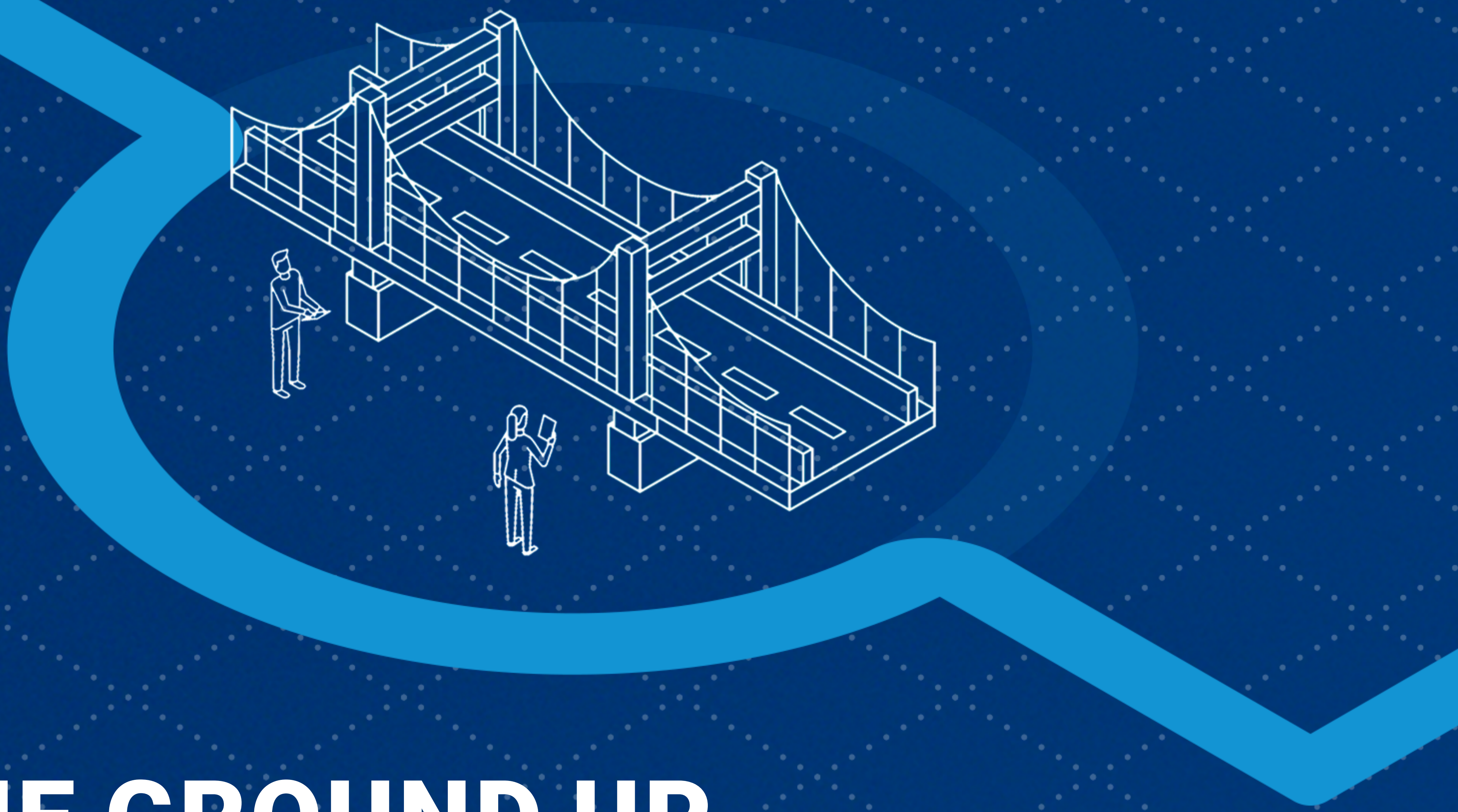
AI FROM THE GROUND UP



CHALLENGES AND OPPORTUNITIES IN THE CONTEXT OF LATIN AMERICA AND THE CARIBBEAN

IDB

AI
FROM THE GROUND UP

CHALLENGES AND OPPORTUNITIES IN THE
CONTEXT OF LATIN AMERICA AND THE CARIBBEAN

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September 2024

Cataloging-in-Publication data provided by the

Inter-American Development Bank

Felipe Herrera Library

AI from the ground up: challenges and opportunities in the context of Latin America and the Caribbean / Guillermo Cruz, Alexander Riobó, María Angélica Pfeifer, Diana Duarte.

p. cm. — (IDB Monograph ; 1247)

Includes bibliographic references.

1. Artificial intelligence-Latin America. 2. Artificial intelligence-Caribbean Area. 3. Infrastructure (Economics)-Effect of technological innovations on-Latin America. 4. Infrastructure (Economics)-Effect of technological innovations on-Caribbean Area. I. Cruz, Guillermo. II. Riobó Patino, Alexander. III. Pfeifer, María Angélica. IV. Duarte, Diana. V. Inter-American Development Bank. Transport Division. VI. Inter-American Development Bank. Energy Division. VII. Inter-American Development Bank. Water and Sanitation Division. VIII. Inter-American Development Bank. Infrastructure and Energy Sector. IX. Series.

IDB-MG-1247

Keywords: Artificial Intelligence, intelligent infrastructure, digital transformation, Deep learning / JEL Codes: O31, O32, O33

Design and layout: .Puntoaparte

December 2024

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Acronyms

AI Artificial Intelligence

ANN Artificial Neural Networks

API Application Programming Interface

ATMS Advanced Traffic Management Systems

CAF Development Bank of Latin America and the Caribbean

CNN Convolutional Neural Networks

DL Deep Learning

DNP Departamento de Planeación Nacional de Colombia

DT Digital Twins

EPMAPS Empresa Pública Metropolitana de Agua Potable y Saneamiento de Quito

ETL Extract, Transform, and Load

FM Foundational Model

GPS Global Positioning System

GPU Graphic Processing Unit

IDB Inter-American Development Bank

IMF International Monetary Fund

iRAP International Road Assessment Program

IoT Internet of Things

LAC Latin America and the Caribbean

LLM Large Language Models

ML Machine Learning

MVP Minimal Viable Product

NLP Natural Language Processing

OECD Organization for Economic Cooperation and Development

SVM Support Vector Machine

UAVs Unmanned Aerial Vehicles

UPS Uninterruptible Power Supply

WEF World Economic Forum

YOLO You Only Look Once

INTRODUCTION

Artificial Intelligence (AI) has become critically important because it can significantly transform diverse economic sectors and multiple dimensions of society. The potential impact of this technology is such that in the international context it has been stated that it is in the process of becoming a general-purpose technology, [1] such as the steam engine, electricity, information technology, and the Internet.

1 See, for example, the Recommendation of the OECD Council on Artificial Intelligence (OECD/LEGAL/0449).

The exponential growth in computational capacity, along with the resulting decrease in costs, the digitalization of information, and the expansion of the Internet, have been key to making this technology accessible to governments and organizations across different economic sectors. Different businesses and entities in the energy, transport, water and sanitation, and solid waste sectors have recently started adopting AI-based solutions for missions and strategies to improve systems planning, optimize operations and maintenance of assets, reduce costs, and deliver better services. Creating value through AI is very important for countries, governments, and public and private organizations because the services provided by infrastructure sectors are critical for economic growth and the normal functioning of societies.

This document offers recommendations and technical considerations to develop and adopt AI-based solutions in infrastructure sectors. These recommendations are based on global evidence, the experience of the IDB, and the lessons learned from the deployment of tools in Latin America and the Caribbean (LAC). The elaboration of this publication included 17 interviews with IDB technical teams and with clients and external actors experienced in developing and implementing solutions using emerging technologies and AI. The document includes as an annex a review of regulatory frameworks applicable to AI in LAC.

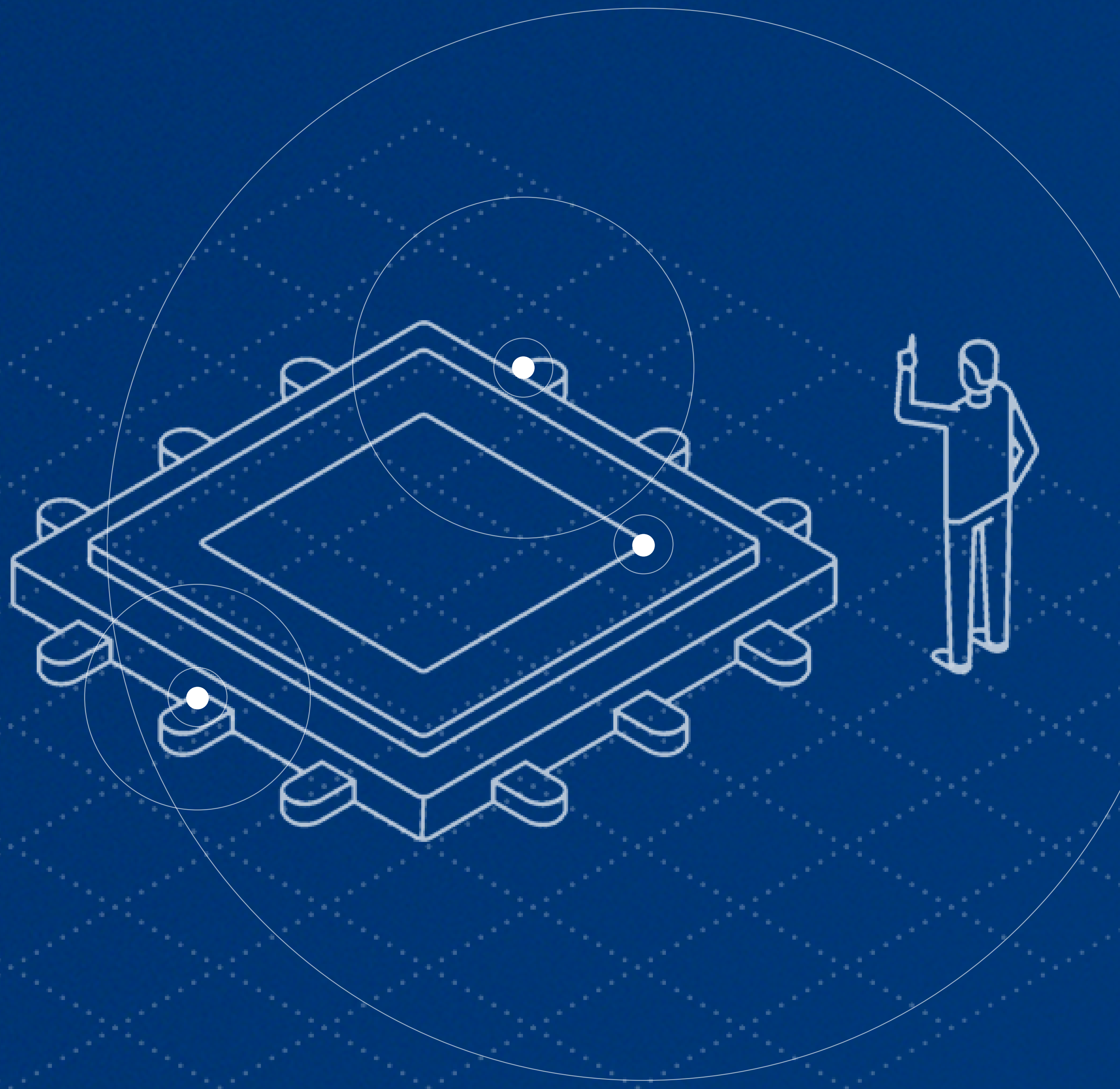
The objective of the document is to provide conceptual and methodological approaches to leaders, policy-makers, project teams, public and private technical units, developers and other actors in the entrepreneurial ecosystem that help strengthen the design and development of solutions in the infrastructure sectors and to maximize the opportunities offered by AI in this area.

