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SERIES Y: GLOBAL INFORMATION INFRASTRUCTURE, INTERNET PROTOCOL ASPECTS, NEXT-GENERATION NETWORKS, INTERNET OF THINGS AND SMART CITIES

Unlocking Internet of things with artificial intelligence

ITU-T Y-series Recommendations – Supplement 63

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Supplement 63 to ITU-T Y-series Recommendations

Unlocking Internet of things with artificial intelligence

Summary

Supplement 63 to ITU-T Y-series Recommendations examines how artificial intelligence could step in to bolster the intent of urban stakeholders to deploy Internet of things (IoT) technologies and eventually transition to smart cities.

The main elements examined in this Supplement are:

– The various technological implementations of artificial intelligence (AI) that may facilitate smart city transformations;

– The role played by AI in managing the data generated within the IoT realm and urban spaces;

– The main benefits of adopting AI and delving into how this technology could be leveraged to attain the Sustainable Development Goals (SDGs).

History

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Introduction

In the last decade, the Internet of things (IoT) has burst into the scene, becoming one of the major research subjects within the information and communication technologies (ICTs) domain.

The advent of IoT holds the promise of optimizing equipment, promoting judicious resource consumption, enabling increased efficiencies in provision of services and fostering a new and more cost-efficient urban development model. However, as the tremendous growth opportunities for IoT development emerge, various challenges associated with the proliferation of devices across networks, exponential growth of data volume and managing the influx of complex data streams have also emerged in parallel, fundamentally impacting the IoT paradigm. These core challenges can best be addressed by incorporating architectures and applications that exploit the value of sensor data through real-time analytics to gain intelligence and respond to events as required. In this scenario, analysis of historical as well as current data can also be utilized to deduce trends, analyse data streams for correlation and formulate suggestions for urban resource management based on patterns determined from collected data-sets. Such an analysis can further enable the creation of new and innovative applications that enhance value and expansion of the IoT realm.

In essence, there are three main motivations for researching and innovating within the IoT ecosystem:

Motivation 1: To expand and collect information in the form of data through shared (open) databases and objects in the real world.

Motivation 2: To enable the sharing of information and controlling of connected objects, sensors and devices in the real world. [b-JournalInnovTech]

Motivation 3: To use open standards to facilitate IoT development in the urban space.

In view of these motivations, it is evident that effective data management will be essential to the success of the IoT paradigm. With the rapid increase in the use of smart devices within the IoT ecosystem, "big data" is being collected in near real time. Owing to the size and complexity of big data conglomerates, it is commonly acknowledged that traditional analysis methods are difficult and cumbersome to dissect this large volume of data and obtain insights for informed decisions.

However, machine learning and AI capabilities are able to push beyond the limitation of linear analysis, enabling effective pattern recognition from large data sets, responding to stimuli based on real time data and determining responses based on the needs of the ecosystem. Being able to manage a large volume of data while deploying highly sophisticated smart services in cities (e.g., for safety, congestion management, etc.) require continuous efforts to upgrade the capacity of the information systems.

In this regard, breakthroughs should be made in basic theories of AI, including big data intelligence, multimedia aware computing, human-machine hybrid intelligence, swarm intelligence and automated decision-making.

Advanced theories which can potentially transform AI (including advanced machine learning, brain-like computing and quantum intelligent computing) should also be examined. Trans-boundary research should be promoted to connect AI with other subjects, such as cognitive science, psychology, mathematics and economics.

A common technology system should be developed based on algorithms, data and hardware. Technologies in the system include a computational knowledge engine, swarm computing, virtual reality modelling and natural language processing. Innovation platforms should be constructed, such as an open-source computing platform, which can promote coordination among different hardware, software and clouds.

Supplement 63 to ITU-T Y-series Recommendations

Unlocking Internet of things with artificial intelligence

1 Scope

As the IoT system continues to expand within the urban realm in keeping with smart sustainable city aspirations, the need to manage big data and establish a self-sustaining urban ecosystem is of paramount importance. In order to create value for the community, IoT data must be translated into information and knowledge by leveraging data analytics and AI. Accordingly, this Supplement examines how artificial intelligence could bolster urban stakeholders' ability to deploy IoT technologies effectively and eventually transition to smart sustainable cities.

The main elements examined in this Supplement are:

– The various technological implementations of AI that will facilitate smart city transformations;

– The role played by AI in managing the data generated within the IoT realm and urban spaces;

– The main benefits of adopting AI and delving into how this technology could be leveraged to attain Sustainable Development Goals (SDGs).

2 References

None.

3 Definitions

3.1 Terms defined elsewhere

This Supplement uses the following terms defined elsewhere:

3.1.1 Internet of things [b-ITU-T Y.4000]: A global infrastructure for the information society, enabling advanced services by interconnecting (physical and virtual) things based on existing and evolving interoperable information and communication technologies.

3.1.2 smart sustainable city [b-ITU-T Y.4900]: A smart sustainable city is an innovative city that uses information and communication technologies (ICTs) and other means to improve quality of life, efficiency of urban operation and services, and competitiveness, while ensuring that it meets the needs of present and future generations with respect to economic, social, environmental as well as cultural aspects.

4 Abbreviations and acronyms

This Supplement uses the following abbreviations and acronyms:

AI	Artificial Intelligence
API	Application Programming Interface
ACT-R	Adaptive Control of Thought-Rational
CA	Cognitive Architecture
CLARION	Connectionist Learning with Adaptive Rule Induction On-line
CHC	Cattell-Horn-Carroll
DMA	Demand Management Areas
DSS	Decision Support System

EI	Epistemological Information
HMI	Human Machine Interface
HPC	High Performance Computing
ICT	Information and Communication Technology
IIRA	Industrial Internet Reference Architecture
IoT	Internet of Things
IS	Intelligent Strategy
IT	Information Technology
LSTM	Long Short-Term Memory
MAS	Multi-Agent Systems
MIS	Minimally Invasive Surgery
ML	Machine Learning
NL	Natural Language
NLP	Natural Language Processing
OGC	Open Geospatial Consortium
OI	Ontological Information
RAMI	Reference Architecture Model for Industry
SDG	Sustainable Development Goal
SDO	Standards Developing Organization
SSC	Smart Sustainable City
SSN	Semantic Sensor Network
SWM	Smart Water Management
URL	Uniform Resource Locator

5 Conventions

None.

6 IoT and artificial intelligence: Reshaping the urban ecosystem

6.1 Internet of things in smart sustainable cities

Nearly 55% of the global population is housed in cities. It is estimated that by 2050, the booming population increase coupled with rural to urban migration will result in approximately 68% of the global population living in cities [b-UN DESA]. This will increase the burden on the ageing urban infrastructures to deliver resources and services to all urban citizens. To deal with the ever-changing urban development landscape, the concept of "smart sustainable cities (SSCs)" has emerged as a buzzword across various disciplines. In 2015, the International Telecommunication Union (ITU) and the United Nations Economic Commission for Europe (UNECE) formulated an internationally accepted definition (based on an analysis of over 100 definitions):

"A smart sustainable city is an innovative city that uses information and communication technologies (ICTs) and other means to improve quality of life, efficiency of urban operation and services, and

competitiveness, while ensuring that it meets the needs of present and future generations with respect to economic, social, environmental as well as cultural aspects".

In view of the above definition, smart sustainable cities are cities that harness the full potential of smart technologies and devices to facilitate sustainable and inclusive growth. As more cities are looking to transition to become a smart sustainable city, there has also been a remarkable growth of digital devices, such as sensors, actuators, smartphones and smart appliances, all of which are interconnected through IoT to enable communications between them.

IoT offers a distinct advantage when it comes to driving sustainable development. It has the unique ability to transparently and seamlessly incorporate a large number of different and heterogeneous systems, while providing open access to selected subsets of data for the development of a plethora of digital services. Hence, urban stakeholders are encouraged to incorporate IoT into existing urban infrastructures in order to facilitate smart city transitions [b-IEEEComm].

In general, the IoT paradigm enables the interaction between a wide variety of devices including surveillance cameras, sensors, actuators, mobile devices, vehicles. Accordingly, this paradigm finds application in several urban domains, such as home utilities, industrial automation, medical aids, mobile health care, pollution control, elderly assistance, intelligent sustainable buildings, smart energy management and smart grids, automotive, traffic management, etc (See Figures 1 and 2 for examples).

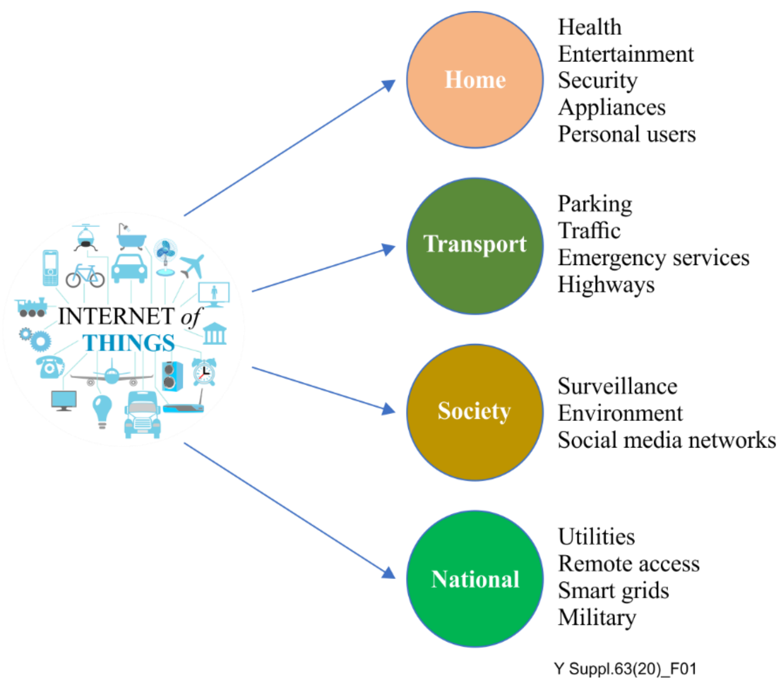

Figure 1 – Uses of IoT within smart sustainable cities (Adapted from [b-Energies])

