsive and interactive observability, allowing operators to visualize and interact with network configurations and projected traffic. This enhances decision-making and troubleshooting capabilities. The solution continuously monitors network traffic for anomalies using ML algorithms.
C) AI modules enforce appropriate security policies in real-time, and simulated attacks on the digital twin help identify and fix vulnerabilities.

This use case addresses the problem of lack of technical expertise for deployment, operations, and security. The AI Model trained in this solution generates Network intent with GenAI, ML/AI, and deploys network slice. This is continuously monitored, and automatically scaled, and the issues are self-healed. Traffic patterns are monitored, anomalies are detected, and security policies are applied accordingly.

4.9 Accessibility

AI-based applications can significantly improve the lives of people with disabilities. The use cases in this section use audio or visual processing designed to assist the communication process for people with hearing or visual impairments. Generalization capabilities of local models and solutions using standard approaches would scale the benefits to different parts of the world.

4.9.1 Machine Translations for Khmer Braille

This use case [43] aims to provide accessibility and facilitate communication for visually impaired individuals in the Khmer Language. The machine translation system for Khmer Braille is publicly available and free to access to the community. The use case collects text data in both Khmer and Braille. The system is particularly targeting educational content so that equitable education can be provided for individuals. To satisfy the needs, specific fine tuning for math and physics formulas will be integrated into the system. For future study, mobile and/or web applications will be developed.

Research on Statistical vs Neural Machine Translations for Khmer Braille [86][87], Khmer word segmentation using conditional random fields [88], and Khmer Braille Book For Blind People [89] are referred to in this project.

The use case aims to develop mobile and web applications to help machine translations for Khmer Braille.

4.9.2 Live Primary Health Care African National Sign Language Translation Tool

This use case [77] [78] [79] aims to solve the problem of difficulties in critical health care and services, especially with effective communication between deaf individuals and service providers. By providing AI-powered Live Sign Language Translation and multi-modal content analysis, it is possible to achieve text-to-speech and speech-to-sign language translation. This approach enables an AI-powered live sign language translation tool that translates between at least 25 African sign languages and spoken/written language in real time.

This use case uses AutoML, which automatically prepares a dataset for model training, performs a set of trials using open-source libraries such as sci-kit-learn and XGBoost, and creates a Python notebook with the source code for each trial run so that revision, reproduction, and modification of the code are possible. It also uses hyperparameter tuning to fine-tune the model. With the abovementioned techniques, speech-to-sign language translation with facial animation and vice versa is achievable.

The tool has been applied to the healthcare sector in Zimbabwe, benefiting deaf people and service providers. Extension of the AI-based African National Sign Translation tool to sectors other than Health care such as Banking, Finance, Insurance, and Investment industries in Africa is planned. Regional sign language dialects may be integrated for best use in Public Healthcare.

4.9.3 Smartphone OS-based Information Accessibility Solutions and Public Welfare for People with Disabilities

The use case [2] [85] introduced the technologies using smartphone that could benefit people with disabilities. The technologies include Automatic Speech Recognition, note recognition algorithms, text-to-speech and speech-to-text translation, and sound recognition that supports Chinese sign language recognition, which fills the gap for Chinese hearing-impaired people. The multimodal large model uses a large language model as its base and adds a visual module to it, enabling the model to simultaneously process data from both text and image modalities. Data used in the use case comes from national and international public data, internal company data, third-party data, user-authorized data, and generated data. Image caption provides a text description of an image, visual question answering combines images and questions to predict answers and audio-visual speech recognition combines sound and video information to identify speech content. By using these techniques, models used in the use case are fine-tuned.

Open data available from [90], [91], and [92] are used along with private and generated data. Multi-modal models with visual Question Answering combining images and questions to predict answers and audio-visual speech recognition combining sound and video information to identify speech content is used in this project.

The technology is deployed in smartphones so that people with disabilities can benefit from the technology. This use case creates online and offline channels to collect feedback from the users so that the performance of such a tool can be optimized.

5 Data Analytics Strategy

In this section, we aim to derive an analytics strategy related to the different features corresponding to each of the AI readiness factors. These features are derived from the "Detailed analysis of the use cases and AI impacts on the use cases" described in Appendix A and "Specific impacts of the characteristics of use cases on Standards Frameworks for AI readiness require further study" described in Appendix B.

Table 1 describes the quantifiable characteristics related to each readiness factor. The potential measurements and a brief description are provided.

Table 1: Characteristics of the AI Readiness factors

AI Readiness factor	Characteristics	Notes/Description
Availability of open data	Number of repositories	The number of open repositories with data corresponding to use cases and scenarios.
	Data license	The terms and conditions for usage of data.
	Data volume	The size of data available for analysis e.g. KB, MB, GB, or the number of rows in the case of structured data.
	Data variety	Number and types of unique data sources, statistical distance between data sources including federation.
	Metadata	Number of columns and modes, distance between features, and context representations such as using Retrieval Augmented Generation (RAG), etc.
	Data velocity	The incoming rate of data collection, for example MB/s.
	Distance between source and sandbox (training model)	The number of hops in connectivity including wireless hops, weightage according to latencies incurred.
	Data collectors	Number and types of data collectors and frequency of collection.
	Pre-processing (PP)	Number (and types) of data preprocessors.
	Data lifetime	The freshness and lifetime of data after which it is considered invalid for the use case in question.
	AAA rules (authentication, authorization, and accounting)	The number of policies configured in the AAA regarding the usage of data and distribution of inferences. number of applicable domains (and other existing AAA metrics regarding policies).
	Number of domains and statistical distance between them	For use cases which span across multiple domains and application verticals, the number of domains involved e.g. computer vision, transport safety, and public safety, as well as the data usage across the domains would be measured based on the statistical distance (this would require further study).