The document concludes with recommendations to successfully develop and implement these solutions in LAC. The main recommendations include the following: (i) implement agile AI development and innovation methodologies and consider the use of Proof of Concept, prototypes, and Minimum Viable Products that are spaces for experimentation, learning, and feedback to improve solutions; (ii) define organizational schemes that facilitate the development and adoption of these solutions, as well as assess and ensure the existence of the skills necessary on the teams; (iii) understand the importance of data and their governance, and in doing so determine the data necessary, available sources, architecture, and the flow of these elements; (iv) identify and evaluate, starting in the design stage, the requirements for technological tools and data infrastructure to design solutions, especially for data storage and processing capacity; (v) define objective criteria to select the models to address the nature of the problem, the type and quality of the information, computational capacity, and performance objectives and explainability; and (vi) pay special attention to ethical, privacy, and security aspects from the initial design stages.

WHAT IS ARTIFICIAL INTELLIGENCE?

2.1
Definition of Artificial Intelligence

The concept of AI has been one of shared use in the discipline of information technology since the 1940s through the work of professors such as Alan Turing and John Von Newman,[2,3] among others. Specifically, this concept was born in a workshop at Dartmouth College in 1956 that included the participation of experts such as John McCarthy, Alan Newell, Arthur Samuel, Herbert Simon, and Marvin Minsky, to whom the term AI is attributed (OECD 2019; Wang 2019).



2 In his work *"Computing Machinery and Intelligence"* (1950), Alan Turing posed the question "Can machines think?" in order to develop a game – "The Imitation Game" – subsequently known as the *"Turing Test,"* where through a series of questions the researcher could determine if an interlocutor was a human or a machine.

3 John Von Neumann developed a series of mathematical principles with the aim of building a computer that could carry out complex calculations in a small amount of time and could even contribute to solving more structural problems.

Different organizations in the international arena have proposed definitions of AI that share certain elements but include specific ones as well. The Institute of Electrical and Electronic Engineers (IEEE) defines AI as "the theory and development of computer systems that are able to perform tasks which normally require human intelligence, such as visual perception, speech recognition, learning, decision-making, and natural language processing" (IEEE-USA 2017).

In different documents, the IDB has referred to AI as a broad concept that includes computer technologies that can emulate typical skills of humans.[4,5] This definition refers to computer systems that can identify their surrounding environment and think, learn, and decide based on inputs received and the purposes of the model.[6] The World Bank defines AI as the capacity of computer systems to carry out tasks associated with human intelligence, such as vision, speech and language, and knowledge and the search for solutions (World Bank 2020). The Development Bank of Latin America (CAF) defines AI as "a field of study that refers to the creation, through the use of digital technologies, of systems capable of developing tasks for which human intelligence is required" (Vélez et al. 2022).

The European Union states that an AI system requires a minimum level of autonomy and that, through data provided by machines and/or persons, meets the objectives defined by the human being. This is done through approximations of knowledge, machine learning, and/or logic. The results generated include content, recommendations, decisions, or predictions that in turn modify that which surrounds the AI system. [7]

The Organization for Economic Cooperation and Development (OECD) defines AI as an automated system that learns through inputs how to create products based on explicit or implicit objectives. The products generated include content, decisions, predictions, and recommendations. An AI system is represented by its components and the manner with which it interacts with the environment in terms of inputs and results (**Figure 1**).

The OECD definition refers to explicit objectives of the model when the programs are developed directly by a human developer, while the objectives are implicit when programs are developed through a set of rules defined by a human, or when the system can learn new objectives. [8]

4 In other documents, such as, for example, *Uso responsable de la IA para las políticas públicas: Manual de ciencia de datos*, this entity makes reference to the definition by the OECD as presented in this document.

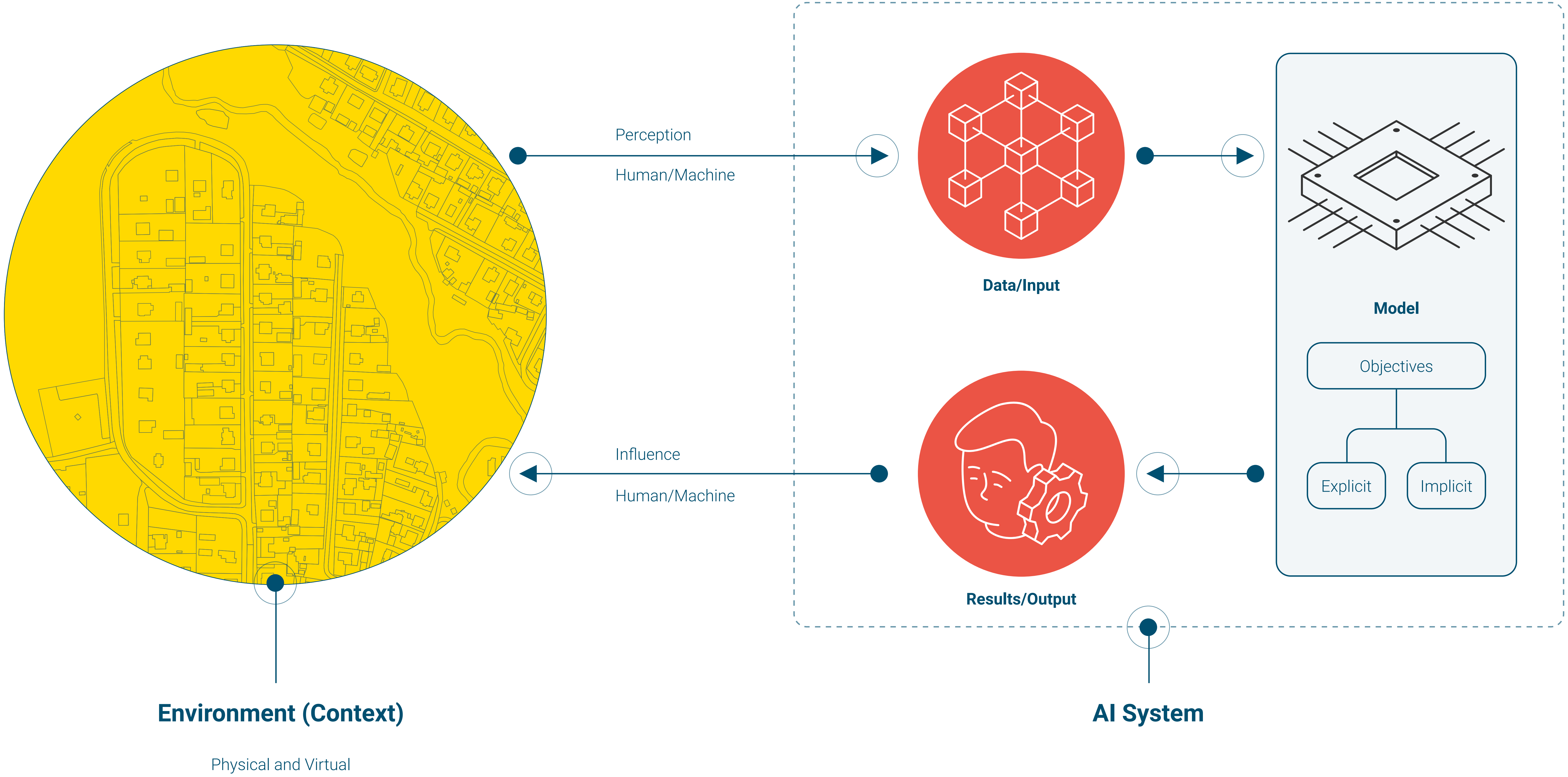
5 "Artificial Intelligence: Basic Concepts and Applications in Development" (2019, February). Available at https://blogs.iadb.org/conocimiento-abierto/es/inteligencia-artificial/

6 "Artificial Intelligence that Supports and Changes in the World of Work" (2022, September). Available at https://blogs.iadb.org/trabajo/es/inteligencia-artificial-que-aporta-y-que-cambia-en-el-mundo-del-trabajo/

7 The EU Artificial Intelligence Act. Available at https://www.artificial-intelligence-act.com/#:~:text='Artificial%20intelligence%20system'%20(AI,logic%2D%20and%20knowledge%20based%20approaches%2C

8 Ibid.

Figure 1. Artificial Intelligence System



Source: Adapted by the authors from OECD (2023), "Updates to the OECD's Definition of an AI System Explained."

In general terms, AI systems can be categorized into three types depending on their functions and capacities:

Narrow or Weak AI:

All the developments regarding AI up to today are found within this classification. Narrow AI systems have the capacity to carry out a concrete task (OECD 2019; Pombo et al. 2020; Vélez et al. 2022) without having consciousness or sensibility, or being influenced by emotions (Vélez et al. 2022). However, in the case of Generative AI, foundational tool models such as ChatGPT, Gemini, or MetaAI can adapt their responses to simulate being empathetic with users.[9]

General or Strong AI:

This refers to systems that have the capacity to understand and carry out tasks in different knowledge areas like humans, including having similar cognitive capacities (OECD 2019; Pombo et al. 2020; Vélez et al. 2022). Up until now these systems are theoretical.

Superintelligent AI:

This third type of AI could surpass all facets of the cognitive capacity of human beings (Pombo et al. 2020). This system continues to be speculative and does not have solid theoretical models that foresee developments in the short term.