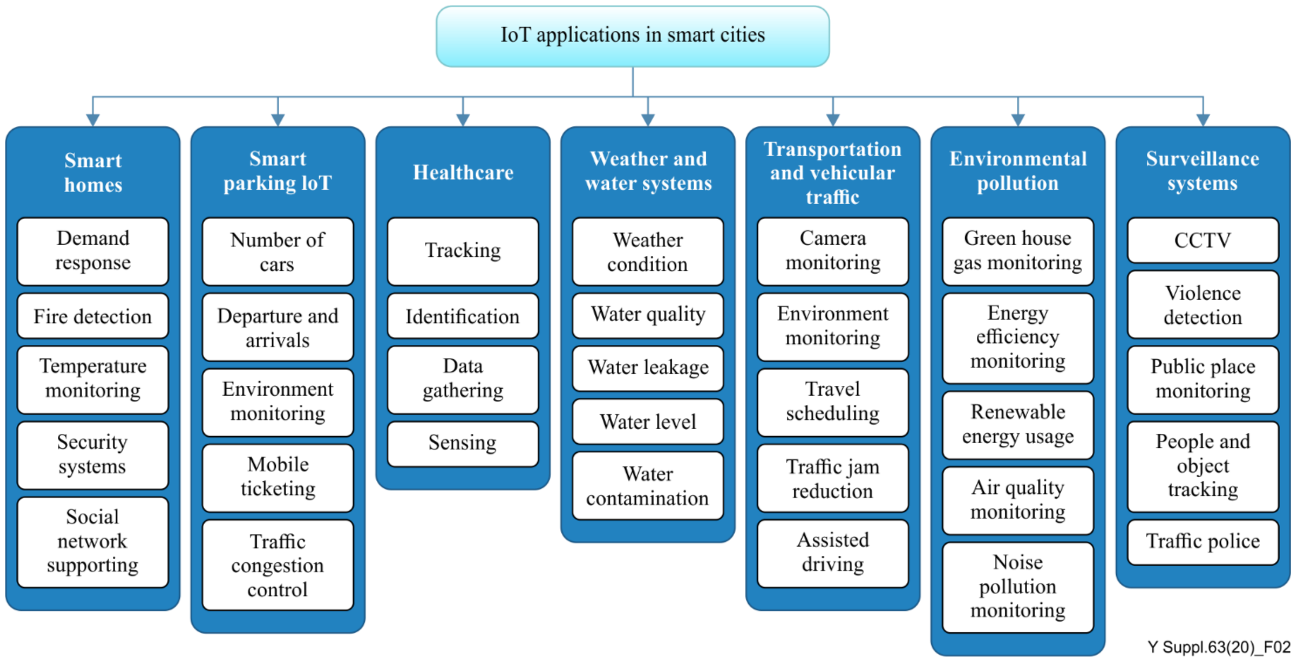

Figure 2 – Indicative IoT Applications in Smart Sustainable Cities [b-Energies]

However, the heterogeneous fields of IoT implementation makes the identification of adequate solutions, solutions that are capable of satisfying the requirements of all possible scenarios, a formidable challenge. This has led to the creation of an IoT ecosystem in which smart devices and platforms are not compatible with each other. Such scenario risks having IoT solutions and applications to develop in silo and data being vendor lock-in. As the amount of heterogeneous data continue to increase, interoperability would be crucial for combining disparate data from different sources and generating actionable insights that would benefit smart sustainable cities as a whole. Smart sustainable cities also need to be able to process extensive data, weed out redundant sources and extract useful information and correlations in real time. In this sense, real-time processing is another important feature of a smart sustainable city that would enable cities to deliver timely responses in various situations [b-ProcediaCmpSc].

Keeping the above aspects in mind, a smart sustainable city needs to be maintained by a complex, ever-evolving system in which data, devices and platforms are able to communicate with one another effectively. In this scenario of constant evolution, it is challenging to make good use of the data only based on predefined models; to address the growing needs of cities, the IoT systems need to be capable of learning and self-adapting in order to effectively process heterogenous data from varying sources and to predict events and forecast upcoming trends. It is to be noted that a clean, interoperable data set is essential for AI to generate insights. Therefore, data must be homogenized to a degree before applying AI capabilities to them, considering their intrinsic heterogeneity.

Multi-agent systems (MAS) capable of conducting distribution computation, based on artificial intelligence linked technologies, are a promising way to make use of data collected within a smart city [b-ComputerScEng].

6.2 Towards artificial intelligence

As highlighted in clause 6.1, the increasing number of smart city projects holds great promise for the economy and citizens. Additionally, smart sustainable cities are data driven and rely heavily on IoT to connect the plethora of devices. However, many cities have yet to adopt a feasible enabler to deal with incoming data streams and answer the fundamental question on the minds of most urban stakeholders – What is to be done with the collected data within the IoT ecosystem? AI and its capabilities offer one of the most compelling answers to this question. Artificial intelligence allows multiple urban systems to work together, optimize resource usage, detect emergent patterns, and provide new responding capabilities to different situations (which traditional analytics tools are found to be devoid of). Data analytics are considered to be a key enabler for AI. In this context, it is important to assess and consider the extent to which they are adequate, effective and appropriate.

AI consists of several technologies that enable devices/computers to gather data from sensors (including but not limited to speech recognition), analyse and understand the information collected (through natural language processing), make informed decisions or recommend action (expert systems), learn from experience (machine learning) and respond based on the needs of the situation (robotics) [b-HawaiiConf].

Table 1 – Key Roles Played by artificial intelligence within the IoT ecosystem

Key roles played by artificial intelligence	Description
Perception	Technologies within this category are used to acquire ontological information (OI)[1].
Cognitive	Technologies within this category convert information to epistemological information (EI)[2].
Decision-Making	Technologies within this category convert EI to intelligent strategy (IS) aimed at problem solving
Execution	These technologies will convert IS into intelligent action (IA) and strategy optimization. Strategy optimization involves taking into account errors as new information and feeding them into the AI system for perception. This helps the system to avoid making the same errors again.

Figure 3 provides an overview of the functional model for AI based on the key roles of AI.

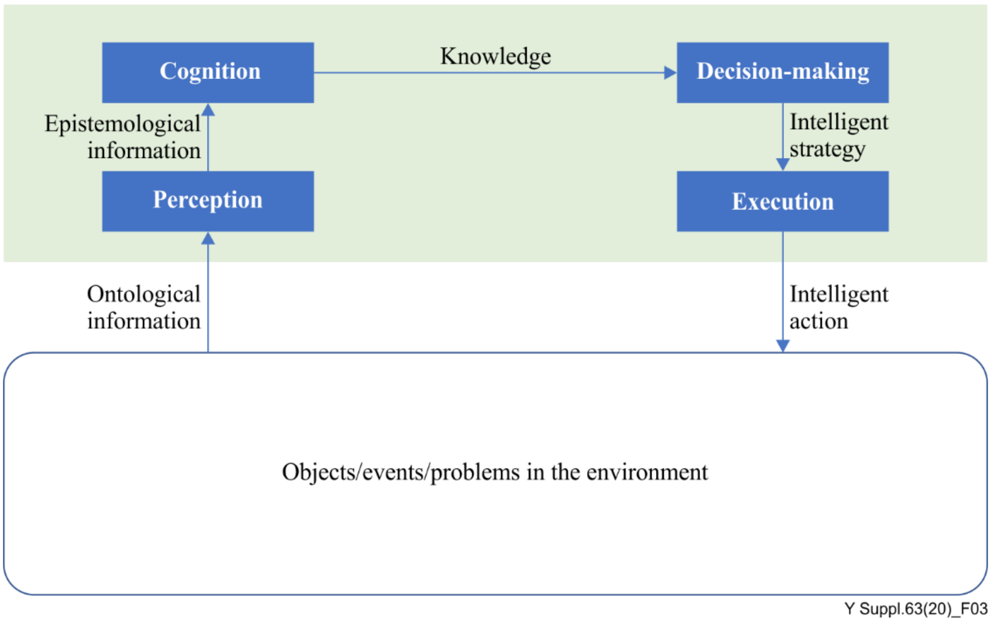

Figure 3 – Functional model for artificial intelligence (Adapted from [b-ZteComm])

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1 This refers to the information on the state and pattern of variance presented by the object/device in the environment.

2 This refers to the information perceived by the subject about the trinity of the form (syntactic information), content/meaning (semantic information), and utility/value (pragmatic information) concerning the OI.

In keeping with the roles played by AI, the core tools associated with artificial intelligence can be sorted into three main domains (see Figure 4):

(1) Cognitive automation: This refers to intelligent automation capabilities that can enhance urban operations by performing high volume and rule-based activities, which will eventually assist in reducing costs and risks.

(2) Cognitive engagement: This refers to unleashing the potential of unstructured data, accessing complex information and performing digital tasks for which personalized engagement maybe required. In such cases, cognitive agents could potentially replace human interactions in service-based sectors.

(3) Cognitive insights: This refers to the extraction of concepts and relationships from various data streams to generate personalized and relevant answers hidden within a mass of structured and unstructured data [b-ProcediaCmpSc].

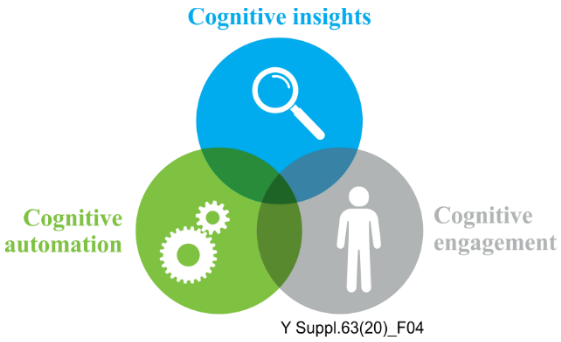

Figure 4 – Domains of Artificial Intelligence Tools [b-Deloitte]

Table 2 – Tools for the application of artificial intelligence[3]

Artificial intelligence tools	Description
Speech recognition	Speech recognition software refers to the technology that is able to transform spoken words into alpha-numeric text and navigational commands. One of the key aspects of speech recognition software is the "language model". The "language model" analyses the speech and determines the keywords thereby markedly improving voice-activated self-services. This falls under the cognitive automation domain.
Natural language processing	In general, natural language (NL) refers to any human written or spoken language that has evolved naturally for human communication. Within AI, the interaction between computers and human comprises: (i) NL understanding and (ii) NL generation. Natural language processing (NLP) underscores the procedure of translating natural language from humans to a machine understandable/readable format to improve machine perception and vice versa. This falls under the cognitive insights domain.
Expert systems	Expert systems embed the knowledge of a human experts (e.g., a highly skilled physician or lawyer) and provide a computerized consulting service which collects, preserves, interprets and disseminates knowledge as required.

[3] This table is not exhaustive. There are various other technologies that could be implemented for artificial intelligence.

Table 2 – Tools for the application of artificial intelligence[3]

Artificial intelligence tools	Description
	Generally, an expert system provides advice derived from its knowledge base, using a reasoning process embedded in its inference engine. There are three aspects to the functioning of expert systems: (i) knowledge acquisition (ii) interpretation and (iii) knowledge dissemination. This falls under the cognitive engagement domain.
Neural networks	Neural networks have the capacity to recognize and classify patterns through training or learning processes.
Machine learning	Machine learning refers to the automated detection of meaningful patterns in large data sets. Within AI, machine learning serves as a key tool for information extraction. Generally, machine learning is based on the study of algorithms that can make prediction based on available data without explicitly being programmed to do so. Machine learning may encompass data mining, unsupervised learning and predictive analysis. This falls under the cognitive insights and cognitive automation domains.
Robotics and robots	Robotics refers to the creation and functioning of robots with sensor feedback, information processing as well as action which may be accompanied by manipulation of the environment). This falls under the cognitive automation and cognitive engagement domains.