Table 1: Characteristics of the AI Readiness factors (continued)

AI Readiness factor	Characteristics	Notes/Description
	APIs descriptions with restful description languages	Availability of API descriptions with standard, well-accepted restful description languages.
	Structured or unstructured	Availability of structured or unstructured data.
	Distance between the serving system and SINK	Number of hops including wireless hops, weightage according to latencies, and other logical costs incurred.
	Data robustness	Effectively eliminating noise from valuable data.
Developer Ecosystem created via Opensource	Number of lines of Code	Number of lines of Code in Reference implementations of algorithms related to the use cases under study.
	Number of code repositories	Number of code repositories with reference implementations of algorithms related to the use cases under study.
	Number of Opensource projects	Number of open-source projects e.g. Linux Foundation, Eclipse Foundation, Apache software foundation, Python software foundation, Open-source initiative, Mozilla Foundation, data, toolsets, and hardware boards to host the edge data processing.
	Number of marketplaces, play stores, app stores, IoT gateways	Number of marketplaces, play stores, app stores, IoT gateways (hosting 3rd party applications, APIs, and SDKs; LoRa gateway and applications, SDKs, and APIs).
	Usage statistics of open source repositories and hosted APIs	Usage statistics for the Cloud APIs used for subscribing/publishing data from portals [49].
	Hosted applications integrating the models	Developer ecosystem to the serving models in the cloud [68].
Access to Research	Number of papers published and cited	Domain-specific research (Collision avoidance, Driver attention, Human detection, Local Innovation, (e.g. Patents, publications, local research); local laws and regulations.
	Maturity levels (validation, standards compliance, certifications, labs)	Technology Readiness Level (TRL), Number of collaborative industry engagements.
	Number of foundational models	Foundational models created by research teams working in the domains related to the use cases, (which leads to domain-specific fine-tuned models).

Table 1: Characteristics of the AI Readiness factors (continued)

AI Readiness factor	Characteristics	Notes/Description
	Number of datasets cited in application research	AI-specific research (Estimation algorithms on controls such as fertilizers and pesticides).
	Number of papers citing the data	The number of papers that use and cite data repositories.
	Startup innovations	The number of innovations (including papers, essential patents, and other types of publications) from startups.
Stakeholders buy-in enabled by Standards	Participation statistics in ITU webinars	The number of registrations and attendances and views related to ITU technology webinars (e.g. Discovery Series).
	Number of standard documents	study group documents, focus group documents citing datasets, models, and AI/ML-based architectures.
	Number of reviewers, annotators, simulators	The number of reviewers for standards, related datasets, and annotators involved in analysing the standards-related datasets. The number of simulators generating data related to the standards.
	Number of ITU contributions and regional use cases	Local involvement and contextualization.
	Number of study groups, focus group editors	Including reviewers in ITU journal and Kaleidoscope; Expert intervention on specific fields of knowledge related to the use cases under study.
	Number of plugfests, and interoperability test events.	Number of compliance specifications, compliance test reports would reflect the level of Interoperability (Alternatives for technology, interaction with users and other stakeholders, data format, and coordination).
	Number of focus areas from national regulatory bodies related to AI/ML	Overlapping focus areas from National regulations and laws, related to the standards, datasets, and other readiness factors.
	Number of documents from national standards bodies which refer to AI/ML	Number of regional and national domain-specific Standards.
	Number of SDGs impacted by the use case	Level of impact of the use case.
	Number and level of funding, and subsidy model	Level of funding decision-making and investment – e.g. who deploys the sensors? Are there subsidies?

Table 1: Characteristics of the AI Readiness factors (continued)

AI Readiness factor	Characteristics	Notes/Description
Data collection and model validation via Sandbox pilot experimental setups	Number of Sandboxes	Number of trusted sandboxes available [ITU-T Y.3181] for validating models and data related to the use cases under study.
	Number of published controllers [ITU-T Y.3061]	Feedback loops (AI/ML feedback loop, collect data, infer, action recommendations and policy application, pre-built traffic plan for specific occasions.
Deployment capability along with Infrastructure	Number of edge deployment options	AI-based resource allocation for low latency, higher throughput, and edge intelligence.
	Number of connectivity options	Networks (4G, 5G, satellite networks, ad hoc networks).
	Number of interface options	Protocols (e.g. MQTT [56], Transport protocols with error resilience such as TCP/IP).
	IoT system (LoRa-based), wireless sensors	Number of sensors deployed related to the use case.
	Percentage of geographies covered	Coverage scale (Roaming across countries and regions for seamless connectivity [50]).
	Number of customizations needed for domain-specific applications	Domain-specific physical infrastructure (In-vehicle Safety accessories (belt, airbags).
	Deployment options and resources available such as devices, CPU, GPU cores, and memory budget.	Computation capability (cloud, ground station, available on the edge. Optimizations for model deployment in resource-limited settings [68]
	Efficiency of energy sources	Energy source: solar panels (for energy autonomy).
	Number of public services visualization dashboards and mobile apps	Regarding the public services offered by governments, the number of citizen dashboards that integrated inferences and models, including mobile applications.