9 Source: Conversations with ChatGPT, Gemini, and MetaAi about sentiments and emotions.

2.2
Types of AI Systems

Generally, the literature refers to a broad set of AI systems that include as subcomponents Machine Learning (ML) and Deep Learning (DL). There are AI systems that are not considered to be machine learning because they are not based on the training of models through data; some examples are expert systems,[10] genetic algorithms,[11] and search algorithms,[12] among others.[13]

10 Those can be defined as "Advanced information systems that model expertise in a specific area in order to imitate the decision-making processes of experts." Source: ScienceDirect. Available at: https://www.sciencedirect.com/topics/social-sciences/expert-systems

11 As mentioned in Section 3.2.2, a genetic algorithm is a computational search technique to find approximate solutions to optimization models and search problems. It is inspired by the process of natural evolution, where the best solutions to a problem are combined and mutated to create new solutions, all within an iterative process that stops when the best solution possible is found. Source: https://www.sciencedirect.com/topics/engineering/genetic-algorithm

12 Search algorithms are computational methods that are used to locate specific data within a collection of data. Definition based on Rouse (2017), *Search Algorithm*. Techopedia. Available at https://www.techopedia.com/definition/21975/search-algorithm

13 William, E. (2023). *Non Machine Learning AI Examples*. Medium. Available at https://emmawilliam.medium.com/non-machine-learning-ai-examples-3e8c8fd85149

Below is a general description of the concepts of ML, DL, and, related to the latter, Generative AI:

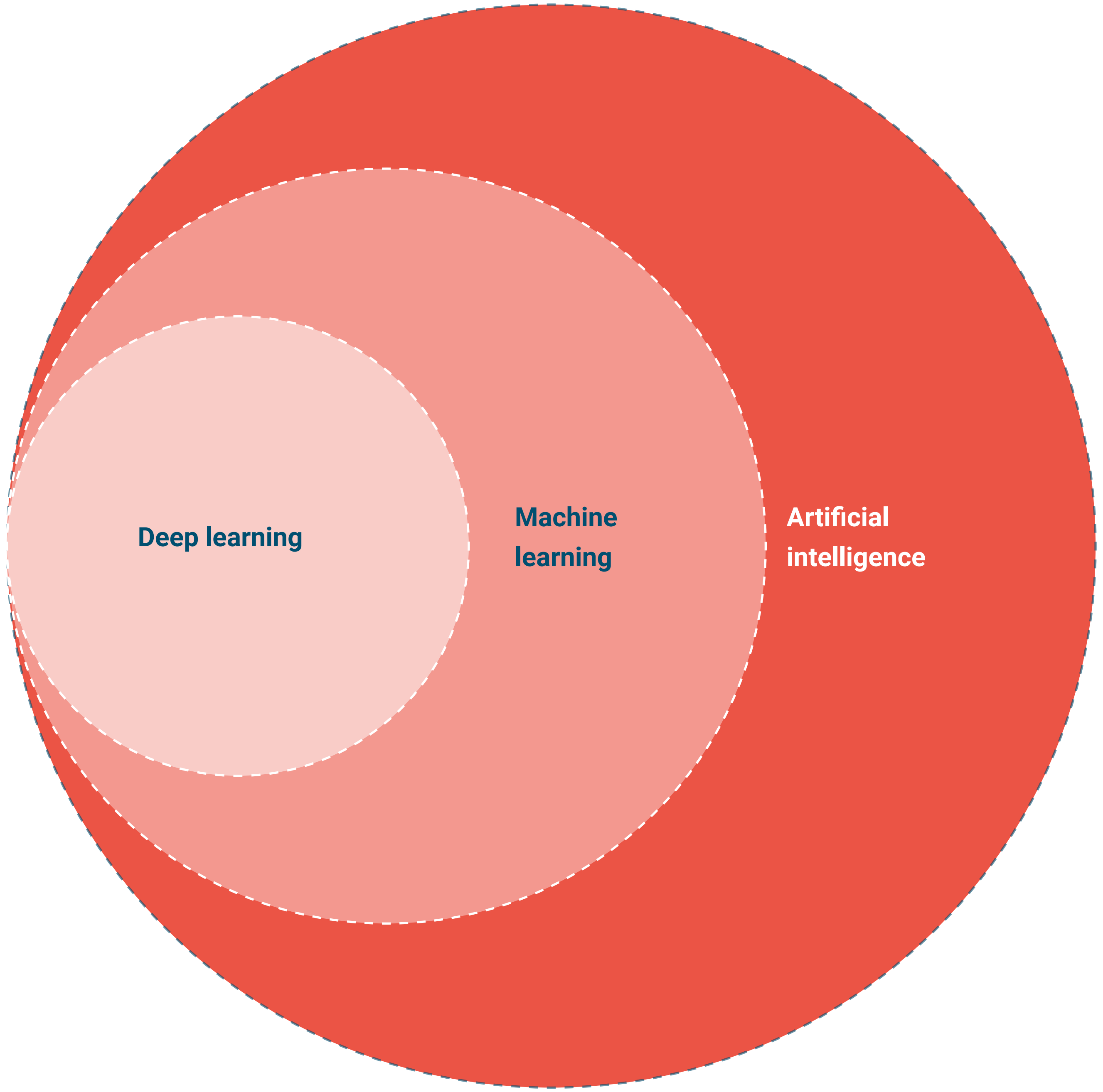
- **Machine Learning (ML):** This refers to computational methods that, through experience, can increase their performance or achieve greater precision in predictions (Mohri et al. 2018). In particular, experience is understood as information that is used so that the model learns (Mohri et al. 2018). ML models have the capacity to resolve problems by discovering patterns based on examples, instead of by being programmed explicitly for that (Li 2023).[14]

14 Li, F. (2023), "The Worlds I See: Curiosity, Explorations, and Discovery at the Dawn of AI" (Chapter 3).

For example, to inspect power network infrastructure, a transmission or distribution company can train a model with images of both a defective network as well as one that is in perfect condition in order to more precisely detect infrastructure that is worn out or in abnormal condition. In this way, preventive and corrective maintenance can be carried out in a timely manner. As can be inferred from the example, ML models are based on the information used to train them, that is, the data with which the model itself learns.

Usually in infrastructure, the most used input data[15] are grouped in time series[16] and in catalogs of images.[17] Although there are a significant variety of models within the ML family, in general terms the models have the capacity to consume relatively simple data, such as numerical series, and find patterns among them to predict a value that is easily interpretable for the user. **Figure 2** presents, in general terms, the cascade of subsets of systems that make up systems of Artificial Intelligence, ML, and DL.

Figure 2. Machine Learning in AI Systems



Source: Services (AWS).[18]

15 Some examples of the types of data used in infrastructure systems are temperature, pressure, voltage, water flow, precipitation, units of consumption of water or energy, humidity, wind velocity, solar radiation, vehicle traffic, frequency of use of certain routes, geospatial location, polluting emissions, and tariffs for services, among others.

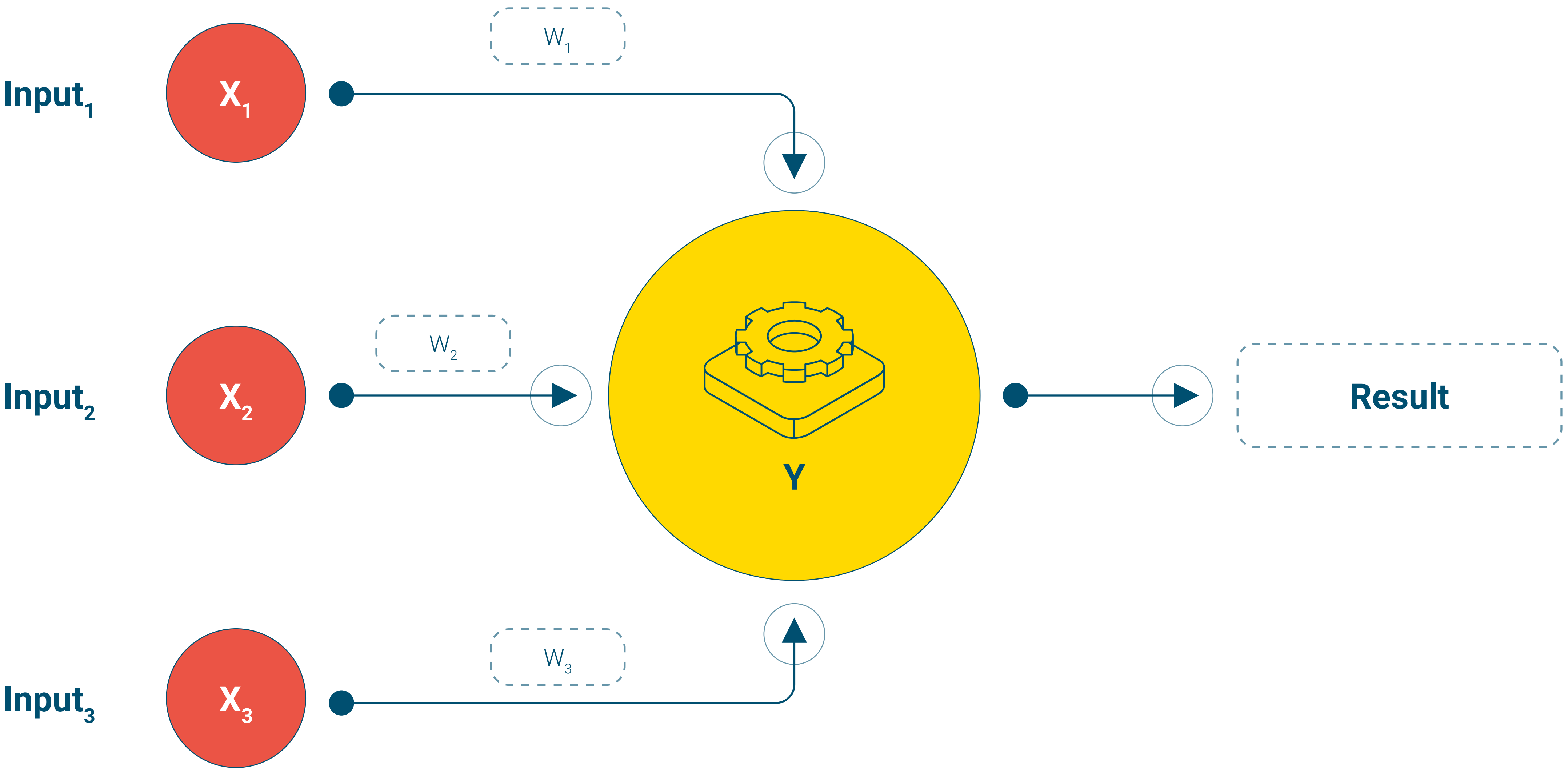
16 Time series can be defined as an ordered sequence of values of a variable distributed in intervals of time equally spaced. Source: National Institute of Standards and Technology. Available at: https://www.itl.nist.gov/div898/handbook/pmc/section4/pmc41.htm

17 The images can consist of photographic material, geospatial maps, technical plans, network diagrams, thermography, radiography, 3D infrastructure models, or architectural renderings, among others.