Despite the buzz surrounding AI, research and advances in this area have been patchy and unpredictable. While AI tools have the capacity to be highly tailored to specific tasks and activities within the urban domain, each of these (inter-disciplinary) technologies will require years of specialized research and controlled implementation before being utilized on a large-scale. Therefore, to build a truly empowering AI, it is essential to adopt a new and broader perspective on building a digital environment, one that underscores the capabilities of AI and enables it to flourish. Hence, the following principles need to be taken into account:

– Building cloud infrastructures to cope with the growing data volumes;
– Creating more socially oriented and communicative systems that interact with individuals and groups in a standardized and structured way;
– Building a supporting digital environment in which AI systems could be navigated and operated both separately and in clusters within smart sustainable cities.

Creating an AI system based on these principles will help exploit the full potential of both digital content and the IoT in facilitating the uses of AI technologies in the future, including self-driving cars and trucks, provisioning physical assistance for elderly individuals, food processing, delivering online purchases and mails through flying drones or other robots etc.

The integration of AI into everyday life should not undermine the importance of human intelligence. On the contrary, it is essential to integrate both human and machine intelligence in AI so that they could coexist in a two-way learning relationship. This will help bring about the division of tasks between man and machines in a complementary manner, and allow policymakers to define the type of knowledge and skills needed to be imparted to future generations. Therefore, while current technological education may be aimed in one direction- "people learning how to use machines for daily chores/functions", with the advent of global viable and applicable AI technologies, machines will increasingly learn from humans, and likewise, humans learning from machines.

6.3 Technological advances driving AI development

Several technological advancements (as given in Table 3) have also contributed to advancing different aspects of AI development. Tables 3, 4 and 5 provide an overview of this evolution.

Table 3 – Technological advancements in the domain of artificial intelligence

Technological advancements	Main characteristics
Big data-based AI	Machine learning (ML) is a very powerful tool within the AI domain which is increasingly managing vast amounts of data for making predictions and providing suggestions based on the data sets. While ML is great for predictive analytics, AI can utilize these predictions and prescribe plans/suggestions to reach a certain goal.
Cross media intelligence	Human intelligence involves the comprehensive utilization of information attained from various forms of perception, including vision, language, and auditory sense, to enable recognition, inference, design, creation, and prediction. In this context, the concept of "cross-media computing" was proposed. Cross-media intelligence allows machines to recognize their external environment. It provides a semantic connection between language, vision, graphical interfaces, and auditory sense to boost autonomic learning and inferencing.
Human-machine hybrid augmented intelligence	Human intelligence constitutes a form of natural biological intelligence. Human-machine hybrid augmented intelligence is a simulation of human intelligence that involves the corporation between computer and humans. The existence of wearable devices, intelligent driving vehicles and exoskeleton devices, indicating that the human-machine hybrid-augmented intelligence system has vast potential for future development.
Autonomous intelligence systems	Intelligent systems can perceive, create action, and learn in an autonomous fashion. Such system can usually function without external supervisory intervention for an extended amount of time.

Table 4 – Examples of various technological advancements in the domain of artificial intelligence

Technological advancement	Example	Description
Big data-based AI	AlphaGo	AlphaGo is a computer program that plays the board game "Go". It transforms big data into knowledge. It is able to learn and develop capabilities to anticipate what the next course of action would be including the memorization of the human chessboard and play patterns.
Cross media intelligence	Pokémon Go	Pokémon Go utilizes augmented-reality technology related to cross-media concepts by organically

Table 4 – Examples of various technological advancements in the domain of artificial intelligence

Technological advancement	Example	Description
		combining 3D graphics with real-time video on mobile phones.
Human-machine hybrid augmented intelligence	Lenddo	Lenddo is a predictor of an individual's character or willingness to pay after taking a loan. It provides a score from 1 to 100, with higher scores representing a lower propensity to default. It can be used to reduce risk for default or prioritize the approval of applications. It is intended to complement traditional credit scores and it relies exclusively on non-traditional data derived from a customer's social data and online behaviour.
Autonomous intelligence systems	ARAKNES- Array of Robots Augmenting the KiNematics of Endoluminal Surgery	ARAKNES aims at bringing a set of advanced bio-robotic and microsystem technologies into a patient's stomach for therapy and surgery. It integrates the advantages of traditional open surgery, minimally invasive surgery (MIS), and robotics surgery into a novel operative system for bi-manual, ambulatory, tethered, and visible scarless surgery.

Table 5 – Future research areas relating to technological advancements in the domain of artificial intelligence

Technological advancements	Future research areas and application
Big data-based AI	– Big data and its conversion into usable knowledge, and from this knowledge into intelligent behaviour and action, connects various fields and innovative services; – In this context, it will be necessary to investigate the forms of knowledge mining that combine data with other technologies to promote software-enabling knowledge computing and autonomic learning; – Further development of these technologies can be applied to develop intelligent medicine, intelligent sustainable building, the IoT ecosystem and smart cities and communities.
Cross media intelligence	– It can be used for analysis, inference, analogies and association in order to establish new intelligent technologies that can "sense the environment" better to provide appropriate responses; – Future applications include security systems, innovative design and digital creativity.
Human-machine hybrid augmented intelligence	– Future research into human-machine hybrid intelligence will require the integration and cooperativity of biological-intelligence systems with machine-intelligence systems; – Development of this area will enhance problem-solving and decision-making abilities;

Table 5 – Future research areas relating to technological advancements in the domain of artificial intelligence

Technological advancements	Future research areas and application
	– Potential applications include wearable devices, robotics and aided education.
Autonomous intelligence systems	– Future research into autonomous-intelligence systems includes the development of autonomous machinery, intelligent manufacturing, and smart vehicles. – Potential applications include unmanned vehicles, service equipment, robotics, human-machine surgeries etc.

6.4 Cognitive architecture for artificial intelligence

One common factor among cognitive architectures is the need to cover human intelligence factors to solve various tasks. Within the domain of artificial intelligence, the design and development of cognitive architectures (CAs) aims at:

(i) Capturing mechanisms of human cognition, including reasoning, control, learning, memory, adaptivity, perception and action.

(ii) Building on the cognitive capabilities through ontogeny over extended periods of time.

Over the last few decades, many different cognitive architectures have been invented and are being tested: SOAR, adaptive control of thought-rational (ACT-R), connectionist learning with adaptive rule induction on-line (CLARION), iCub and Cattell-Horn-Carroll (CHC). These models and systems have been extensively tested for various cognitive tasks involving reasoning, learning, perception, action execution, selective attention, recognition.

The CHC model is commonly used as it is well-known for showing human intelligence factors. Hence, when the CHC model is used as the basis of a new cognitive architecture, the proposed architecture will cover all the known human intelligent factors used for solving various tasks [b-ProcediaCmpSc].

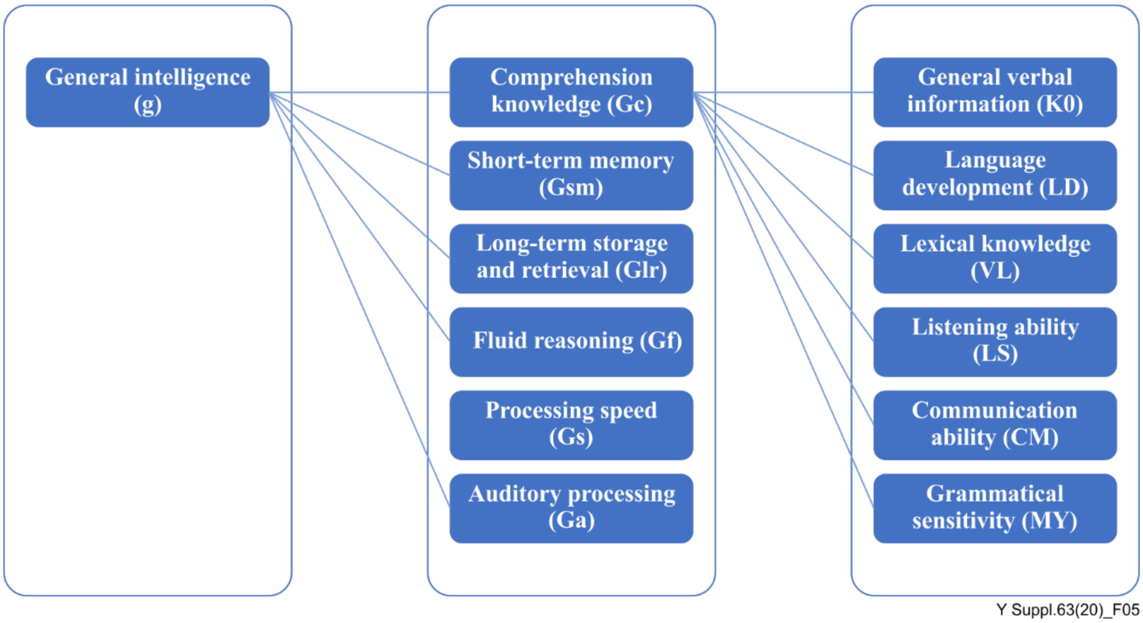

Figure 5 – CHC Model (Adapted from [b-ProcediaCmpSc])

The CHC model is organized in three layers [b-ProcediaCmpSc]:

(i) General: consists of the intelligence factor called "General Intelligence (g)", which is the integrated factor of human intelligence.

(ii) Broad: consists of 16 intelligence factors such as "Comprehension-Knowledge (Gc)" and "Fluid reasoning (Gf)". These are the basic factors of human intelligence that divide "General intelligence (g)":

- *Comprehension-Knowledge (Gc)*: cultural knowledge related to language development and communication.
- *Fluid Reasoning (Gf)*: ability to perform induction and reasoning.
- *Short-Term Memory (Gsm)*: ability to use working memory.
- *Long-Term Storage & Retrieval (Glr)*: ability to store and retrieve information over long time periods.