6 Future work and conclusion

Currently, our work captures the analysis of the Artificial Intelligence (AI) readiness study, the goal of which is to develop a framework assessing AI readiness to indicate the ability to reap the benefits of AI integration. By studying the different actors and characteristics in different domains, the bottom-up approach allows us to find common patterns, metrics, and evaluation mechanisms for the integration of AI.

The main AI readiness factors identified in this report are Availability of open data, Access to Research, Deployment capability along with Infrastructure, Stakeholders buy-in enabled by Standards, Developer Ecosystem created via Opensource, Data collection, and model validation via Sandbox pilot experimental setups.

In future, the number of case studies, use cases, and scenarios would be scaled to include diverse set of domains and regions. Specifically, the following future steps are proposed:

Step-1: An open repository of data would be set up to address the corresponding AI readiness factor for the availability of open data. In combination with existing ITU initiatives such as AI/ML Challenges, this repository would be mapped to pre-standard research from ITU partners.

Step-2: Creation of an experimentation Sandbox with pre-populated standard compliant toolsets and simulators, curated by ITU experts would help in studying the impact of the readiness factors, and measuring their impact in specific case studies, use cases, and scenarios.

Step-3: Derivation of open metrics and open source reference toolsets for measurement and validation of AI readiness in specific domain-wise case studies would further contribute to the ecosystem of AI readiness. In addition, a Pilot AI Readiness Plugfest is planned to give an opportunity to explain the AI Readiness factors to various stakeholders and allow them to "plugin" various regional factors such as data, models, standards, toolsets, and training.

These steps would not only help us to evaluate the AI readiness along the dimensions of (1) domains (2) regions (3) AI technologies, but also create a live ecosystem where this measurement and evaluation could be validated in the real world.

The inputs from these steps would help in two types of decisions:

1) Macro decisions: Controls for the type of factor-centricity (e.g. may be based on the policy: providers and users). These include the "plug-in" of various regional focus on factors such as data, models, standards, toolsets, and training. E.g. increasing the number of providers. Additionally, the metadata regarding the providers is to be described (so that micro decisions can be taken as below).
2) Micro decisions: Internal Decisions on the combo of characteristics (e.g. may be based on the technology choices). These include the "plug-in" various regional focus on factors such as technology choices. E.g. wifi vs. 5G, satellite data vs. Drone collected images. Additionally, the metadata regarding the providers to be selected based on the characteristics.

The next version of this report along with the results of the Pilot AI Readiness Plugfest would be released at the AI for Good Summit in July 2025.

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Appendix A: Detailed analysis of the use cases and AI impacts on the use cases.

Table 2: General use case analysis and AI impacts

Examples	Potential AI impacts
Actors	
edge actors	1. Smart or autonomous vehicles. Sensors (e.g. Lidar, cameras, radar), including passengers and drivers, drones [60]. 2. Commercial vehicles (e.g. delivery trucks). 3. Remote-controlled/driven vehicles. 4. Edge data acquisition e.g. soil, leaf, and weather sensors, Piezometer, and water level sensor. [66] [71]. 5. Sensors with specific capabilities (e.g. night vision) and underwater capabilities (e.g. pH, O2, turbidity), sound sensors with noise filtering [66]. 6. Pre-processing to enhance the image quality (e.g. Robotflow [55]), data augmentation using AI/ML [60] 7. Data capture using drones (e.g. drone-mounted cameras), Drones with object detection, and satellite-based coordination for rescue operations. Drone-2-drone or drone-based station communication. Drones with limited batteries at the same time route optimization algorithms to increase Area coverage [52]. 8. IoT gateways [22], LoRa gateway 9. Open Data portals maintained and updated by government actors [3]. E.g. from [50] on early warnings and weather data, aggregated data from local farmlands [66] [71] [41] from IEEE, [13] from Kaggle. 10. Actors involved in Cross-border logistics e.g. transporters, insurers, and government agencies [50]. 11. Local communities and tribes [51] 12. Power utilities and companies [51]f 13. Doctors, patients, medical history records [2] [68], farmers [60], and persons with disability [77] 14. State regulators [57] [58] 15. Public users and citizens [59] 16. User devices and smartphones [68] [2] [43] 17. Wind power plants, rooftop solar panels [80] 18. Camera inputs and edge models with cloud based large model combination [1] 19. 5G/6G Network operator using Digital twins, extended reality for network resource allocation [93]
Deployment capability with Network-based actors	1. AI-based resource allocation for low latency, higher throughput, and edge intelligence [11] 2. Private 5G networks. Managed/operated by enterprises 3. Protocols e.g. MQTT [56] 4. Transport protocols with error resilience such as TCP/IP 5. Wifi 6. LoRa

Table 2: General use case analysis and AI impacts (continued)