18 AWS, "What Is Artificial Intelligence (AI)?" Available at https://aws.amazon.com/what-is/artificial-intelligence/

- **Deep Learning (DL):** The concept of deep learning is directly related to neural networks. Research in Artificial Neural Networks has been motivated by the observation that human intelligence comes from non-linear and relatively simple neural networks that learn through adjustments to the strength of their connections (Bengio et al. 2021).[19] **Figure 3** presents a single-layer neural network (the most simple abstraction possible), where each sphere represents a neuron or node. The inputs are characterized by or attributed to the information that is analyzed. The weights, which are identified by W_n, represent the importance that the model is giving to each input in order to produce the result. As is the case with neurons, the electrical signal must be sufficiently strong to be able to transmit the information to the other neuron. In the case of the model, the calculation between the inputs and the weights must pass a certain threshold[20]

Figure 3. Representation of a Single-Layer Neural Network (Perceptron)



Source: Prepared by the authors.

19 Bengio, Y., LeCun, Y, & Hinton G. (2021). Deep Learning for AI. Communications of the ACM, 64(7), 58-65. http://dx.doi.org/10.1145/3448250

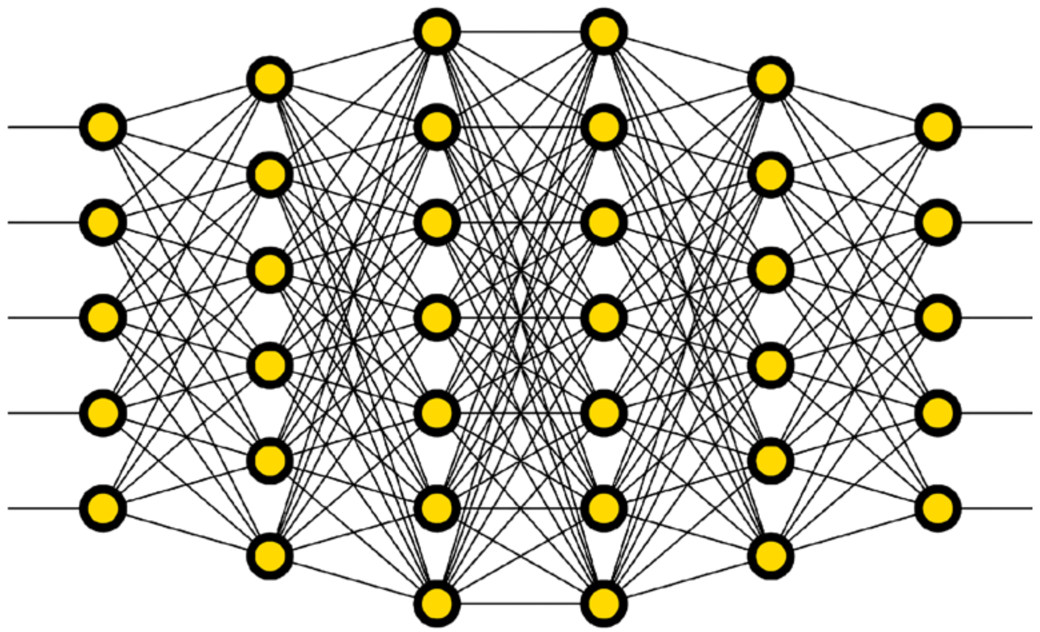
20 For more information on activation functions, see Sharma et al. (2020). Available at <https://www.ijeast.com/papers/310-316,Tesma412,IJEAST.pdf; and Manoharan, I 190, "Demystifying the Gears: Activation Functions & Loss Functions for Neural Networks" (2024, March). Available at https://medium.com/@ilakk2023/190-demystifying-the-gears-activation-functions-loss-functions-for-neural-networks-778f29d7780f

in order to attain the objective. The model then learns, rearranging the weights until it obtains the best possible result.

DL models therefore function with multiple layers (**Figure 4**), with each layer being a different form of extraction and transformation of the information that is used as an input (Patterson and Gibson 2017). The layers (set of neurons or nodes) allow for optimizing and refining the precision of the result of the model.[21]

These types of models usually receive relatively complex inputs, such as images or text, and through the complex processing of each part of the input produce simple results such as the classification of an object or the summary of a document. For example, in inspecting the safety of a road, it is possible to train a deep learning model using images that represent the key characteristics that determine the road's level of safety. This model can function as a classifier capable of identifying with a high level of precision the road segments that require interventions to reduce risks for pedestrians, bicyclists, and drivers.

Figure 4. Multi-Layer Neural Network



Source: Thajeb, S. "Introduction to Deep Learning" (2020, July). Available at https://medium.com/swlh/introduction-to-deep-learning-50d971374dd2

- **Generative Artificial Intelligence:** This type of AI uses machine learning not to classify based on existing information, but to produce "new" content, whether it be numerical data, text, video, audio, or images, among others, through analysis of patterns in the data (Brynjolfsson et al. 2023; Cevallos et al. 2023). Recent advances in Generative AI are due in part to the progress made in areas such as computational scale, architecture of the models, and the training of models using large volumes of unlabeled data (Brynjolfsson et al. 2023).[22]

The most common example of Generative AI since the rise of ChatGPT is Large Language Model (LLM). These models form part of the Natural Language Processing (NLP) family of models that automate language functions by analyzing, producing, and modifying the human voice and writing, as well as the response to them (OECD 2023). LLMs are trained with large quantities of data (it is estimated that GPT-4 includes 1.8 trillion parameters and is trained with nearly 13

21 Ibid.

22 An example of unlabeled data could be a series of images of animals without information related to what types of animals they are (that is, whether it is a lion, rabbit, dog, or cat).

trillion tokens).[23] This enables them to classify and simulate the understanding of the structure of texts, grammatical complexities, and the different context of sentences. This in turn gives them the capacity to hold conversations, give precise responses, and create "new" texts (Brynjolfsson et al. 2023; Cevallos et al. 2023).[24] Although ChatGPT[25] is the most well-known generator of text, there are other platforms such as LLaMA[26] of Meta, Gemini[27] of Google, and Claude,[28] developed by Anthropic, among others.

Foundational Models (FM),[29] which include LLMs, have the capacity to adapt to any topic to the extent that they are trained with millions of data. In contrast to what happens with machine or deep learning models that are designed to carry out a specific task, FMs have the capacity to analyze complex inputs in order to produce more advanced forms of knowledge such as, completing programming codes or analyzing text.[30] However, FMs can also generate incorrect results in terms of biases or hallucinations when there are problems with the quality and integrity of the data with which they are provided.[31] These types of models can help improve the administrative efficiency of infrastructure sector entities, for example, by improving document management or citizen response systems.

Types of Learning in Machine Learning Models

This subsection presents a review of the main types of learning that are used in ML systems. As mentioned previously, ML has the capacity to discover patterns and relationships in large quantities of data, which helps to create classification or prediction tools with a high level of precision. In general, the type of problems ML models are used for can be summarized into three categories:

23 In NLP models, a token refers to a basic entity of text, which can be a word, number, punctuation mark, or any other significant linguistic entity.

24 "What Are Large Language Models (LLM)?" Available at https://aws.amazon.com/what-is/large-language-model/

25 For more information, see https://chat.openai.com/

26 For more information, see https://llama.meta.com/

27 For more information, see https://gemini.google.com/

28 For more information, see https://claude.ai/chats

29 FMs are neural networks that carry out deep learning and are trained with large quantities of data and composed of a significant number of parameters. They can carry out different general tasks such as generating text or images, and understanding human languages and holding conversations, among others. Source: "¿Qué son los modelos fundacionales?" Available at https://aws.amazon.com/es/what-is/foundation-models/).

30 Amazon Web Services, "What Are Foundation Models?" Available at https://aws.amazon.com/what-is/foundation-models/#:~:text=Foundation%20models%20are%20a%20form,form%20of%20human%20language%20instructions.

31 Google Cloud, "¿Qué son las alucinaciones de la IA?" Available at https://cloud.google.com/discover/what-are-ai-hallucinations?hl=es-419

1

Classification:

In this case, the problem to be resolved pertains to identifying the category or categories to which each element being analyzed corresponds. The most common example is the classification of images. In general, these types of models learn with training information that is labeled. The techniques that can be used include a simple threshold, regressions, Markov model, random forests, or neural networks, among others. For example, an electricity network must rapidly identify failures or anomalies that can cause interruptions in the supply of energy. A machine learning model can do this by classifying events in the network into different categories, such as "normal operation," "overload," "power failure," or "equipment failure."

2

Clustering:

These models help identify relationships between series of data in such a way that those that have characteristics in common are part of the same group or cluster. An example in the transport sector is the clustering of trajectories of vehicles to optimize public transport routes. In the case of a city, the aim is to optimize the routes of buses or public transport based on the real trajectories of the vehicles and the demand patterns of passengers. This identifies routes with high demand and those that could be optimized, by aggregating or eliminating stops, or adjusting the frequency of service on key routes according to demand patterns.

3

Prediction:

Based on historical information, predictive models forecast current or future values – for example, the demand for electricity, demand for transport services, levels of traffic congestion or accidents, or flows of water and sewage systems. In the latter case, this model can be used by water utilities, since they need to anticipate future demand in order to prevent water system overloads or shortages. Using predictive models enables utilities to efficiently adjust the supply of water based on future needs, which is crucial for sustainable management.

A critical characteristic of ML models is their capacity to learn from the information available. This is why their structure is differentiated mainly through the algorithms they use to learn (Rebala et al. 2019). Therefore, there are generally considered to be three main types of learning models within ML: (i) supervised learning, (ii) unsupervised learning, and (iii) reinforced learning.

The main characteristic of ***supervised learning*** is that the training of the models is carried out based on labeled data; that is, the model is trained with the knowledge of the correct responses. This type of learning has two main problems: classification and regression. As previously indicated, classification refers to identifying the category to which each element of what is being analyzed pertains. For its part, the regression technique discovers the relation in different dimensions of the distinct variables in order to predict the behavior of a variable of interest (Rebala et al. 2019). Some applications of this type of learning are diagnosing the condition of infrastructure for maintenance or identifying failures; detecting fraud in the consumption of water and energy; classifying images to detect dump sites or vehicle congestion; and predicting prices or demand for energy, water, or transportation services, among others. For the problem of classification, the most used algorithms are Support Vector Machines (SVM), K-Immediate Neighbors (KNN), Naive Bayes, decision trees, random forests, and Convolutional Neural Networks (CNN), among others. For the case of regressions, those generally used are linear regression, polinomial regression, SVM, and gradient boosting, among others.