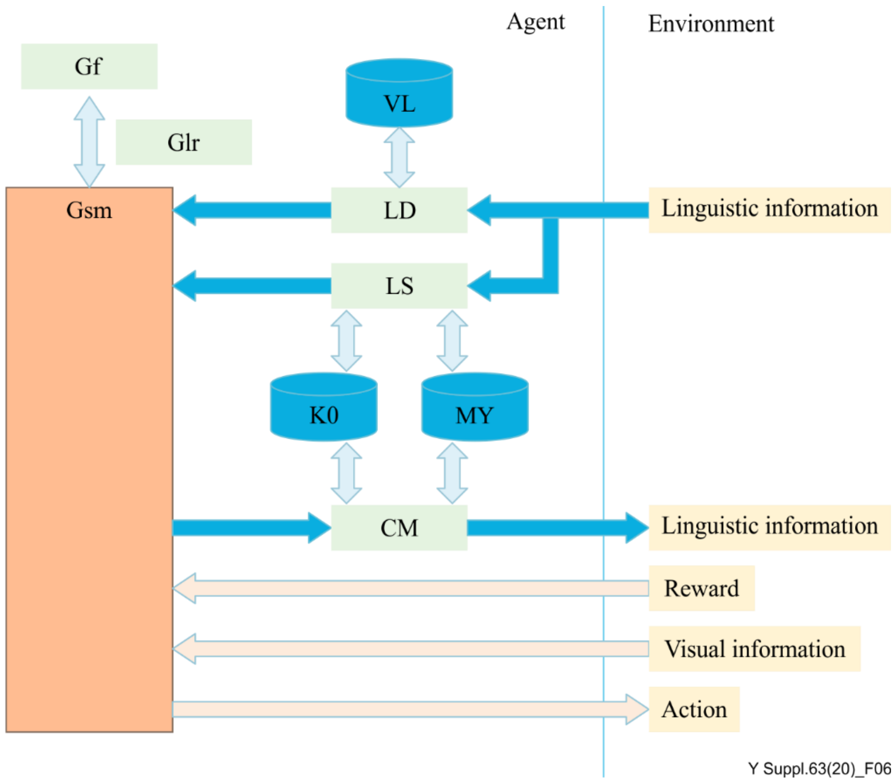

Figure 6 – Cognitive architecture for AI based on CHC [b-ProcediaCmpSc]

Table 6 – Abbreviation list relating to the CHC Model [b-ProcediaCmpSc]

Abbreviation	Function	Description
K0	General verbal information	Knowledge available in society
VL	Lexical knowledge	Knowledge of definitions of words and concepts
MY	Grammatical sensitivity	Knowledge of grammar morphology of words in speech
LD	Language development	Ability for understanding the speech at the level of words, idioms and sentences
LS	listening ability	Ability to understand speech
CM	Communication ability	Ability to use speech for communication

(1) The architecture in Figure 6, developed based on the CHC model, highlights that the linguistic information from the "environment" is processed by two components namely the

LD and LS with the aid of VL, K0 and MY. For these two components to freely interact, the architecture facilitates the linking of given words and concepts to their definition. In this scenario, it is essential that the LD components must be able to derive lexical knowledge stored in VL.

(2) Following the linking of the given words and concepts to their related concepts through the LD component, the results are sent to the Gsm. It is noted that if new concept/definitions are created during step (1), LD will store this new knowledge in VL.

(3) LS also creates new knowledge, which is stored in K0 and MY.

(4) The data are processed further by Glr for memory conversion and retrieval and by Gf for reasoning. These components then update the Gsm data. CM is used for data processing.

(5) CM uses K0 and MY data for deciding the output. Both types of data are first processed via various mechanisms, after which the results are put on the Gsm for further processing by Gf and Glr.

(6) Finally, depending on the Gsm condition, an action is created thorough various mechanisms depending on the AI application [b-ProcediaCmpSc].

7 Towards smart water management: The role of IoT and artificial intelligence in the water sector

Water quality and quantity is essential for maintaining human wellbeing and ecosystem services. Water is indispensable to produce energy, grow food and manufacturing goods (commonly known as the water-energy-food nexus). Indeed, a change in the nexus can directly impact the preservation of the ecosystems, economic activities and human life [b-H2020NAIADES]. Considering this interdependent relationship, the persistently high demand of water would eventually exceed its availability, producing water stress over freshwater sources that would put natural and human development at risk. If the world continues with the business-as-usual model, soon, it will reach ecological deficit and water scarcity will become a common occurrence. Thus, it is crucial to move towards sustainable water management and address the current stress factors more efficiently. These factors include:

- Population growth: Water scarcity is already a major issue for slightly less than one half of the population. By 2050, it is predicted the population grows from 7.7 to 10 billion people so it is expected around a 57% will suffer water scarcity [b-npjClearWater]. Population growth would not only increase water demand but also affect water quality. Indeed, the more water is polluted, the more treatments will be required, in terms of amount of chemicals and operation time (considering also its inherent costs) [b-Sustainability].
- Climate change: Climate researchers predict that global temperatures will rise by 4°C by the end of the century, resulting in more frequent and severe weather events (floods, drought, uneven distribution of rainfall). Apart from the evident problems related to safety and water scarcity, these events are also expected to trigger economic and water quality losses [b-GeogStudies].
- Human factors: Excessive water pollution is commonly attributed to human activities, from pesticides and fertilizers contaminating groundwater to toxic chemicals being released during manufacturing process. The dependence on water resources is estimated to increase as global population continues to grow [b-EncycFood]. Therefore, it is necessary to identify viable solutions and methodologies to reduce freshwater extraction from natural resources while ensuring water quality is up to standard.
- Aging infrastructures: water infrastructures in Europe are old and becoming outdated [b-ResilientWater]. Apart from the urgent necessity of repairing and renewing outdated infrastructure, it is necessary to strengthen present and future water infrastructure to mitigate water leakages and improve operational efficiency. The modernization of the water

infrastructure is moving in several ways. On the one hand, there is a trend to improve water processes through newer water technology (newer membranes, treatment procedures, etc.). On the other hand, there is a trend to digitalize the water sector. Smart technologies (e.g., smart sensors) are being deployed to enhance water infrastructure (pumps, valves, pipelines, etc.), enabling the monitoring of water quality, leakages, delivering early warning in case of any faulty event, etc. The digitalization of the water sector has been identified as a significant contribution to the operational improvement of water management, resulting in business growth and social well-being [b-IEEM].

- Inter-domain communications: It is common that the water sector is poorly connected to other sectors. Thus, the lack of integration on information regarding key sectors, include energy, pollution etc., is impeding the water sector from fully harnessing the potential of digital technologies. This is also happening in the other direction, so other sectors are missing valuable information regarding water quality, demand, availability etc. [b-EnvSc]

Managing water resources is becoming increasingly important and smart water management (SWM) has become a critical component for sustainable development worldwide. SWM enables the assessment of water availability, water quality and estimate future demands. AI is the key to support cities in unlocking SWM, boosting sustainable economic growth and protecting water resources [b-H2020NAIADES].

7.1 Reshaping Smart water grids: The role of IoT in the water sector

The current situation in the water domain is characterized by a low level of maturity concerning standardization of Information and Communications Technology (ICT) solutions and business processes [b-H2020NAIADES]. Improved and novel digital technologies (smart sensors, actuators, communication, high performance computing (HPC) portable boards) and data analytic models are being developed at a rapid pace, allowing deeper insight into water management processes to be gathered and analysed [b-H2020POWER]. To manage the required amount of resources, standardized procedures are necessary as well as enhanced communication between the digital assets of critical infrastructure. Standardization and interoperability in the water sector will serve to ensure interoperable, safe, reliable and efficient smart infrastructures. This requires a strong, competitive and dynamic ICT ecosystem in which the water sector can carry out the necessary research and innovations to exploit new technologies such as IoT and AI.

The digitalization of water infrastructures will generate large amounts of data related to water utilities. The generated data then, will be exploited according to three computing paradigms: edge, fog and cloud [b-IEEEAccess].

In contrast to cloud computing, edge computing will process data where the data is gathered, which is usually at the sensory level. The processing will be focused on specific locations or processes, having multiple edge computing points (nodes). Edge computing has the distinct advantage of faster data processing since data does not need to be sent between the cloud, enabling decisions to be made locally in real time. Edge computing can also reduce network traffic, reduce data management costs and reduce risk of a single-point failure. Combing with AI capabilities, edge computing can effectively generate Situational Intelligence that improves application and operational efficiency of water management. This analysis is based on the physical location of the monitored elements, on the analysis taking into account measurements variations with time, and on the analysis concerning all the components part of the edge (node).

Fog computing processes data at further distance from the sensors/devices than edge computing. Fog computing gathers information from all monitored processes and analyses it at the end users' infrastructure (aggregators such as local area network hardware). For example, fog computing could process outcomes from the edge computing nodes. The difference with edge computing in terms of analysis capabilities is Fog computing's widest scope, being able to generate operational intelligence i.e., analysis results providing relevant information related to operational management; and situational intelligence by obtaining results for specific processes. The analysis are based on techniques such as machine learning that extract insights from the information and then, provide valuable operational and maintenance information to water infrastructure.

Cloud computing is the paradigm that presents the widest scope and its processing is completely separated from the end users' infrastructure. All the monitored data is aggregated locally and sent to high computing capable cloud platforms; where it is processed. This approach allows to gather information from various facilities and end users, thus being possible to generate not only Situational and Operational but also Business Intelligence, offering water stakeholders (public authorities, water managers, consumers, etc.) tools and information to make effective the management of water or even more, strengthen the relation between water industry and their customers [b-H2020NAIADES].

Nowadays, IoT is more integrated in smart cities (i.e., industry where it is possible to find reference architectures such as Reference Architecture Model for Industry (RAMI) [b-RAMI] or Industrial Internet Reference Architecture (IIRA) [b-IIRA] rather than the water sector. Considering the advances in the industrial domain, the water sector is also looking to harness the potential of IoT and implement IoT architectures. Commonly, these architectures are composed of:

- Perception/Data acquisition: This layer includes low level communication between water systems of the infrastructure (SCADA, Smart Meters, sensors, actuators, etc.), and the acquisition of those measurements through different gateways, APIs, URLs and other representative data access points.
- Data management layer: It is the core of the architecture and it is in charge of data pre-processing, homogenization (common data models, ontologies), distribution and storage.
- Application layer: This includes all the applications that will be used for water management; from local water quality and quantity predictions, delivering early warnings to facilitating decision support systems (DSS) for water management, operation and planning.
- Presentation layer: This layer corresponds to any human machine interface (HMI) that commonly, are based on web tools that consumes information from REST APIs. They will display the raw data and any other relevant information from the applications that will be useful for the users.
- Security layer: The security layer is transversal to the aforementioned layers. It can be considered as an essential component embedded in the whole architecture (this is, not as a layer on itself) and it should comprise of all the security mechanisms required to ensure data privacy, access and authentication control, certified data, etc.

An edge layer could also be added to bring computation and data storage close to the data source. Therefore, this layer comprises of all the submodules required for this purpose: local data repository, data management and application; and local user interfaces. This layer is also connected to the data management layer, so the data and results of the local processing also reach the core of the architecture.