Examples	Potential AI impacts
Actors	
	7. Roaming across countries and regions for seamless connectivity [50] 8. Satellite networks [51] e.g. provide inputs on wildfire. 9. Ad hoc network design between drone clusters [52] 10. Mobile data network [2] 11. Model updates and data collection (for training and finetuning) over the network [68] 12. Communication network reachable in remote regions [71] 13. Connectivity between edge and cloud models for distributed image processing [1] 14. 5G/6G network operations, autonomy, and optimizations [93].
Experimen-tation and controllers with Sand-box-based actors	1. AI/ML feedback loop, collect data, infer, action recommendations and policy application, pre-built traffic plan for specific occasions. 2. Opensource boards with ruggedization to IP65 standards. 3. Autonomous flight mechanisms for drones with image capture mecha-nisms. 4. Continuous improvement of models using feedback and optimizations is part of future work [50]. 5. Fire detection, propagation models, and alarms to local communities and utilities [51] 6. Closed loop: UAV network designed to autonomously perform essential tasks within disaster-stricken areas [52]. UAVs can learn and adjust their operations (including route navigation, returning to charging stations, and data detection and transmission) based on feedback from the envi-ronment. 7. Summary report generated and monitored via doctor dashboard [2] 8. Closed loop for Models which continuously learn from user feedback to enhance accuracy [59] 9. Validation of TinyML models in AI Sandbox [67] 10. Finetuning general models with regional data in local Sandbox [68], [71] 11. Simulation environments such as Matlab/Simulink and SimPy [71] can create experimentation abilities for various scenarios. 12. Experimentation and selection of the best model with a set of trials using open-source libraries such as scikit-learn and XGBoost, with several runs and for each trial run so you can review, reproduce, and modify the code [77] 13. Cloud-based internal deployments for validation [80] 14. Cloud-hosted annotation sandbox [27] for international collaboration of data annotation. 15. Digital twin of cloud resource management for simulation and optimiza-tion in 5G/6G networks [93].

Table 2: General use case analysis and AI impacts (continued)

Examples	Potential AI impacts
Actors	
Inputs from Domain management systems and research actors	1. e.g. RSU (roadside unit), smart traffic signals, centralized cloud, smart camera, and other sensors and actuators. 2. e.g. crop monitoring sensors, smart irrigation systems. [67] 3. Measurement and validation systems e.g. water usage. 4. Domain specific classification and expert labelling e.g. asphyxia and voice image analysis [68], plant leaf images with disease labels. 5. Verification of data with truth values from the Malaysian Meteorological Department (METMalaysia [48] 6. Early warning systems with cross-border corridors. 7. Fire propagation models [51] 8. Khmer ASR (speech engine), TTS (fast speech), chatbot (sentenceBERT for finetuning), for medical vocabulary and accent handling [2], customization in formulas or equations for math, physics, and chemistry for Braille translation for Khmer [43]. 9. Public procurement documents analysed using anomaly detection algorithms [57] [58] 10. Documents on government schemes and services [59] 11. Plant leaf images database and associated flowcharts [60], local rain and wind audio, and other types of sensor measurements with an embedded device without any moving parts [65]. 12. Weather data from the Tanzania Meteorological Authority (TMA), plant profile data from the Ministry of Agriculture, and irrigation historical data from the National Irrigation Commission [71]. 13. Live translation of Sign languages to speech [77] [2] 14. AIGC technology for generating training data samples to improve AI recognition ability [1] 15. The feature information extracted from the large model is further analyzed and predicted by using the small target detection model [1]. 16. Finetuning of models and context enhancement techniques such as RAG 17. GenAI, and NLP for network slice resource allocation [93].

Examples	Potential AI impacts
Characteristics	
Regulations and vision, including standards	1. Level of impact of the use case – does it affect human lives 2. Preventive interventions vs. post-facto interventions (e.g. how to prevent accidents vs. How to save victims of accidents) 3. Decision-making and investment – e.g. who deploys the sensors? Are there subsidies? 4. Goals and priorities – determine the timelines for deployment of different solutions. 5. Standard offline validation tests (e.g. Field Sobriety tests) 6. Explainability of models and validation by experts in the loop. 7. Regulation and standards on Power saving for low-resource deployments such as farm sensors. 8. Ruggedness, water/dust proof IP66 [15], IP65 [15] 9. Domain-specific Standards e.g. BAP 1000, ASC shrimp standard, Global GAP Aquaculture standards, ISO 9001: 2015, ISO 22000: 2018 10. Regulations related to data capture e.g. drones with geo-restrictions, height restrictions on flight) 11. tropical peatland fire weather index (FWI) system by combining the groundwater level (GWL) with the drought code (DC) [48] 12. Time series, government data related to agriculture, including crop production, land use, water use, market prices, weather patterns, and government schemes. Dissemination of best farming practices, and resource distribution plans [67]. 13. Interoperability and compatibility of cross-region data (e.g. early warning) and generated advisories [50]. 14. Regulations and penalties related to Power availability KPIs [51] 15. Regulations on ethical usage of such emerging technologies and enabling data security interoperability and user privacy in similar platforms [59] 16. Drone field of vision, height of the flight path [60] during image capture. 17. Human expert oversight and supervision is important for medical diagnosis [68], integrating expert feedback in AI model inferences [71] 18. International sign languages and regional sign languages [77] [2] and accessibility standards such as machine translation systems for specific languages [43]. 19. Authorized CCTV camera usage [1], When using open-source models, ensure that the copyright and license agreements for the models are adhered to [1]. 20. AI-based Autonomous Operations of 5G/6G networks require monitoring and human supervision [93]

(continued)