In unsupervised learning, the algorithms are not based on predicting or explaining an objective variable, but rather on identifying existing patterns or relationships between the data. These types of models learn to identify similar characteristics among variables that they make them belong to the same group (Rebala et al. 2019). In general, this type of learning uses clusterization or grouping algorithms, which allows for obtaining the main particularities of the data using a set of unlabeled data as an input. Since this type of learning often involves databases with high dimensionality (a large quantity of variables), it uses algorithms to reduce dimensionality, such as Lineal Discrimination Analysis (LDA) or Main Components (CPA). By reducing the number of variables, the most important information from the database is captured.[32] Among other things, this improves the interpretability of the model, its performance, and its computational efficiency.[33] Unsupervised learning can be used to segment clients, classify the condition of infrastructure assets, detect unusual patterns in the performance of motors or machinery, and design public policy programs. The most used clusterization or grouping algorithms are K-Means, K-medoids, DBSCAN, and Gaussian Mixture Models (GMM), among others.

Reinforcement learning aims to make the best decisions based on experience forged through trial and error.[34] For this, learning occurs through "rewards and punishment," where the model does not indicate what decisions to take, but rather the objective that must be met, as well as the type of "reward" and "punishment" that corresponds to each action implemented (Sutton and Barto 2018). One of the fundamental characteristics of this type of learning is that it has the capacity – depending on how advanced its training – to find the optimal path to meet its objective, taking into account the long-term impact of its decisions. In other

32 Brown, I., "Feature Selection vs Feature Extraction: Navigating Dimensionality Reduction in Machine Learning" (2024, March). Available at https://medium.com/ai-in-plain-english/feature-selection-vs-feature-extraction-navigating-dimensionality-reduction-in-machine-learning-7c60e6742710

33 Ibid.

34 Amazon Web Services, "¿Qué es el aprendizaje mediante refuerzo?" Available at https://aws.amazon.com/es/what-is/reinforcement-learning/#:~:text=El%20aprendizaje%20por%20refuerzo%20(RL,utilizan%20para%20lograr%20sus%20objectives.

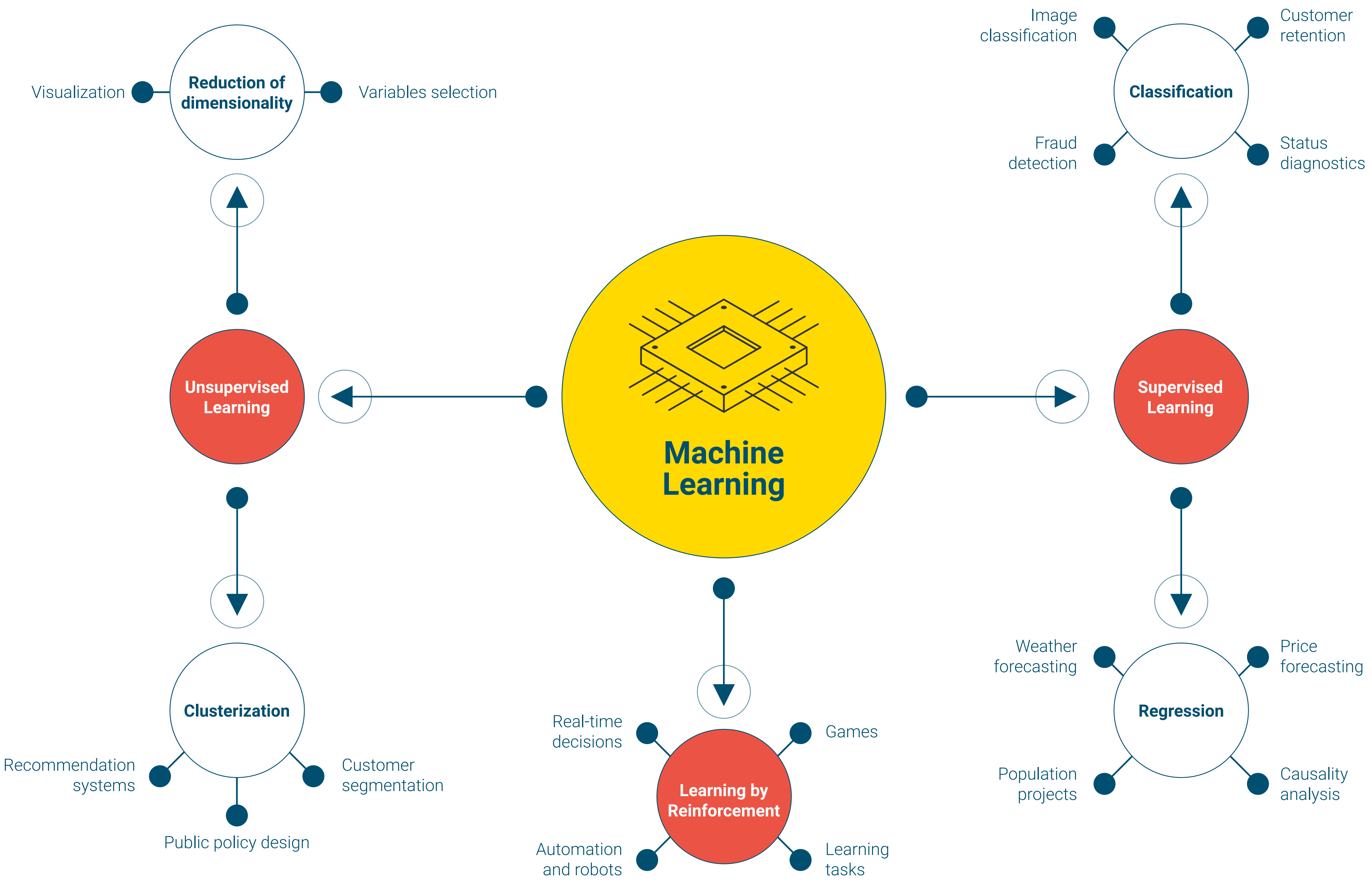
words, along the way it can intentionally receive "punishments" to obtain the objective (Rebala et al. 2019). The most notable applications of this type of learning are for the autonomy of robots, management of vehicular traffic through the use of traffic lights, and the training of games (for example, AlphaGo).[35] The most used algorithms in this type of learning are Q-Learning, Deep Q-Network (DQN), Proximal Policy Optimization (PPO), and the Monte Carlo Tree Search (MCTS), among others.

Figure 5 summarizes the main types of learning in ML systems, as well as the problems they address and some of the applications that are used.

It should be noted that AI models depend significantly on the input data. So when these models are developed, there can be problems with scarce or poor quality information, existing biases in the available data, and the legal and ethical limitations of processing personal data. One tool that addresses these challenges is synthetic data. This type of data is generally defined as information generated artificially through algorithms or simulations that re-create the behavior of the "real" data (Lu et

35 For more information, see <https://deepmind.google/technologies/alphago/>; and AlphaGo, available at https://www.youtube.com/watch?v=WXuK6gekU1Y&t=1028s

Figure 5. The Three Main Types of Learning in Machine Learning



Source: Adapted by the authors from Artificial Intelligence. Machine Learning Definition (Complete Guide). Available at https://medium.com/@artificialintelligenceai/machine-learning-definition-complete-guide-4cd615dd424d al. 2024). Although this artificially generates large quantities of data when data are scarce, of poor quality, or biased, synthetic data do not always capture the complexity and interactions in the real data. The conclusions drawn from the analysis and verification of the hypotheses are therefore generally weaker when synthetic data are used than when real data are used, for which the statistical significance of the analysis must be adequately adjusted. In addition, the use of synthetic data makes it difficult to recognize links between different sets of real data and to create broader databases that contain new information about the correlations between the linked data sets (Jordon et al. 2022).

Generative models trained to re-create the characteristics and properties of real-world data are usually used to create synthetic data of images and videos,.[36] Models generally used for this are Generative Adversarial Network (GAN), Variational Autoencoders (VAEs), and auto-regressive models, among others. For example, to detect fraud in water or energy consumption, it is common to generate synthetic variables that complement the limited availability of real data.

Another relevant technique that solves the problem of insufficient information is *data augmentation*. This technique artificially increases the original set of data and modifies the original data of low quantity. This not only increases the sample but also enables including diversity in the training data in order to improve the scope of the model. [37]

Finally, a constant problem in classification models is the imbalance between the categories. This can cause the predictors of class to perform poorly in that they rarely predict the minority class (which has less data). Therefore, the evaluation of the model only takes into account the performance of the majority class. Some solutions to this problem are related to the subsample of the dominant class, with replications of the minority class or the weighting of each class done in such a way that the total weight of each of the classes ends up balanced through different weightings, among other solutions (Ávalos et al. 2021).

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36 Shah, D., "What Is Synthetic Data in Machine Learning and How to Generate It" (2022, June). Available at https://www.v7labs.com/blog/synthetic-data-guide#h1

37 Amazon Web Services, "What Is Data Augmentation." Available at https://aws.amazon.com/what-is/data-augmentation/#:~:text=Data%20augmentation%20is%20the%20process,machine%20learning%20(ML)%20models.

3 ARTIFICIAL INTELLIGENCE IN INFRASTRUCTURE SECTORS: OPPORTUNITIES AND APPLICATIONS

3.1 The Importance of Critical Infrastructure

Economic infrastructure is a central component of the capital base of countries that facilitates economic activity and the functioning of society, and it has positive effects on the well-being and quality of life of the population. The World Economic Forum (WEF 2012) defines economic infrastructure as the set of projects that generate economic growth and enable the functioning of society in sectors such as transport (ground, air, river, and sea) and public services (water, gas, and electricity, protection against flooding, and waste management, among others).

In considering the importance of economic infrastructure, its different systems and elements have been denominated as "critical infrastructure." This is because, in addition to the economic and social impact of this infrastructure, its failure to function adequately is a considerable risk for countries. Infrastructure is thus defined as critical if its possible interruption could generate a significant socioeconomic crisis. This in turn could have strategic, political, and security repercussions for society (Laubshtein 2023).