The architecture modules should also be defined to preserve interoperability with other platforms for the same or other sectors, such as smart cities and industry platforms; i.e., modules that can be exchanged with others modules or that can connect and easily share information with other platforms' modules. Sharing sensors for common measurements and sharing processing and storage capabilities will reduce the required investment and take full advantage of the already deployed IoT. Furthermore, sharing common results between platforms will improve the management, control and planning decisions and increase the social, economic and environmental impact by introducing factors from other sectors that indirectly affect those areas (business, social and environmental).

Most of the analysis and aforementioned results, provided by the application layer, are derived from the combination between mathematical modelling, simulation and AI services, providing newer insights for different sectors related to the nexus and the smart sustainable cities. In the next section, AI applications and tools for the water sector are described.

7.2 AI new smart and digital water services and their benefits for smart cities

The water sector has been benefited from AI techniques since decades ago. Traditionally, AI relied on using a single machine learning method to solve a problem. Nowadays, the process has evolved towards the combination of different models to tackle a specific problematic. This evolution is mainly driven by the increase of available data sources (thanks to advances in IoT) and the increase in processing capabilities of digital systems (GPU processing).

Indeed, the use of AI in the water sector was derived from the field known as hydro-informatics. This field is in charge of generating applications for the nexus in terms of water management, leakage detection, strengthening customer relationship with water utilities, risk detection and mitigation, etc. Currently, hydro-informatics is in charge of researching advances in IoT, AI and other disruptive techniques to improve water management and the intrinsic decision-making [b-IAHR]. The following paragraphs depict some of the most useful approaches in water sector related to data analytics and AI techniques:

- AI applied to trend analysis and forecasting (by analysing time series, for example by using long short-term memory (LSTM) networks) considering multivariate data applied to:
  - Water Consumption/Demand forecasting: this service provides insights about the consumption trends of the consumers or demand management areas (DMAs) during defined periods of time (day, month, year). It considers information such as water consumption, water flows, water availability and weather predictions [b-Biosystems]. Such information can be used to determine short-term forecast with relatively high accuracy. For long term predictions, AI algorithms can be implemented to improve the accuracy and reliability of forecasting by enabling time series analysis [b-CCWI].
  - Water Quality forecasting: this service is similar to the water consumption/demand forecasting, but the data used is mainly water quality parameters (pH, chlorine, bacteria, etc.) [b-Hydrology]. The outcomes of this service are very useful for water quality assurance and to plan future actions related to treatments, maintenance to prevent health problems related with isolated water contamination events on drinking, swimming/bathing and irrigation water. The Water Treatment Monitoring service can suggest the best treatment procedures by relating treatment and quality parameters.
  - Digital Twin for the water sector: water models that simulate the functioning of a system (distribution network, city geology for flooding) under different circumstances and configurations can generate valuable data that would allow the water systems and utility providers to optimize operational efficiency, simulate "what-if" scenario and conduct predictive analysis [b-EnvMgment]. The results of this service are essential for improving water distribution and water quality thanks to the models' capability to create data required for deep learning and simulate responses during critical situations [b-WaterResources]. This data is also crucial for predictive maintenance techniques such as Autoencoder Neural Network, which uses simple regression algorithms to detect anomalies. This is particularly useful for detecting leakages and predicting other forms of intrusion that would help providers to plan future maintenance actions [b-Knowledge]. These services, sometimes in combination with DSS, are widely used for energy efficiency, reducing energy use in water treatment processes and pumping stations [b-ICCSA].
- Decision-Making AI being applied to the water nexus: AI techniques such as machine learning, symbolic and reasoning AI can provide high level insights on the water system as a whole.
  - Decision support system (DSS) services: DSS can generate suggestions for planning, management and operation (from local to global decisions) based on the results of a variety of data sources (raw data from sensors, outputs of AI services, financial, social and data from other sectors). For example, by monitoring the water stress of plants, soil

moisture, the availability of water (by observing natural water reservoirs) and weather patterns, it becomes possible to provide the best irrigation schedule and to determine the amount of water required to increase crop productivity, income and land management, all of which are crucial for supporting rural development [b-Geophysical].

– User awareness services: these services provide useful information for the consumers providing an automated feedback loop between water utilities and water consumers, so both collaborate to make more efficient use of the resources. These services have been proved effective in the energy sector [b-Atmosphere].

– Marketplaces: it is essential to have a service that is able to provide information about all the services, tagging them with the sectors where they can be applied so new users can obtain information and be able to purchase the ones they require [b-3ICT].

The combination of the services from different sectors are also necessary to solve specific problems. Many cities face problems that require inputs from smart cities and smart water sectors. For example:

- Optimizing irrigation of city gardens requires data on weather, water availability and water consumption monitoring. Furthermore, this information can be combined with traffic information to suggest the best routes and watering schedules.
- Maintenance of water related city infrastructures requires information from different services and sectors depending on the purpose of the infrastructure. Data from different sectors can affect the predictions of failures (including infection/pollution of pools, fountains, etc.) depending on the circumstances: water quality prediction, population density, weather predictions, pollution predictions. Those predictions combined with city management strategies are very useful for schedules planning.
- Flood prevention in city areas requires information about weather predictions, urban geology, drainage network and any programmed/ongoing work that will modify them. Due to climate change, many cities are suffering from severe weather phenomena; therefore, this service provides hints about the weakness and the more susceptible areas so to actuate in advance.

All those services, on their own or combined, are proposing solutions with high social, economic and environmental impact; paving the way towards the achievement of SDGs. Clause 7.2.1 summarizes the link of water AI services and SDGs.

7.2.1 Smart water services for SDGs

Water services are designed to solve issues of water users (water utilities and consumers), and also to provide solutions to support the SDGs [b-UN DESA]. Table 7 shows the current water-related AI services that propose solutions for specific SDGs.

Table 7 – Water IoT and AI Services Impact on SDGs (X=Directly linked; x=Indirectly linked)

AI Water Services	SDG																
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Water consumption/demand prediction	X	X	x					x	x		X	X	x				
Natural reservoirs monitoring	X	X	x			X		x	x		x	X	X	X			
Irrigation management	X	X	x					X	X	x	X	X					
Water quality monitoring and forecasting			X			X			X		X			x			
User awareness				X							X	X					
Water treatment monitoring						X			X		X						

Table 7 – Water IoT and AI Services Impact on SDGs (X=Directly linked; x=Indirectly linked)

AI Water Services	SDG																
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
Predictive maintenance of water infrastructure							X	X	X		X	x	x				
Flood and drought predictions													X		x		
DSS	X	X	X	X		X	X	X	X		X	X	X	X	x		x
Marketplace																	X

7.3 The pathway and recommendations towards cognitive water architecture and AI

AI capabilities are driving a water 4.0 paradigm in which the involvement of relevant stakeholders has been crucial (consumers, academic, industry, standards developing organizations (SDOs) and administrations). Indeed, "water-smart-society" entails a better exploitation and stewardship of water. The smart-water-society will bring solid responses to overcome the existing water challenges and pave ways to the achievement of the SDGs. This vision envisages: i) avoidance of water scarcity and pollution of ground and surface water; ii) efficient use of water resources, reducing water stress; iii) minimization of environmental impacts caused by undesirable water infiltrations/exfiltration or storm water overflows; iv) effective circularity thanks to cross-domain collaboration (urban, agriculture, food, health, and energy); v) nexus aware strategies considering water and related resources (energy, food, land, under climate change); vi) contribution to carbon footprint reduction optimizing the operation and management of water infrastructure; and vii) resiliency of water infrastructures to the failure of other infrastructures (cascading effects).

To realize this vision, the water sector has been adopting open standards, such as Open Geospatial Consortium (OGC) and INSPIRE standards, to avoid vendor lock-in between physical and digital systems [b-INSPIRE]. The integration of such information is collected with reference IoT platforms that harmonize and interrelate the information using semantic technology.

Considering semantic technology approaches, the paradigm has shifted from using semantic sensor network [b-SSN] and custom semantic models to ensuring semantic interoperability towards the adoption of SAREF and NGSI-LD vocabularies in order to integrate data from IoT devices and allow for the sharing of data between water platforms and services [b-NGSI-LD]. Thus, the use of standardized platforms and semantic interoperability approaches can promote cross-domain (i.e., water, energy, food) data sharing and linkages, strengthening the decision-making process to make better decisions and to create win-win strategies based on the data correlation at cross-domain.

At the architectural level, the water domain is facing the challenge of offering cloud-based services as a result of the information coming from IoT devices. In this regard, the sector has been experimenting with FIWARE architecture, which is an open source platform, in order to standardize the collection and exploitation of water digital services [b-FIWARE]. Such reference architecture will also permit the linking of services with other relevant domains under the nexus (i.e., water, energy, food).

Indeed, cognitive AI and architectures are bringing a big paradigm shift to the water sector:

1. **Collaborative decision-making**. AI capabilities permit learning and reasoning in architectures just as humans do. With AI capabilities, the water sector can incorporate

context-aware and autonomous tools, enable cross-sectorial management of water assets and allow for the free-flowing of personal data across platforms and sensors etc.

2. **Orthogonal models**. They are used to foster and promote the collaboration between systems, people and organizations. Indeed, the orthogonal models will promote fully interoperability at the semantic and business level by facilitating process linkage between sectorial and interrelated domains. To do so, semantic interoperability (e.g., SAREF [b-SAREF]) and context-based data models (NGSI-LD) are the main drivers to provide interaction between digital systems and processes at different scales.
3. **Prescriptive management**. As a mechanism to model the human brain and adopt strategies as humans will reason. In this regard, semantic technology and natural language processing (NLP) combined with AI techniques will permit to reason and understand data and derive proper decisions considering existing situations.

Before moving towards to this innovative and future vision, there are several key considerations that need to be taken:

1. **Mature and final adopt IoT and semantic interoperability approaches**. This action point relies on using a reference IoT architecture to make interoperable water digital service across sectors.
2. **Incorporate digital mesh to enable a secured mechanism for data exchanging**. Digital Ledger technology and other identity mechanism can be incorporated to secure data exchange across the entire water value chain.
3. **Cross domain modelling for cognitive AI**. Incorporate as an intelligence layer, cross-domain AI techniques enable digital twins and other relevant algorithms to acquire and analyse knowledge from different sectors, which is crucial for formulating long term strategies and recommendations similar to those that humans can offer (i.e., techniques that allow AI to learn from the previous experience and apply this knowledge to upcoming situations).
4. **Full elaboration of cognitive architectures**. Combining analytical algorithms, IoT architectures, semantic interoperability, security and privacy with also NLP or similar approaches, water companies could offer the end-users digital services with the ability to interact in different ways with the stored information (through the voice, eyes, etc.) and then, accelerate the decision-making. This is known as cognitive services. Indeed, these techniques expose digital services through open APIs and immersive visualization engines.