Examples	Potential AI impacts
Characteristics	
Open data: Type of data	1. Open data, authorization to access data, location of data, e.g. core cloud, edge cloud, federations, crowd-sourced data, e.g. distracted driver dataset [12] 2. A combination of open data available nationally, or internationally, along with private and 3rd party procured data [2] 3. Multi-modal, + sensor fusion. 4. Domain specific measured medical data e.g. Heartbeat, breathing, chest movement, helps in inferring the DUI levels. 5. Data formats, data structure, and APIs. Collected from specific frameworks such as OM2M [22]. 6. e.g. pH and NPK levels, EC (electric conductivity) of the soil, weather parameters (wind speed and direction, solar radiation), leaf wetness. 7. Quality of images – the type of cameras used, and the setting HD/optimized. 8. Volume, frequency of collection, quality – e.g. Number of images – Surface area coverage, Obstruction of cameras – background, foreground objects and humans, Frequency of image capture – the number of flights of the drone and stages of plant growth. 9. Drone-mounted cameras feed for video and still images and satellite images [52] 10. Time series market data on crop prices, 11. Real-time streamed data from cameras [51] 12. Data includes audio speech data, e.g. history recording in audio and later converted to text [2] [77] captioned images [2], voice data collected using newborn's cry recordings (with background noise) [68] 13. Open data for accessibility such as Sign language data includes facial expressions [77] and Braille books [43] 14. Schemes, policies, and related portal contents from various government portals and other websites. [59] 15. Labelled data related to plant leaf images [60] correlated to the field of vision of the drones. Local rain and wind audio and other types of sensor measurements with an embedded device without any moving parts [65] 16. Collecting local data for fine-tuning of general (globally available, existing) models [71] and refining models based on local weather patterns and soil characteristics, optimizing irrigation practices for enhanced water efficiency 17. Wind power plant and solar panel energy production [80] 18. The project opened a total of 50,000 + algorithms for intelligent video analysis scenarios [1]. 19. Use of open standards as open data for training and assisting contributors [27] 20. Network intent expressed as natural language [93]

(continued)

Examples	Potential AI impacts
	Characteristics
Computer and Deployment capability: Infrastructure	1. e.g. Speed bumps, Barricades, Banners, and Advertisements 2. Route planning 3. Extensions 4. Fiber to the RSU 5. Computation available on the edge 6. Wireless sensors and capabilities in the vehicle, between the vehicle and RSU, etc 7. In-vehicle Safety accessories (belt, airbags) 8. Secure communication networks. 9. Geo spatial capabilities and infrastructure. 10. Energy source: solar panels (for energy autonomy). 11. visualization dashboards and mobile apps 12. Application of AI-based synthesis and Generative AI for Dubbing [77] 13. Cloud hosting of open data, schemes, policies in machine-readable format [49], open portals, and real-time updates from agencies [50] 14. Satellite data coordination [51] 15. Ground stations [52] coordinate the ad-hoc networks for drones used for disaster management and charging stations for drones. 16. Data augmentation capabilities [60] 17. Deploy the tinyML model on an embedded device in the field and measure how well the model performs in real life [65] 18. The feature information extracted from the cloud from the large model is further analyzed and predicted by using the small target detection model at the edge [1]
Research: Models, Algorithms, and Technology	1. Collision avoidance, driver attention, human detection, local innovation, (e.g. patents, publications, local research) 2. Maturity (e.g. validation, standards compliance, certifications, labs) 3. AI models (image processing) 4. Real-time In-vehicle measurement of various inertia from the response times of the driver and signal processing on the driver controls. Inferred values of DUI levels are output. 5. Estimation algorithms on controls such as fertilizers and pesticides 6. Prediction algorithms on Yield. 7. Classification algorithms on the mapping between crops and fields. e.g. pest and disease management. Pesticide usage. Prediction of diseases and irrigation schedules. 8. Random forest and MARS (Multivariate Adaptive Regression Splines) algorithms, ensemble models [68]. 9. Model (YOLO for unique object counting) [60] [1] 10. CBAM (convolutional block attention mechanism) – model 11. Prediction models such as GWL prediction and Fire Danger Rating System (FDRS) indices such as Drought Code (DC), Duff Moisture Code (DMC), and Fire Weather Index (FWI) prediction based on the GWL. [48] 12. GPT-like static models vs. RAG-based dynamic updates to the policies database [49]. 13. generation (advisory generation) and prediction (forecasting) 14. Fire prediction detection, propagation models 15. RL, multi-agent, collaborative intelligent solution [52]

(continued)