The economic literature finds that infrastructure sectors make a significant economic contribution and have positive effects on the economic development of countries.[38] For example, the International Monetary Fund (IMF 2016) reports a positive relation between the quality of a country's infrastructure and the level of its development, as measured, for example, by per capita income. According to the IMF, investment in infrastructure contributes to future economic growth, and the condition of infrastructure is an important determinant of countries' competitiveness and investment flows. According to the OECD (2023), the transport and telecommunications sectors can serve as catalysts of economic growth by enabling businesses to create connections with markets at the national, regional, and global levels, while quality infrastructure in the energy and water sectors contributes to the sustainability and green transition of countries to the benefit of their citizens.

In addition, different authors have found that there is a positive relation between investment in infrastructure and the creation of employment. Moszoro (2021), for example, evaluated the impact of public investment in critical infrastructure on employment creation in 41 countries over a period of 19 years. The author found that each US$1 million of public investment in infrastructure induces the creation of 3 to 6 jobs in advanced economies, 10 to 17 jobs in emerging economies, and 16 to 30 jobs in low-income economies. Thus, at the global level, an increase in public investment amounting to 1 percent of global GDP in these sectors can create more than 7 million jobs.

38 See, for example, Zhang and Cheng (2023); Hong, Chu, and Wang (2011); and Jiwattanakulpaisarn, Noland, and Graham (2012).

3.2 Opportunities and Applications of Artificial Intelligence in Infrastructure Sectors

AI and the Digital Transformation of the Infrastructure Sectors

AI has become one of the technologies with the greatest potential to facilitate economic transformations in markets in the coming years, in that its adoption can open the door to multiple opportunities to create value for both organizations and consumers. Deloitte (2021) points to six ways that AI creates value for organizations:

- **Reduction of costs**: AI reduces costs through the automation of repetitive and low-value tasks, thus increasing efficiency and quality.
- **Speed of execution**: AI shortens the time needed to obtain operational and business results.

- **Reduction of complexity:** This technology helps to improve business understanding and decision-making through data analytics that is 'more proactive, predictive, and capable of detecting patterns in increasingly complex sources.'
- **Transformation of involvement:** AI modifies the interaction of persons with technology, enabling businesses to connect with clients on human terms.
- **Drive towards innovation:** AI facilitates innovation in new products, markets, and business models, which induces a redefinition in the business strategy.
- **Strengthening of confidence:** AI helps protect businesses from risks associated with fraud and cybercrime, and also improves the quality, consistency, transparency, and confidence of users.

AI also has enormous potential to create value in terms of the performance of governments and for them to successfully carry out their functions and objectives. Public organizations have taken advantage of AI to transform themselves into smarter and more efficient and receptive organizations with better decision-making processes (Pombo et al. 2018).

In this context, developing and adopting AI offers significant opportunities to foster the digital transformation of economic infrastructure sectors in countries. This transformation is understood to be the process of using data and adopting digital technologies, such as AI, to restructure processes, organizations, or systems to create value.[39]

Economic infrastructure sectors have common characteristics that facilitate their digital transformation based on AI. They are composed of complex systems, organized through network architectures, involve the intervention of multiple actors, and are intensive in physical capital, as well as the generation and consumption of data. The organizations in these economic areas face common challenges that can increasingly be addressed by AI as a fundamental tool to develop supply and demand predictions, monitor construction of projects, inspect and maintain assets, detect losses in networks, improve the sustainability of systems, and make infrastructure more resilient to climate change and natural disasters.

Moreover, digital transformation in the infrastructure sectors has had a disruptive role at three levels (Calatayud et al. 2022): (i) improvement in the efficiency of productive units, (ii) reconfiguration of productive chains, and (iii) formation of new markets through the surge of bilateral platforms known as marketplaces. Although the speed of technological adoption and digital transformation in these sectors has been heterogeneous,[40] in most sectors the digital technologies have become a factor of change.

39 There are different definitions of digital transformation. For example, the OECD defines it as the impact of technologies and digital data and their use on existing and new activities. Amazon Web Services (AWS) defines digital transformation as the process through which an organization integrates digital technology in all business areas. McKinsey defines it as the reconfiguration of an organization in order to create value by continuously deploying technology at scale. Sources: OECD,. *Digital Transformation*. Available at: <https://www.oecd.org/en/topics/digital-transformation.html>; AWS, "¿Qué es la transformation digital?" Available at: https://aws.amazon.com/es/what-is/digital-transformation/; and McKinsey & Company. What Is Digital Transformation? Available at https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-digital-transformation

40 The energy sector historically has been an early adopter of technology, in contrast with traditional sectors such as water and sanitation.

An IDB survey of 275 representatives from the transport and energy sectors in LAC found that 71 percent of energy sector businesses use computation in the Cloud, and that more than 50 percent of businesses in that sector as well as in the transport sector have adopted data analysis tools and Big Data solutions. The organizations in these sectors are employing elements of data collection, processing, and analysis that include sensors, drones, and electrical networks to implement systems to improve interaction with clients, conduct monitoring in real time, and manage supply and demand, among other applications (Irigoyen and Mayorga 2024).

Emerging technologies associated with more advanced stages of digitalization such as AI are recently starting to attract the attention of economic sectors in LAC. In the infrastructure sectors, the above-mentioned survey found growing interest to push forward with deploying AI in the coming years, in addition to developing and adopting technologies that reduce environmental impact.

There are opportunities for infrastructure sector entities to create value and generate positive impacts in diverse phases of the project life cycles: (i) planning and design, which involves the identification of needs, formulation, structuring, and design; (ii) construction and management of assets, which includes the deployment of the infrastructure and management of the related assets; and (iii) operation and maintenance, which refers to the functioning of the infrastructure, maintenance of the assets, delivery of services, and consolidation of systems for sustainability and climate resilience.

In each of these phases, AI offers significant opportunities. In the planning and design phase, it facilitates advanced modeling of systems and improves risk management and decision-making based on data and advanced predictions. During the construction and management of assets phase, it increases efficiency in executing and supervising works, which optimizes the identification, monitoring, and maintenance of assets. In the operation and maintenance phase, AI improves the efficiency and sustainability of systems, improves maintenance times, strengthens management of assets and monitoring of the quality of services, and strengthens processes related to users.

Opportunities and Applications in Infrastructure Sectors

Planning and Design of Infrastructure Systems

AI offers infrastructure sector entities opportunities to optimize planning and design processes for projects and systems. In the energy sector, technological advances, population growth, increased production, and improved living conditions in recent decades have generated a significant increase in electricity consumption at the global level (Bedi and Toshniwal 2019). In this context, in recent years there has been increased use of predictive demand models to carry out short- and long-term projections, as well as to forecast consumption at the micro level (individual consumers) and the macro level (cities and even countries) (Del Real et al. 2020).

Moreover, in different countries AI models have been used to optimize the design of power plants and calibrate their dimensions (Kumar and Saini 2021). Senthil Kumar et al. (2013) used an Artificial Neural Network (ANN) model to predict the sediment load in water basins, which improves the design and generating capacity of hydroelectric plants. AI algorithms have also been used to identify the elements that affect a plant's generation in order to optimize its design (Kumar and Saini 2021). In Iraq, for example, researchers forecasted the energy production of a small hydroelectric plant in a dam at Himreen Lake using a model based on ANN. They found that the variables that most affect energy generation are the water flow and the net height of the turbine (Hammid et al. 2018).

Similarly, AI offers opportunities to improve the design of wind parks in a way that optimizes the use of the land and the number of turbines installed. An example of this is the use of genetic algorithms,[41] which can help make the installation of wind parks efficient and maximize the energy production capacity (Grady et al. 2005). These algorithms consider the variations in the direction and velocity of the wind and the location of the turbines, thus identifying the best design to minimize the cost per unit of energy generated (Grady et al. 2005).

In transportation planning, societies face challenges in mobility, congestion, road safety, use of public spaces, and gas emissions, among others. Developing well-connected and multi-modal transport systems is one of the most important objectives for agencies responsible for planning to increase efficiency, reduce barriers to access, and reduce congestion in metropolitan areas (Yang et al. 2018).

AI models play a leading role in this field because they enable, for example, increasing the precision of origin-destination matrices to adapt the management of traffic lights to the vehicle flow, or optimize the operation of public transport to respond to demand shocks during specific time periods. Some of the most-used models are regressions[42] that predict the traffic flow between different points of origin and destination based on variables such as location, time period, day of the week, and weather (Gutiérrez Puebla et al. 2020; Yang et al. 2018). Similarly, the use of neural network, graph theory, and simulation models, among others, is common (Rodrigues et al. 2019).

In some cities, transport models process data provided by new information sources such as social networks (X, Instagram, TikTok, Waze, Strava, among others), web services (Google Maps, Waze), smartphones, transit smartcards, and sensors installed in passive infrastructure (traffic lights, security cameras), as well as geo-referenced information on buses, bicycles, taxis, and other modes of public transport (Gutiérrez Puebla et al. 2020). In LAC, the IDB Transport Division produced an exhaustive analysis of the characteristics and costs of urban congestion in 10 cities using Big Data and AI to analyze congestion and its impact on direct and indirect costs for the countries (Calatayud et al. 2021).

41 A genetic algorithm is a computational search technique to find approximate solutions for optimization models and search problems. It is inspired by the process of natural evolution, where the best solutions to a problem are selected, combined, and mutated to create new solutions, all within an iterative process that stops when the best possible solution is found. For more information see https://www.sciencedirect.com/topics/engineering/genetic-algorithm

42 Lineal, logistic, and polynomial regressions, among others.

Another relevant case is the application of predictive models of supply and demand for transport system planning. An example is the predictive model developed by the IDB for the Metropolitan Area of San Salvador in El Salvador. To build the model, the IDB employed LUCA-Telefónica's Smart Steps Model.[43] Trough information provided by Call Detail Record (CDR)[44] and information on traffic obtained from crowdsourcing on Google, the researchers identified trips made and created origin-destination matrices (Rendón Rodríguez et al. 2020).

The model provides information regarding the busiest roads, traffic flow, the system's critical infrastructure, public transport occupancy rates, and the busiest time periods, all of which make it possible to evaluate the impact of various infrastructure projects through simulations. The projects that can be analyzed include the reorganization of public transport routes and stations, changes in the direction of roads, expansion of the road network, and inclusion of new transport models (Rendón Rodríguez et al. 2020).

AI is also starting to be used in planning stages to expand the response capacity of transport, energy, and water infrastructure to meteorological events and natural disasters. In the hydroelectric sector, as mentioned previously, the projection of flows represents one of the main challenges for planning. Traditionally, plant operators have used historical data and basic models to predict water inflows, but with the recent meteorological variability these traditional methods have become unreliable. AI processes large quantities of data from multiple sources, generating more timely and precise predictions about flows. In India, for example, the company HydroGrid helped a hydroelectric operator manage its plant safely during the period of seasonal rains (monsoons). According to the company, the AI-based smart planning solution enabled the operator to increase the efficiency of revenue during this period and improve safety for the local population.[45].