8 Connecting the dots between big data and artificial intelligence: Leveraging data science for the Internet of things and sustainable development

With the spanning of IoT technologies across various smart city projects, there has been an explosion in the number of connected devices and data volumes. These streams of often unstructured data and meta data would be rendered useless without the analytical capabilities to interpret and dissect values. It is too common that the ability to process data is a lower priority than the IoT technologies that are used to collect data. Data generated within an IoT ecosystem is instrumental in helping AIs to learn, think and act. By accelerating AI capabilities within a robust IoT ecosystem, AI would be able to carry out predictive data analysis and execute sound strategies based on the data. The higher the volumes of data that needs to be processed, the better the chances of the AI system would be able to detect useful patterns and limit errors in future responses to external stimuli [b-ZteComm].

From the perspective of functioning, an IoT system can viewed as a set of smart devices that work together to achieve in a common goal. The coordinated operations of these smart devices serve as the foundation for smart city transitions. Such an IoT system for smart cities will consist of several components, each will have related functions to the processing of data and internal communication between devices.

Based on the above, an IoT system can be divided into four main elements relating to the data that is being transmitted within the system:

– *Data capture:* This step involves the collection of data from sensors. It is important to note that a device can have more than one sensor. During this step, data is obtained from the environment and pre-processed by the device itself.

– *Data communication:* The data can be exchanged between similar devices. This exchange can be achieved by wireless or wired technologies.

– *Data aggregation:* Once the data has been collected and preliminary processing has been conducted at device level, the aggregation of IoT data will be initiated and delivered to different data centres.

– *Data analysis and processing:* The data transferred to the data centres is analysed, processed and presented to the user with the use of appropriate applications. This processing takes place in specialized servers. The processed data is sent to the device again, so it can respond accordingly [b-FedConfCompSc].

As the volume of data continues to increase and data sources become more diversified, storing, transmitting, updating and processing data within an IoT system may become more difficult. AI capabilities offer the most viable solutions to tackle this challenge.

The initial spurt of AI growth was stunted as a result of limited data sets. However, at the dawn of the IoT era, real-time data is readily available. This has propelled AI revolution and allowed the transition to a data-centric approach in IoT systems. AI technologies are now agile enough to access increasing colossal datasets and adapt to the changing life-style related behaviours.

In the context of increasing number of data streams, big data is characterized by increased data volume, velocity and variety. The continuously increasing volume of structured and unstructured data, data categories, and the speed at which data is generated offer both challenges as well as opportunities. The convergence of big data and AI has emerged as the single most important development for supporting urban functioning through the utilization of data and analytical capabilities. Artificial intelligence allows the automation and enhancement of complex descriptive and predictive analytical tasks that would otherwise be time consuming and labour intensive if performed by a human.

In light of the above, it is evident that data and AI share a synergistic relationship within the IoT domain as data in itself without the adequate means for analysis and interpretation is devoid of any value. In the same vein, AI without data to fuel its applications cannot create a self-adaptive learning system within the IoT domain [b-IBA].

The unleashing of AI on big data is expected to have a significant impact on how cities operate and the overall quality of life. As the various aspects of human life (including travel time, customer satisfaction, assessment of the quality of services, delivery time of services) become predictable, AI could provide this information before-hand, thereby allowing for improved planning, prior scheduling, and overall better decision making. Accordingly, the benefits of AI can be summarized as the following [b-JournalInnovTech]:

– It utilizes a large amount of continuously changing data streams as the basis for decision support;

– It enables the monitoring of value streams based on associations and patterns for the detection of anomalies as well as for generating adequate responses to depending on the situations;

– It increases the incidence of model optimization for prediction of events based on existing data patterns;

– It is able to utilize data emerging from the IoT ecosystem to improve coordination between devices. This aspect brings forth the idea that the concept of IoT would also remain stagnant without AI technologies.

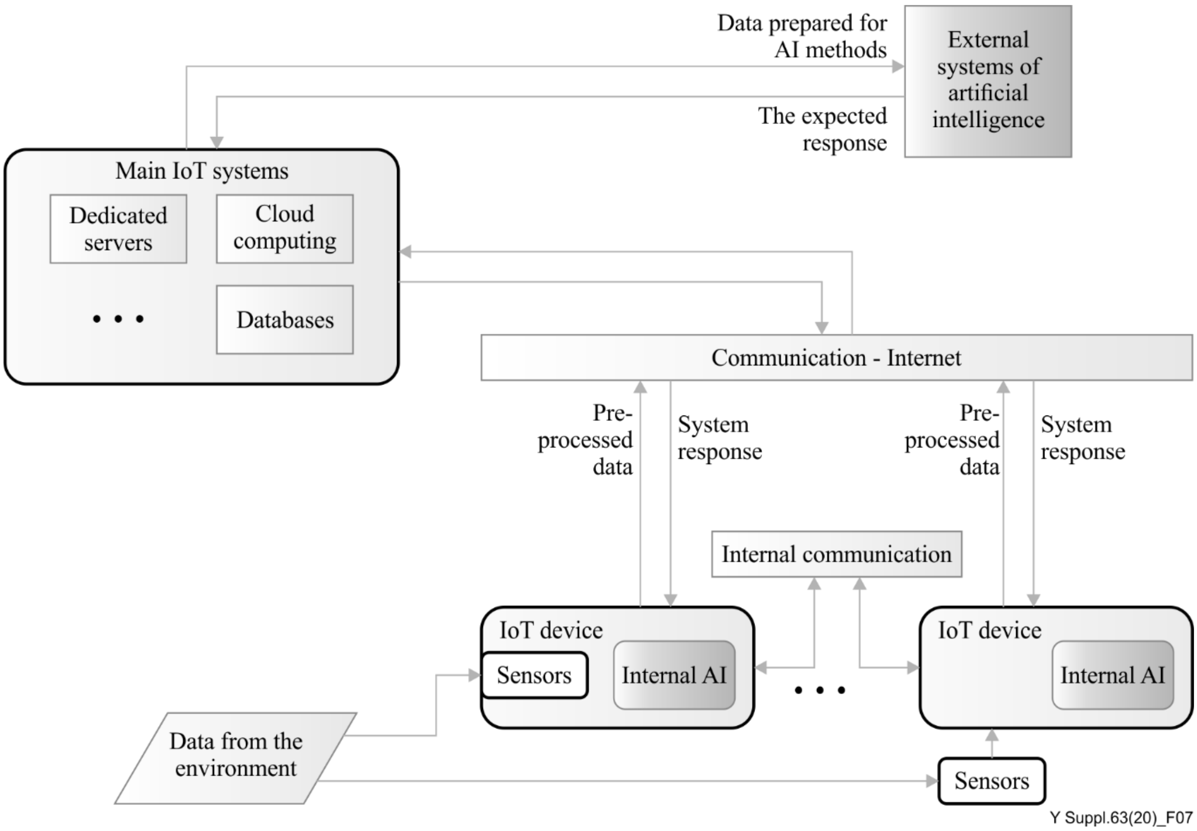

Figure 7 – Information Flow in the IoT Ecosystem with AI Methods [b-FedConfCompSc]

As such, the concept of IoT is not simply based on sensors that transmit information among themselves. IoT systems are increasingly becoming more complex, especially in the transition to smart sustainable cities. They can make decisions in a number of key aspects in cities. Thus, IoT systems need to be able to process and derive actionable insights and intelligence from a large amount of datasets in near real-time in order to add values to city services. Such characteristics cannot be achieved by using ordinary statistics or simple equations. The system needs more sophisticated tools, namely artificial intelligence.

The application of AI methods and tools can influence the IoT ecosystem in a positive way. In this regard, AI plays an important role in the IoT ecosystem as it removes the need for monotonous supervision of devices and data from the point of use. The main element associated with the operation of IoT system using artificial intelligence is its location in the architecture [b-FedConfCompSc]. Another important aspect is the performance and the appropriate amount of place for available data, which is a knowledge of the system, so the AI tools cannot be placed at each level. Figure 8 depicts the generic framework of implementing artificial intelligence in IoT architectures. The most appropriate place for adding AI capabilities are the servers because of their computing power [b-ZteComm].

The functioning of artificial intelligence can often be considered synonymous to the human brain. All the knowledge and the associated inference and learning processes are placed in the server rooms (i.e., the brain). Figure 7 presents a general scheme of information flow in the IoT systems with artificial intelligence. There are several key elements in this flow of information:

– Preliminary communication: Data sent from the real world.

– Context communication: Data processed by systems that already have the appropriate context and make the IoT systems and devices can respond accordingly and take appropriate decisions.

– Initial communication: This is taken as an additional channel of communication between IoT devices. The first stage is referred to as "preliminary communication". During this step, data from the environment (real-world) is collected by devices in the IoT ecosystem. Depending on the situation, the data is further transmitted between other devices to gather all relevant information from the real world. Within such systems, it is essential to ensure the temporary storage of information in case there is intermittent access to the web. When all the data in the context of a particular cycle, is already in the main IoT systems, respectively, it is prepared for external artificial intelligence systems.

– Determining relevant information: This process involves selecting appropriate specific information to use with the artificial intelligence tools.

– Context communication: This step involves providing the concrete systematic answers to the IoT devices and to the subsystems that are designed to take actions in the context of the relevant decisions. When the artificial intelligence tools have operated to give a reply, it should be properly interpreted. At that time, the answer provided by the IoT tools include digits that do not make much sense without the proper context. Therefore, it is important to link the answers with the knowledge located in the IoT system to be able to conclude the overall response of the system, and support smart autonomous decisions within the IoT ecosystem [b-FedConfCompSc].