Examples	Potential AI impacts
Characteristics	
	16. The Models include Khmer ASR (speech engine), TTS (fast speech), and chatbot (sentenceBERT for finetuning), for accent handling more data collection is needed, currently this model is based on central City. [2] 17. Context DB, local information about government services [59] 18. chatbots, LLM models, and AI/ML algorithms for finetuning, recommendation, prediction, and generation [59]. 19. Combining AI model results from YOLO models and drone imagery [60] 20. Models optimized for energy consumption, to enable a long battery lifetime (e.g. tinyML models for weather stations [67], optimized for smaller memory and resource usage [68]). 21. LSTM model, useful for time-series data [71] 22. Explainable AI for interpretation, Ray Tune for fine-tuning [80] 23. Combining images and multi-modal data inputs to predict answers, Audio-visual speech recognition combines sound and video information to identify speech content [2] 24. "application and algorithm" dual decoupling service combination of distributed cluster, based on cloud edge resource collaboration technology [1]
Standards and Interoperability	1. Alternatives for technology 2. Stepwise scenario. E.g. exchange of information between various actors. 3. Inter-PLMN mobility for connected and automated mobility of enterprise vehicles. 4. Connected vehicles with competing standards such as DSRC [47] and IEEE 802.11p [42]. 5. MQTT (message queuing telemetry transport) [56] 6. Data formats between different government data portals [49], [50] 7. Coordination of satellite data and orbits [51] 8. Combination of camera and satellite data formats [51] 9. Ad hoc network protocols for coordination between drones from different vendors/providers [52] 10. Protocols and interfaces for multiagent systems and transfer learning approaches for models trained using different ML frameworks [52] 11. generalization formats across a diverse variety of disaster scenarios [52]. 12. Regulations and guidelines for public services management such as procurement and tenders [57], [58] 13. Data aggregation, model optimization, and deployment standards [67], [68], [62]. 14. Generalizability and informational guidelines on reusing models with integrated local expertise 15. National sign languages and regional sign languages [77] [2] and machine translation for Braille for local languages. 16. Energy usage substitution [80] 17. Standards for AIGC – creation and selection of samples for addressing the availability of samples and edge/cloud collaboration for federated learning [1] 18. Annotation formats for interoperable annotations [1]. 19. 5G/6G Network Intent input using natural language [93]

(continued)

Examples	Potential AI impacts
Characteristics	
Human factors, trust, interop-erability, and standards	1. Awareness and training 2. Trust and security 3. Driver certification with awareness of the technology and usage of the technology. 4. Upgrade of training for both drivers and pedestrians. 5. Adoption level including consent to provide data. 6. Human feedback, surveys, training, and simulations. 7. Supervision and oversight [68] 8. Usability of visualization apps, websites, and mobile apps for advisories. 9. Involvement of local communities, taking into account traditional knowl-edge from communities [51]. Deployment of tinyML models in a farm [67], for example, to provide local conditions and assist farmers in deciding when to plant crops. 10. Local accent handling e.g. Khmer ASR (speech engine), TTS (fast speech), a chatbot (sentenceBERT for finetuning), for accent handling [2], dialects and math, physics and chemistry formulae [43]. 11. Expert annotation of the anomalies and irregularities in public service documents [57], [58], plant leaf images [60], and other public information related to agricultural water usage [71]. 12. Signed consent by operators to the State actors for collection and use of video data [1]. 13. Verification of answers provided by Question-answering models [27].
Open data: Data handling	1. SRC (source) - real-time - is the driver, RSU (roadside unit) sensors, Weather conditions 2. C (collector) 3. PP (preprocessor) 4. M (analytical model) 5. P (policy) 6. D (distributor) 7. SINK (where the action is applied) Example: 1) Data collection – conversion – quantization/aggregation/range-checking – network – model – users [15] 2) Data format Conversion of sensed data to formats to protocols such as LoRa. [48] 3) Local contextualization and mapping to local regulations and policies. 4) RAG-based backend database with dynamic update capabilities. 5) APIs for asynchronous update of warning systems and endpoints for consuming generated predictions [50] 6) Streaming formats for camera data for fire detection [51] 7) Satellite data formats and APIs for heat sensing and detection of wildfires [51] 8) Historical records of procurement-related text documents, mostly in local language [57], [58]

(continued)

<table>
<tr><th>Examples</th><th>Potential AI impacts</th></tr>
<tr><th colspan="2">Characteristics</th></tr>
<tr><td>Developers and Opensource ecosystems</td><td>1. Reference implementations of algorithms
2. Opensource toolsets
3. 3rd party applications, APIs, and SDKs
4. Open data, collected from various crowd-sourced mechanisms
5. Transfer learning mechanisms for wider applications
6. Opensource boards to host the edge data processing
7. MQTT [56] and OM2M [22] applications
8. IoT gateways such as LoRa gateway and applications, SDKs, and APIs
9. Cloud APIs for subscribing/publishing data from portals [49]
10. Satellite data usage in fire propagation model [51]
11. Keras libraries for data augmentation [60]
12. Opensource tools such as AutoML for automating algorithm selection, feature generation, hyperparameter tuning, iterative modeling, and model assessment [77].
13. Open multi-modal data for accessibility.</td></tr>
<tr><td>Experi-mentation, Deployment capability</td><td>1. LoRa-based IoT system for peatland management and detection was deployed in Raja Musa Forest Reserve (RMFR) in Kuala Selangor, Malaysia [48]
2. According to the World Economic Forum, the pilot study of agriculture-related AI technology on 7000 farmers in the Khammam district of Telangana (India) showed promising results, where the net income of the farmers using the AI technology had doubled ($800 per acre) from the average income in 6 months [33]
3. Possible PoC in IMEC (India-Middle East-Europe Economic Corridor) [50] is considered in the future.
4. [51] has pilots in India, Portugal, and Brazil, currently monitoring more than 117 million hectares of Brazilian wetlands, currently studying the involvement of communities from Amazon (tribes).
5. Simulation approaches such as (sim2real [53]) – including sim2real transfer (for leveraging simulated data) and curriculum learning (for achieving a smoother learning curve from simple to complex scenarios) are used in combination with drone-based disaster management [52].
6. Pilot deployments include deployment (https://asr.idri.edu.kh/) https://hal.science/hal-03865538/ in Partnership Ministry of Post and telecommunication and publications for Khmer ASR are available. [2]
7. Greenhouse deployments [60] for drone swarms.
8. AI-enabled Soil Analysis and Weather Station for Local farmers using tinyML models [67].
9. Pilot deployments in hospitals [68] with background noise and low-quality microphone conditions.
10. Pilot deployment of water conservation use case in the Dodoma region, selected for its representative soil types, crop varieties, and climate conditions prevalent in Tanzanian agriculture [71]
11. Application and deployment of AI-based accessibility solutions as described in [77] for specific domains such as affordable healthcare.
12. Deployment of energy consumption and prediction models [80] in Zhejiang China.
13. The pilot models deployed on China Mobile's internal network for federated learning [1].</td></tr>
</table>