Another example of these applications is predicting wastewater flows to support effective planning and administration of treatment plants (Zhang et al. 2019). Some predictive models for wastewater flows have focused on simulating the behavior of the collection systems; however, these types of models can present challenges related to the assumptions required because it is not easy to simulate the behavior of rain, leaks, snowfall, and the adaptation of infrastructure already installed. As a result, predictive models have been developed with deep learning techniques that use data collected by treatment plants. For example, an exercise carried out with information from the treatment plant in Ontario, Canada implemented a multi-layer neural network and obtained a satisfactory prediction (Zhang et al. 2019).

43 This is the first service of Big Data for telephony that collects, anonymizes, and aggregates mobile data of the telephony network in order to understand how segments of the population behave collectively. With a different approach depending on the sector under study, the tendencies and behaviors of the masses, less so individuals, are analyzed.

44 This refers to the detailed record of a call. The information generally captured in this type of record is the time and date of the call, its duration, the numbers involved, the locations, the cost, and any information of quality related to the call.

45 Source: International Water Power (2024), "Harnessing AI to Transform Hydropower." Available at: https://www.waterpowermagazine.com/analysis/harnessing-ai-to-transform-hydropower/

Construction, Deployment, and Management of System Assets

The power sector is capital-intensive because it is supported by generation, transmission network, and distribution infrastructure, as well as other physical assets. In this sector, activities to monitor and inspect infrastructure are generally costly because the assets can be located in areas that are isolated and difficult to access, require highly specialized personnel (Lekidis et al. 2022), and generally must be carried out with operational teams. To address this, different companies have designed programs for remote inspection and real-time monitoring in order to optimize infrastructure management and maintenance, provide early alerts, reduce the time required for operators in the field, reduce accidents, and improve team availability indicators.

In this sector, three approaches supported by technology (including AI) that are being used by businesses stand out: (i) the use of Unmanned Aerial Vehicles (UAVs) together with algorithms to analyze images and video, which reduces the cost of undertaking topography, reduces work time, and improves precision (Rennie et al. 2020); (ii) the use of the Internet of Things (IoT) through the placement of sensors in different components of the infrastructure and the development of advanced analytics based on the information collected (Rennie et al. 2020); and (iii) the development of "digital twins" (DT) to model and simulate, using machine learning techniques, the behavior of elements of the network.

In recent years there has been increasing use of AI models that process data gathered by UAVs in order to detect objects and identify failures and anomalies. These models[46] identify all the elements of the network and their condition in a way that can raise alerts for preventive maintenance. In addition, they can be used to develop systems to classify[47] failures and anomalies in order to optimize corrective maintenance activities. For example, the operator of a hydroelectric plant in Greece implemented a monitoring and inspection pilot based on UAVs that included analysis of images and videos through Convolutional Neural Networks. The initiative reduced the number of accidents per year by almost 70 percent, increased the identification of failures and anomalies by 80 percent, and generated approximate savings of 85 percent of the maintenance budget (Lekidis et al. 2022; Liu et al. 2020).

Similar programs are being developed in different countries in the region. In Colombia, Interconexión Electricity (ISA), an electricity transmission company, has used AI to detect failures in electricity transmission and improve efficiency in maintenance planning. The AI tool has significantly reduced intervention times by analyzing photographs associated with field inspection reports and building classification models to identify failures or anomalies, through object detection algorithms.[48]

There are also AI-based systems that monitor the condition of transformers in electricity networks in order to manage their planning and maintenance, and to prevent failures. These systems generally use information collected by sensors from generated gases, temperature, current, and voltage, among other elements (Li 2023). An example is Ronin AI, a platform in the Cloud developed by the firm Seetalabs that enables monitoring in real time of the condition of transformers in

46 Subsequent sections of this document explain these types of models in greater detail in order to understand their scope, the opportunities they present, and their limitations. However, in general, for the types of solutions described here, Coding Neural Networks (CNN) and You Only Look Once (YOLO) have been used.

47 Subsequent sections of this document explain these types of models in more detail in order to understand their scope, the opportunities they present, and their limitations. However, in general, for the type of solutions described here, clusterization models such as DBSCAN and classification such as Random Forest and XGBoost (Extreme Gradient Boosting) have been used.

48 "ISA Intercolombia depends on Artificial Intelligence to detect modes of failure in transmission lines" (2023, 18 December). Available at https://news.microsoft.com/es-xl/isa-intercolombia-le-apuesta-a-la-inteligencia-artificial-para-detectar-modos-de-falla-en-lineas-de-transmision/

order to prevent abrupt power outages and adequately plan the maintenance of that equipment.[49]

As mentioned, a Digital Twin is a tool that uses machine learning algorithms and has great potential for use in infrastructure sectors. This tool consists of a virtual and real-time representation of an object, system, process, or physical infrastructure that is bidirectionally connected to its physical counterpart (Fuller et al. 2020; Latorre et al. 2024; Sharma et al. 2022). This connection enables the Digital Twin to collect, process, and analyze data from a physical object in real time, which facilitates monitoring, simulating, and optimizing the functionality of the element, as well as predicting future preventive maintenance requirements (Fuller et al. 2020; Latorre et al. 2024; Sharma et al. 2022). An important characteristic of this tool is that it not only replicates the condition and behavior of the physical infrastructure, but also predicts its future performance, which contributes to optimizing its functionality. Furthermore, it allows for simulating the effects of changes in the physical object without it suffering real damage. This makes it possible to test modifications to the processes at low cost (Fuller et al. 2020; Latorre et al. 2024; Sharma et al. 2022).

49 Source: Seetalabs. Available at: https://seetalabs.com/product/

Digital Twins have been commonly applied in the energy sector to improve the operation of generating plants and transmission and distribution systems (Latorre et al. 2024). For example, the Spanish electrical energy firm Endesa,[50] which mainly operates in Spain and Portugal, has implemented Digital Twins in 38 main hydroelectric plants representing approximately 70 percent of installed capacity. This has enabled the company to analyze relevant information such as temperature, velocity, pressure, and vibration, among other elements, to improve the functioning of the stations and to provide alerts about anomalies and possible failures. Similarly, in Finland, the transmission system operator *Fingrid*, together with the Siemens firm, implemented a Digital Twin model to optimize the transmission network. This has helped improve the efficiency, precision, and consistency of the models used for management of the network (Sharma et al. 2022; Gámiz et al. 2020).

50 "Endesa applies Artificial Intelligence to create 'digital twins' of its hydroelectric plants" (2024, 8 January). Available at <https://elperiodicodelaenergia.com/endesa-aplica-inteligencia-artificial-crear-gemelos-digitales-centrales-hidroelectricas/>Endesa. For Endesa (2024), see https://www.endesa.com/es/sobre-endesa/nuestro-negocio

In the transport sector, improving the monitoring and maintenance of assets can help create value. First, AI models help anticipate failures and anomalies in the infrastructure, which makes it possible to carry out preventive maintenance to increase availability and reliability. Second, when failures occur, the models identify with greater precision the need for intervention, and they generate relevant information for effective repairs of the breakdowns. This in turn helps optimize maintenance budgets in contexts of limited resources (Calatayud et al. 2022).

The use of technology and specifically AI for early detection of failures in road infrastructure helps reduce the number of road accidents. A reference case in the region is the *Pavimenta2* tool developed by the IDB and implemented by transport and road safety authorities in 11 countries in LAC. *Pavimenta2* uses videos of roads based on deep learning and computational vision models to diagnose pavement and signage conditions, prioritize road maintenance, and optimize resources. In the countries in LAC where it has been implemented, this open-source tool has facilitated the analysis of 50,000 kilometers of roads and improved efficiency in detecting their condition (**Figure 6**).

Another example of failure detection for road safety is *VíaSegura*, an AI solution based on machine learning and computer vision developed by the IDB and IRAP.[51] This application carries out precise monitoring of roads and detects elements of road safety such as the layout and number of lanes, lighting, and the presence of service stations, among others to generate alerts for preventive and corrective maintenance.[52] With this open-source solution more than 61,000 kilometers of roads have been processed in Brazil, Ecuador, Guatemala, and Peru[53] (**Figure 7**). Similarly, the Ministry of Transport and Public Works in Uruguay, in collaboration with the IDB, conducted a pilot survey of failures in the country's road network based on analysis of images through an AI model. The results enabled the ministry to determine the elements needed to make inspection and maintenance activities more efficient.[54]

Another important component of road network management is to identify roads in rural areas. This work is difficult because it involves areas of the countries that are isolated due to their location and topography. In different countries the conventional way to identify and monitor these types of roads has been manual, using crews that travel out to identify the roads and report on their condition. But in Colombia, the National Planning Department (DNP) developed an application that analyzes satellite images and uses machine learning models to conduct an inventory of the country's tertiary road network. This inventory serves as an input for the design of the Comprehensive Road Network Strategy of Colombia (Consejería Presidencial para asuntos económicos y transformación digital, 2020).