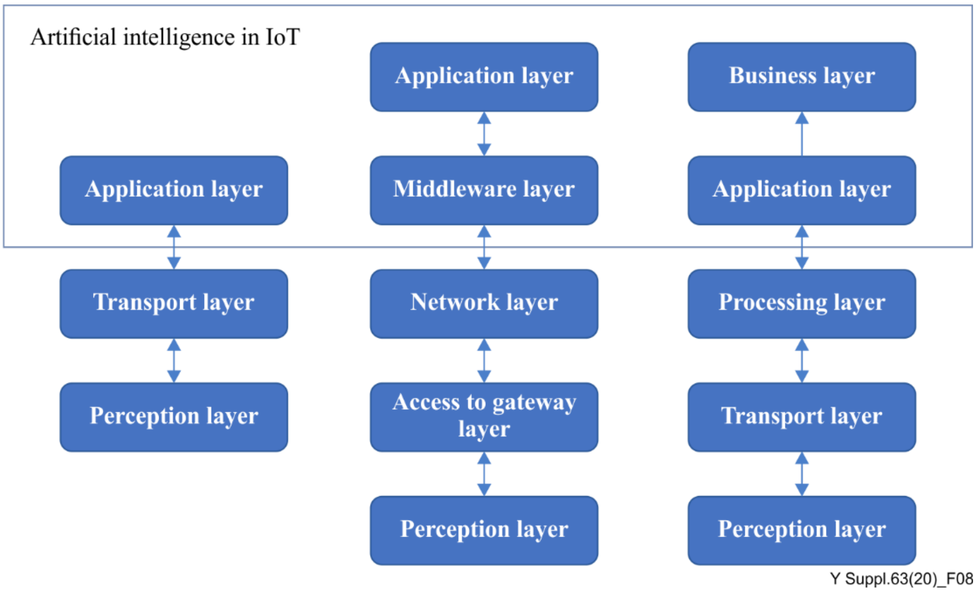

Figure 8 – Integration of AI into the IoT Ecosystem [b-FedConfCompSc]

While the "three musketeers" *(IoT, AI and data)* hold the promise of establishing a self-sustaining urban ecosystem in the form of smart sustainable cities, certain measures need to be taken into consideration by decision-makers in order to facilitate an AI-friendly environment and foster public acceptance (See Table 8). Given the potential of AI in breathing life into the IoT realm while taming the ever-increasing data streams, AI technologies could play an important role in two very important domains of smart sustainable cities: urban planning and cybersecurity.

Table 8 – Suggestions for creating AI friendly environment

Suggestion (s)
Suggestion 1: Private and public entities are encouraged to examine how they may responsibly leverage AI to benefit their area of work along with the society as a whole.
Suggestion 2: It is pertinent to have dialogue between international stakeholders, to exchange up to date information and facilitate collaboration on research and development pertaining to AI and its expansion.
Suggestion 3: Relevant stakeholders should analyse the role that AI could play in cybersecurity, while ensuring that AI systems and ecosystems are secure and resilient to external attacks or malicious incursions.
Suggestion 4: Training should be provided to professionals and scientists to facilitate further development in the AI domain
Suggestion 5: AI should be applied to national security, including military command, equipment and drills
Suggestion 6: Domestic AI companies and researchers should be encouraged to cooperate with leading foreign AI teams and consider merging with or investing in foreign companies, setting up joint research centres and AI international organizations.
Suggestion 7: Appropriate laws, regulations and ethical principles relating to AI should be formulated along with ethic principles on data collection.
Suggestion 8: Technology standards, an intellectual property rights system, and a supervision mechanism should also be adopted.
Suggestion 9: AI should be applied in the public service and social management to build a safer, more comfortable and convenient society. Smart education, healthcare and elder care should be promoted. AI should also be applied in public administration, court, urban management, transportation, environmental protection and public security.

8.1 The role of artificial intelligence in cybersecurity

IoT platforms are currently threatened by a myriad of external dangers. New attacks target IoT platforms by taking advantage of existing vulnerabilities in devices, poorly managed/configured security settings (i.e., default passwords) or even by using social engineering techniques that engage users to install malware or disclose passwords. National governments are increasingly relying on data-driven AI applications to deal with security and privacy concerns. In this regard, machine learning platforms could essentially identify erroneous or incomplete data and prevent making misleading decisions. Such platforms could also help detect and isolate infected or malicious software immediately and additionally suggest effective policy and laws for governing and safeguarding sensitive information.

As such, the heterogeneous, distributed and dynamically evolving nature of IoT and growing data streams have increased the incidences of unexpected risks that cannot be protected using just the current state-of-the-art security solutions [b-IBA].

For this, new paradigms and methods are required in order to build security at the outset, adapt to changing security conditions, create a self-adaptive system, and provide the assurance that the system is secure. The aforementioned aspects are being dealt with under the ANASTACIA project (carried out under the EU Horizon 2020 Programme), which is built on top of IoT platforms to protect against external threats.

ANASTACIA [b-ANASTACIA] has been conceived as a policy-based framework where system admins (at the user plane) set a specific security policy that must be fulfilled within an IoT platform. This project aims to develop a holistic solution enabling trust and security by-design for cyber physical systems (CPS) based on IoT, AI and cloud architectures.

Based on the core concept of AI, ANASTACIA is developing a trustworthy-by-design security framework which is expected:

- to address all the phases of the ICT systems development lifecycle (SDL)

- to take autonomous decisions through the use of new networking technologies such as software defined networking (SDN) and network function virtualization (NFV) and AI-assisted, dynamic security enforcement and monitoring methodologies and tools to enact smart security planning, enforcement and monitoring strategies.

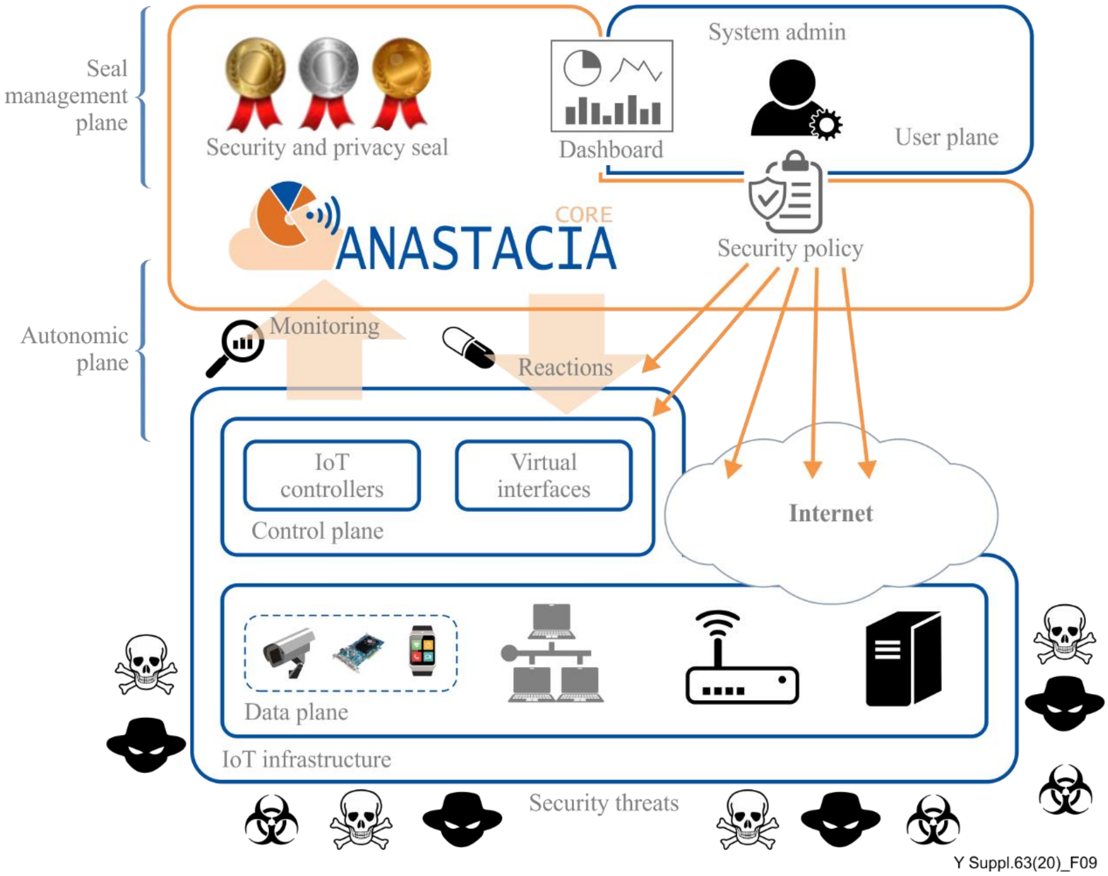

Figure 9 – ANASTACIA system model [b-ANASTACIA]

The current system model seeks to enable trust and security by-design for Cyber Physical Systems (CPS) based on IoT and cloud architectures. ANASTACIA implements AI at the Autonomic plane to identify security threats, and trigger relevant reactions, mitigating the effects of attacks. Furthermore, at the Seal Management plane, security insights from other planes are enriched with AI insights to identify potential privacy breaches. These are finally displayed in the Dynamic Security and Privacy Seal to enable end-users, DPOs and CISOs to easily understand any potential affectation to the IoT platform.

8.2 Complementary AI activities in SDOs

Complementary standardization activities related to AI for IoT are carried out in other SDOs, including the International Organization for Standardization (ISO) and the European Telecommunications Standards Institute (ETSI).

ISO/IEC JTC 1/SC 42 was created in 2017 and is exclusively focused on artificial intelligence with a dual scope of:

– Serving as the focus and proponent for JTC 1's standardization program on artificial intelligence.

– Providing guidance to JTC 1, IEC, and ISO committees developing artificial intelligence applications.

ISO/IEC JTC 1/SC 42 consists of 11 working groups on AI management systems standard; AI systems engineering; dissemination and outreach; liaison with SC 38; intelligent systems engineering; governance implications of AI; foundational standards; big data; trustworthiness; use cases and applications; computational approaches and computational characteristics of AI systems.

Currently, there are three published ISO standards under the direct responsibility of ISO/IEC JTC 1/SC 42 in the field of big data reference architecture. Additionally, 13 ISO standards in the field of AI are under development, covering a variety of topics such as risk management, the trustworthiness in AI, framework for artificial intelligence (AI) systems using machine learning (ML), bias in AI systems and AI aided decision making, use cases, ethical and societal concerns, computational approaches for AI systems, process management framework for big data analytics, governance implications of the use of artificial intelligence by organizations [b-ISO].

ISO/IEC JTC 1/SC 42 is in liaison with ISO/IEC JTC 1/SC 41 on Internet of things and related technologies. At this time, the work carried out by ISO/IEC JTC 1/SC 42 contributes to SDG 11 'Industry, innovation and infrastructure'.

Additional work in the field of AI is carried out by ETSI, particularly through the creation of the Industry Specification Group on Securing Artificial Intelligence (ISG SAI) in 2019. The group seeks to address issues stemming from the deployment of AI throughout multiple ICT-related industries. The scope of the specification group is threefold:

– Securing AI from attack.
– Mitigating against AI.
– Using AI to improve security measures against attack from other things.

The future work of SAI will include developing best practices and recommendations of mitigating mechanisms to be implemented in the domains most likely to be impacted by threats to/from AI [b-ETSI].

8.3 Innovating the way towards the Sustainable Development Goals: How artificial intelligence can secure our future

As seen in Table 9, AI tools, such as machine learning, deep learning and neural networks, can pave ways for achieving Sustainable Development Goals (SDGs). Studies indicate that AI can act as an enabler of 134 targets out of 169 targets, or 79 percent, of the SDGs [b-nature 2019]. For example, traditional data collection methods such as frequent household surveys tend to be financially prohibitive as well as time consuming. Jean et. al., has demonstrated the combined use of machine learning and deep learning techniques to help train the neural networks in predicting and targeting poverty in developing countries. This can help governments to make effective decisions that can further pave the way towards achieving no poverty which is the first Sustainable Development Goal (SDG 1).