In this table, we aim to collect the characteristics of each use case in different domains and summarize them based on each factor. While studying these use cases, the different actors (vehicles, sensors, roadside units, networks, controllers) and characteristics (regulations, infrastructure, technology, interoperability, human factors, data types, data handling) are listed to find common patterns, metrics, and evaluation mechanisms for the integration of AI in different domains. The goal of this multi-domain study is to develop a framework assessing AI readiness to indicate the ability to reap the benefits of AI integration. Efforts could then be extended to scale this research across different regions of the world and other domains and use cases.

Standard frameworks may (a) offer clear metrics for measuring readiness levels in terms of enabling factors derived from the case-based analysis, (b) empower organizations, regions, and countries to evaluate their preparedness to benefit from AI effectively, with respect to the characteristics identified in the case-based analysis (c) study the various risk factors in simulated and experimentation scenarios so as to make informed decisions and (d) apply regional and domain-specific preferences while deploying AI-based solutions.

So, a methodological bottom-up approach is employed to study various use case scenarios and to study the corresponding impacts of artificial intelligence.

Two main parts of our analysis are actors and characteristics related to the use case. Some examples of actors are vehicles and humans, networks, controllers, and traffic management systems. Actors may be equipped with or utilize sensor technologies that enable AI integration. AI integration may require network connection with specific requirements such as low latency, high throughput, and edge intelligence capabilities. Controllers, such as the AI/ML feedback loop and pre-established traffic plans for specific scenarios, are integral in leveraging existing infrastructures for AI implementation. Lastly, traffic management systems, encompassing Roadside Units (RSUs), smart traffic signals, and sensor-equipped cameras, act as primary data providers in the AI-integrated system.

Some of the characteristics studied are regulations and standards, data types, infrastructure, algorithms and technology, interoperability, human factors, data handling, environmental factors, and developers and open-source initiatives.

Appendix B: Specific impacts of these characteristics on Standards Frameworks for AI readiness require further study.

Table 3: Analysis of use case scenarios

Use case	Scenarios	Type of sensor/ actor	Deployment as Integral/add-on controls	Thresholds for validation and compliance	Experiments and Specifications for validation.
Driver distraction	Drowsiness detection	Eyeball tracking visual cameras	Add-on	For future study	Volunteer based tests
	Texting while driving	Gesture determination	Add-on	For future study	Volunteer based tests
	Lane discipline	RSU	Add-on	[100]	Test driving with sensors
	proximity	V2X	Integral	[100]	Test driving with sensors
	Action detection	Facial features classification	Add-on	For future study	Volunteer based tests
AEB based collision avoidance	Lane merging	Angle detection sensor	Add-on	For future study	Testing on test tracks
	Blind spot alarms	Angle + proximity	Add-on	For future study	Testing on test tracks
	Emergency braking and crash	Deployment and strength/ stability	Integral	For future study	Dummy based
	Platooning of trucks	Proximity and distance	Add-on	For future study	Testing on test tracks
DUI detection	Offline Validation by field tests	Blood alcohol levels, breath analyser	Add-on	For future study	Certified Medical labs
	Realtime inference by algorithms	Response times of the driver	Integral	For future study	Vendor tests

Table 3: Analysis of use case scenarios (continued)

Use case	Scenarios	Type of sensor/ actor	Deployment as Integral/add-on controls	Thresholds for validation and compliance	Experiments and Specifications for validation.
Crop management	Pesticide optimization	Environment and soil sensors Visual data sensors (cameras)	Add-on	Sensor specific [31]	Outdoor, in the fields In simulated scenarios
	Local farming decisions and resource distribution plans	IoT sensors, training, awareness campaigns, IoT-based Smart Irrigation System (I-SIMS) Agriculture data collection, processing, and decision-making services [20]	Additional support mechanisms [16] [20], analysis methods [17]	[16][17][20]	Farmers' awareness of IoT technologies and benefits [16] Grey Relational Analysis (GRA) and Analytical Hierarchical Process (AHP) methodologies [17], recommendations to cultivate differently in the desert areas of Saudi Arabia [20]
IoT Sensing for Agriculture	Water usage optimization	Soil sensor, weather data, Soil data, plant profile data [94]	Add-on	Sensor parameters [15]	Ruggedization, calibration, and e2e validation
Underwater sensing for Aquaculture	Productivity and quality in aquaculture	Camera and water sensors	Add-on	[39]	Pilot setup in the lab
Plant disease identification	Leaf image-based Disease identification in wheat crops [38]	Drone mounted cameras	Add-on	[38]	Outdoor fields
	Leaf image-based disease identification from UAV swarms in greenhouses [60]	Drone mounted cameras and greenhouse sensors	Swarms	Height and field of view, correlation between sensor data and drone captures [60]	Greenhouse deployments
Peatland fire prediction	GWL prediction and DC prediction [48]	Weather station, water level sensor, and soil sensor	Add-on	[48]	Lab testing and deployment testing