Several private organizations are also taking initiatives in developing AI technologies that focus on achieving the SDGs such as sustainable cities and communities (SDG 11), life on land (SDG 15) and life below water (SDG 14). For instance, the health of coral reefs is essential as it provides jobs to millions of people in coastal areas while supporting fish stocks that feed a much larger population. NVIDIA, in partnership with the University of California, Berkley's Artificial Intelligence Research Centre and the University of Queensland's Global Change Institute have helped scientists to make quick and effective assessments on the health of the reefs to take necessary protective actions with the help of a deep learning process, using image-analysis and deep learning algorithms [b-NVIDIA]. Another prime example is, Sadako Technologies, a start-up based in Barcelona, which is combining machine learning with robotics to help see, identify and select targeted recyclables and other items for recovery. Their technology uses real-time monitoring and AI/computer vision to determine the product composition (kind and quantity) in a cost-effective and efficient manner [b-Sadako].

This encompasses the goals within SDG 11 and SDG 12 which deals with sustainable cities and communities and responsible consumption and production, respectively.

Biometrics is another valuable tool in AI that can be efficiently deployed to achieve the targets in various SDGs. For instance, biometrics can be used to ensure that distribution of food reaches those in need to enable effective management of food aid which is one of the targets of SDG 2 i.e., Zero Hunger. An example of such a system being implemented is a project being undertaken by the United Nations World Food Programme (UNWFP) on behalf of the Government of Odisha (a state in India) to reissue ration cards based on biometric systems [b-BiomTech]. A ration card is a document that has been issued by an authority of a State Government, to provide essential commodities such as food grains, oil etc. at subsidized rates to people who are economically weak. The implementation of biometric based ration cards can help reduce frauds while at the same time ensuring that the benefits are transferred to the needy [b-BiomTech]. Similarly, biometric systems are being implemented in various countries for the purpose of digital registration of the population including support to national ID card systems. This is in line with SDG 16 which focuses on Peace, Justice and Strong Institutions. In addition, the various AI tools can help in predicting and modelling potential pandemic outbreaks. With the aid of medical data and by constant monitoring of the patient population, it is possible for the AI to recognize and help identify any potential outbreaks and provide valuable input for the health authorities to take preventive actions [b-ITUNews]. Modern smart devices also utilize AI based applications to continuously monitor an individual's well-being.

Another aspect where AI tools play a key role is in the field of climate change. A recent article published by the World Economic Forum (WEF) highlights the use of AI by various technology giants to become smarter in their energy consumption [b-WEF]. A prime example is the use of Deep Mind, an AI platform created by Google to predict when its data centres will become too hot. One of the primary sources of energy use in Google is the cooling of its data centres which house servers powering Google search, Gmail, YouTube, etc. As these data centres are dynamic in nature, they witness huge fluctuations in load thereby making efficient cooling of the servers non-optimal. With the implementation of Deep Mind, Google began applying machine learning to make the data centres more efficient. By using a system of neural networks to train the data centres to operate under different scenarios and parameters, Google was able to create a more efficient and adaptive framework to understand data centre dynamics and optimize efficiency. The result was that Google was able to achieve a 40% reduction in their energy consumption [b-Deepmind]. It is evident that AI can help organizations to achieve reduction in energy consumption and thereby reducing their impact on the climate in line with SDG 13 on climate action.

Access to Clean water and sanitation as mentioned in SDG 6 is a basic necessity which is still lacking in many parts of the world. It is predicted that AI based systems can be put to the advantage of providing clean water to the consumers. In this regard, JEA Management, an electric, water, and sewer utility in the USA, has introduced an automated supervisory control for regulating the amount of water pumped from the aquifer by evaluation of data from various sources [b-WaterWorld]. Similarly, other companies are also implementing AI tools to ensure supply of clean water to the end users. SCADA based systems can be used to notify the operators/managers of these water supply and/or treatment plants to provide real time data of the plant status, thereby, enabling them to take the necessary corrective actions [b-Weftec].

The concept of neural networks, though discovered 50 years ago, has only gained practical applications in the last 20 years [b-McKinsey]. These tools have been used by researchers for the purpose of modelling in renewable energy systems. Solar water heating (SWH) systems using AI based tools have been successfully installed in various locations in Greece helping to optimize the energy extracted by the system [b-AppliedEnergy]. Such AI based tools can be developed for various renewable energy sources to develop smart systems in line with SDG 7, which promotes the use of affordable and clean energy. Similar progress has been made in the field of smart manufacturing as highlighted in SDG 9 "Industry, Innovation and Infrastructure". Several industries now employ advanced robotic systems in the manufacturing process that aid in reducing unplanned downtime by 10 percent to 20 percent [b-BusinessInsider].

Table 9 – Examples of AI Contributions to SDGs

SDG	SDG description	Example of AI contributions to SDGs
1	No poverty	Using machine learning and deep learning techniques to help train the neural networks in predicting and targeting poverty in developing countries
2	Zero hunger	Using biometrics to ensure that distribution of food reaches those in need to enable effective management of food aid
6	Clean water and sanitation	AI based systems to the advantage of providing clean water to the consumers. SCADA based systems to notify the operators/managers of these water supply and/or treatment plants to provide real time data of the plant status, thereby, enabling them to take the necessary corrective actions
7	Affordable and clean energy	AI based tools developed for various renewable energy sources to develop smart systems
9	Industry, innovation and infrastructure	Advanced robotic systems in the manufacturing process that aid in reducing unplanned downtime
14	Sustainable cities and communities; life below water; life on land	Making quick and effective assessments on the health of the reefs to take necessary protective actions with the help of a deep learning process, using image-analysis and deep learning algorithms
11, 12	Sustainable cities and communities, responsible consumption and production	Combining machine learning with robotics to help see, identify and select targeted recyclables and other items for recovery
13	Climate action	Applying machine learning to create a more efficient and adaptive framework to understand data centre dynamics and optimize efficiency
16	Peace, justice and strong institutions	Using biometric systems for the purpose of digital registration of the population including support to national ID card systems

8.4 Challenges of using AI to achieve the SDGs

While AI can contribute up to 79 percent of all SDG targets, the development of AI may also negatively impact up to 35 percent of the targets across the SDGs [b-NatureC 2019]. The chief among concerns over AI is the replacement of jobs. The additional qualification requirements for jobs related to AI may also act as a barrier to sustainable economic growth. Moreover, while AI can dramatically improve productivity, low-income and the least developed countries may not have access to the resources needed to participate in the digital economy, further risking to widen the gap between the "haves" and "have-not" countries and facilitating inequalities. This can directly impact SDG 9 build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation" and SDG 10 "Reduce inequality within and among countries".

In addition, the energy consumption of AI and, by de facto ICTs, is also growing at an exponential pace. Growing data traffic, consumer devices, network equipment and other products of ICTs are contributing rising energy demand. While the ICT sector only accounts for roughly 2 percent of global electricity demand, studies have projected that the demand will grow to 20 percent in the worst-case scenario [b-nature 2018]. Recent studies also suggest that training a single AI could emit more than

626,000 pounds of carbon dioxide, almost five times the lifetime emissions of an average American car [b-MIT 2019]. The growing energy demand of AI and ICTs can become an inhibitor to achieving SDG 9, SDG 11 "Makes cities and human settlement inclusive, safe, resilient and sustainable" and SDG 13 "Take urgent action to combat climate change and its impacts".

Another concern of machine learning through AI is the fact that dataset biased will also be reflected in AI algorithms, producing results that have inherited human biases. Studies indicate that there are mainly three types of biases that can be found in datasets; interaction bias – e.g., people being misidentified in facial recognition due to lack of information; latent bias – e.g., people being incorrectly identified based on historical data and stereotype; and selection bias – e.g., when the dataset has overrepresented certain groups or underrepresented certain groups and swayed selection process based on biased data [b-Forbs 2020].

In order to harness the full potential of AI and steer the development of AI in the direction that would bring benefit to all citizens, a change of paradigm is needed to refocus on promoting open collaboration, improving environmental efficiency and investing in human resources for the next generation through a participatory and inclusive process.

Annex A

Existing international standards on AI related technologies

The study of standardization has been carried out by Standards Development Organizations (SDOs). This annex provides a brief overview of the standardization related work carried out in the domain of AI.

ISO/IEC JTC 1/SC 35

Standards published:

– ISO/IEC 20382-1: 2017, Information technology – User interfaces – Face-to-face speech translation – Part 1: User interface.
– ISO/IEC 20382-2: 2017 Information technology – User interface – Face-to-face speech translation – Part 2: System architecture and functional components.
– ISO/IEC 30113-5:2019, Information technology – User interface – Gesture-based interfaces across devices and methods – Part 5: Gesture Interface Markup Language (GIML).
– ISO/IEC 30122-1:2016, Information technology – User interfaces – Voice commands – Part 1: Framework and general guidance.
– ISO/IEC 30122-2:2017, Information technology – User interfaces – Voice commands – Part 2: Constructing and testing.
– ISO/IEC 30122-3:2017, Information technology – User interfaces – Voice commands – Part 3: Translation and localization.
– ISO/IEC 30122-4:2016, Information technology – User interfaces – Voice commands – Part 4: Management of voice command registration.

ITU-T SG5 "Environment, climate change and circular economy"

Title	Timing
Recommendation ITU-T L.1300, Best practices of green data centres	2014
Recommendation ITU-T L.1301, Minimum data set and communication interface requirements for data centre energy management	2015
Recommendation ITU-T L.1303, Functional requirements and framework of green data centre energy-saving management system	2018
Recommendation ITU-T L.1305, Data centre infrastructure management system based on big data and artificial intelligence technology	2019
Recommendation ITU-T L.1320, Energy efficiency metrics and measurement for power and cooling equipment for telecommunications and data centres	2014
Recommendation ITU-T L.1380, Smart energy solution for telecom sites	2019

ITU-T SG16 "Multimedia"

Title	Timing
Recommendation ITU-T H.703, Enhanced user interface framework for IPTV terminal device" – Gesture Control Interface	2016
Recommendation ITU-T F.749.10, Requirements for communication services of civilian unmanned aerial vehicles	2019
Recommendation ITU-T F.746.5, Framework for a language learning system based on speech and language processing (NLP) technology	2017
Draft Recommendation ITU-T F.AUTO-TAX, Taxonomy for ICT-enabled motor vehicle automated driving systems	2018
Draft Recommendation ITU-T H.861.0 Requirements on communication platform for multimedia brain information	2017
Draft Recommendation ITU-T HSTP.MBI-UC, Use-cases of e-health applications and services using brain data	2020

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