Table 3: Analysis of use case scenarios (continued)

Use case	Scenarios	Type of sensor/ actor	Deployment as Integral/add-on controls	Thresholds for validation and compliance	Experiments and Specifications for validation.
Chatbot for Agriculture	AI-based chatbot for farmers	Open data from government portals	Add-on	[49], [33]	Cloud-based API validations, subjective testing by test users
Disaster warning	Context-specific disaster warnings	Open data from government portals, and satellite images	Not applicable	[50]	Simulation environment and a small-scale version that will demonstrate the feasibility of managing disaster and climate risks to their business processes along the India-Middle East-Europe Economic Corridor (IMEC)
Wildfire detection	Fire detection, propagation models, and predictions	Private data from camera instalments and satellite data (heat sensors)	Add-on installations for monitoring	[51]	Labview and Python-based models and verification mechanisms Pilot deployments in India, Portugal, and Brazil Monitoring currently more than 117 million hectors Brazilian wetlands Traditional communities from the Amazon (tribes)
Disaster management	Damage assessment in the network, search and rescue operations	Drone-mounted cameras and satellite images	Generalized platforms complemented with add-ons	[52]	Sim2real-based studies for RL and transfer learning for multiagent
Public services monitoring	Detecting irregularities in Public Procurement	Cloud-hosted AI model, trained on historical tender documents	Cloud-hosted models used as add-on deployments	Not available	Validation of decision support systems with regulatory experts
	Transparent access to public services	Chatbots interfacing with LLMs trained on government documents and content	Web-based and WhatsApp integration as an omnichannel approach as add-on.	Future studies on ethical considerations, data security interoperability and user privacy	Closed loop validation with user feedback

Table 3: Analysis of use case scenarios (continued)

Use case	Scenarios	Type of sensor/ actor	Deployment as Integral/add-on controls	Thresholds for validation and compliance	Experiments and Specifications for validation.
Healthcare Applications	Early detection of critical conditions	Classification and ensemble models	Smartphone-integrated model deployments.	To be studied based on local requirements and ethnicity	Pilot deployments in hospitals [68]
Accessibility	Live Sign Language Translation	Patients and healthcare professionals. Gestures, audio, and text	Mobile integrated GenAI and synthesis Applications	Dialects related to sign languages [77]	Zimbabwe's Primary Healthcare [77]
	Audio-visual speech recognition	Accessibility features hosted in smartphones	Mobile integrated application with Multimodal Large Model with audio and visual inputs	Chinese Sign language	Smartphone OS-based Information Accessibility Solutions [2]
Clean Energy	AI-based clean energy prediction	Weather sensors, Power plant measurements, and solar panel monitoring	Add-on: Ray tune hyperparameter tuning	[80]	Regional State Grid [80]
Video Analysis	Target detection	CCTV camera image information	Add-on: AIGC-based generation of training data samples, use of annotation formats, federated learning	[1]	Network operator internal deployment [1]
Training and knowledge creation	Assisted content generation	Editing tools for content creation	Assisting bots are addons for editing tools	Not available	Proposed sandbox for African contributors [27]
5G/6G connectivity	Resource optimization and autonomy	Natural Language Processing (NLP) module	Overlay (add-ons) based GenAI, digital twin and Recommendation engine solutions	Thresholds for anomaly detection, in 5G/6G, slice resource configurations	Digital twin-based sandbox

Table 3 covers the analysis of different scenarios under different use cases in clause 4. For each scenario, the type of actor, controls, thresholds for validation and compliance, and experiments for validation are studied.

The type of actor in each scenario determines the interaction between AI model and the external world. For example, in the scenario where the aim is to detect driver distraction, drowsiness detection relies on cameras that can track eyeball movements whereas the monitoring lane discipline utilizes sensors or roadside units. Thus, determining the interaction point via the actors would point us to specific requirements of deployment scale and support needed.

Integral/add-on controls point to the nature of the AI integration in the actors needed in the scenarios. External, overlay or add-on deployment of sensors or other types of hardware may have specific requirements in terms of cost and regulations. The gradients of thresholds for the limits of application of the scenarios, point to compliance and validation requirements. For example, in accessibility scenarios, we aim to provide sign language to audio and video translation, different set of thresholds may be applied based on dialects of sign languages. Further study is needed, on a use case scenario basis to derive the thresholds and corresponding validation requirements for each use case.

Finally, experiments for validation of the scenarios determine the tools, sandbox setups, validation test suites and testing infrastructure needed in each scenario. Feedback from the real-world deployments is more reliable and authentic. However, in rarely reproducible scenarios such as massive natural disasters, it is important to use simulated sandboxes to validate and prepare for such failure scenarios.

To conclude, a scenario-based study of the type of actors, type of controls, thresholds for validation and compliance, and experiments for validation leads us to the relations between specific parameters for the AI readiness factors and corresponding benefits which can be obtained.

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