51 The International Road Assessment Program (iRAP) is a registered charity that aims to save lives by eliminating high-risk roads across the world. For more information, see https://irap.org/about-us/

52 VíaSegura. Available at https://irap.org/es/rap-tools/light-ratings/viasegura/

53 VíaSegura. Available at https://fairlac.iadb.org/piloto/viasegura

54 Source: Interview with officials from the Ministry of Transport and Public Works of Uruguay.

Figure 6. Description of Pavimenta2

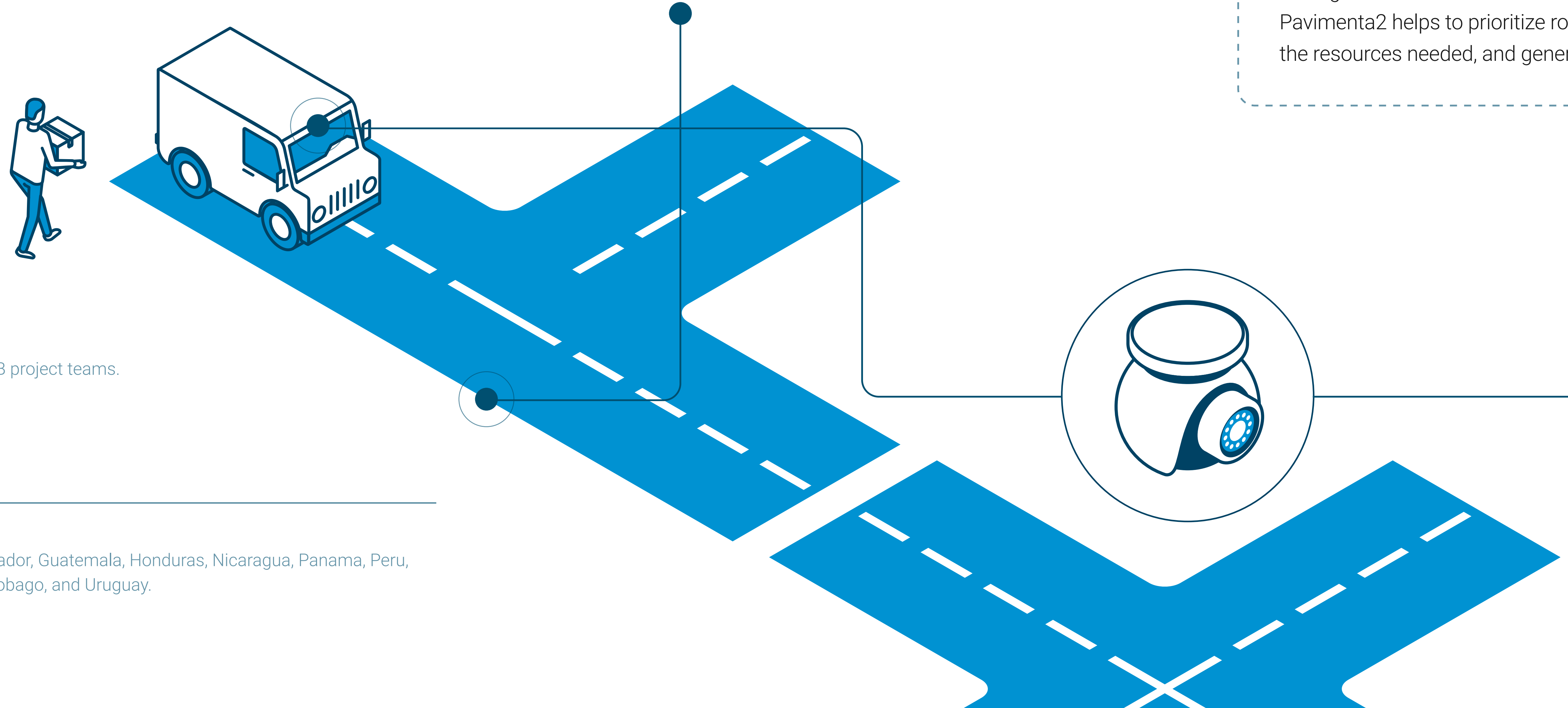
Pavimenta2 is an AI-based solution developed by the IDB that facilitates management of the inventory of road assets by detecting the condition of signage and pavement. This tool has been used by transport and road safety authorities in 11 countries in Latin America and the Caribbean.[55]

The Problem to Resolve

Analyzing road infrastructure and road assets is time-consuming, costly, and requires expert personnel with the capacity to manually analyze the roads. There are estimates that the budget needed to analyze 10,000 kilometers of roads exceeds US$3 million a year, on average. AI provides alternatives to make the analysis more efficient, facilitating vehicle flow and timely and frequent maintenance of road assets, minimizing the associated road risks, and activating logistics and economic integration integration.

Description of the Solution

Pavimenta2 is an open-source solution that uses videos recorded by cameras using the Global Positioning System (GPS) in conventional vehicles as an input. This information is analyzed through AI deep learning and computer vision tools and is incorporated in reports that geo-reference and quantify the findings, which include detecting, classifying, and measuring pavement defects such as cracks, bumps, fissures, and potholes. The findings also help to identify vertical road signage and classify it by type. By complementing these findings with information on travel times and accidents, Pavimenta2 helps to prioritize road maintenance, estimate the resources needed, and generate budget estimates.



Source: IDB; interviews with IDB project teams.

55 Brazil, Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua, Panama, Peru, Suriname, Trinidad and Tobago, and Uruguay.

Results and Impact

The implementation of Pavimenta2 has facilitated the analysis of 50,000 kilometers of roads in the region and has improved efficiency in detecting road conditions with levels of precision greater than 85 percent. In addition, the adoption of Pavimenta2 has allowed for a reduction of costs by 53 times and processing times by 39 times in the analysis of road network, compared to the manual alternative. Furthermore, this solution has reduced human errors and promoted better decision-making through visualizations.

In addition, in 2023 the IDB launched a free virtual course entitled "Artificial Intelligence in Transport" for professionals from LAC whose work is related to the transport sector. The course provides a general introduction to AI and presents some of the applications currently available in the transport sector. It also examines specific technologies such as machine learning developed for the Pavimenta2 solution.

Conclusiones

According to interviews, Pavimenta2 has enabled geo-referencing the road network and its defects, and prioritizing the interventions and types of repairs needed. The advantages of this tool have made beneficiaries receptive to implementing it. Among the lessons learned are the importance of having the digital skills to manage similar tools, the involvement of other sectors such as academia, and the importance of having the necessary IT infrastructure.
Source code: https://github.com/EL-BID/pavimentados
Course on Artificial Intelligence in Transport: https://cursos.iadb.org/es/indes/rea-inteligencia-artificial-en-el-transport

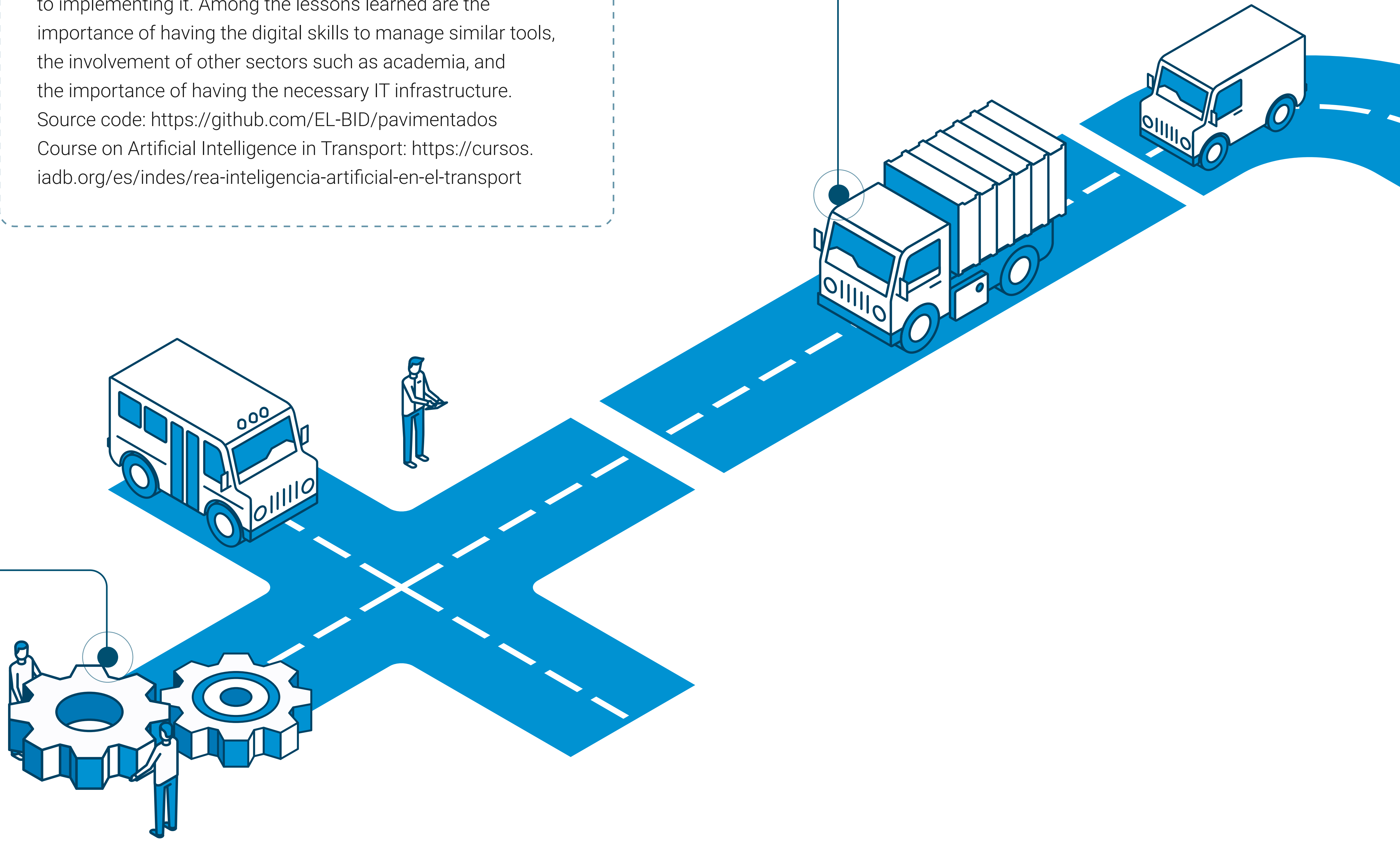


Figure 7. Description of VíaSegura

VíaSegura is a pilot project developed by the IDB and the International Road Assessment Program (iRAP) that uses AI for early detection of road conditions of roads and to improve road safety in four countries in the region (Brazil, Ecuador, Guatemala and Peru).

Description of the Solution

VíaSegura automates the analysis of road classification using AI tools, in particular, machine learning, deep learning, and computer vision. These models were trained with more 60,000 images from roads in Brazil.

Results and Impact

Through this project, road infrastructure images covering more than 61,000 kilometers of roads in the region have been more rapidly and efficiently labeled. This has enabled transport authorities to take corrective actions for this infrastructure. In fact, the IDB and iRAP have reported that use of the tool has reduced road infrastructure inspection time from 78 to 2 weeks for each 10,000 kilometers of roadways, with precision greater than 85 percent. This in turn has brought about significant reductions in the associated costs. Source code: https://github.com/EL-BID/VIAsegura.

The Problem to Resolve

Defects in road infrastructure can cause accidents that result in injuries and deaths. To address this, iRAP created a protocol (Star Rating) to determine the level of safety of road infrastructure for the different actors involved through the manual classification of roads using images and videos. The classification uses a scale from 1 to 5, where 1 is the least safe and 5 the safest. VíaSegura automates this process through AI and optimizes the identification of different elements of road safety such as the delineation and lighting of roadways, number of lanes, the quality of curves, and resistance to landslides, among others.

Source: IDB, iRAP.

In the water and sanitation sector, physical losses of water in water supply systems represent one of the major challenges for the industry, as this has a major impact on billing of the companies. These losses generally are associated with leaks in distribution pipes caused by problems such as the deterioration of the infrastructure and ground subsidence.

Traditional strategies to control water losses are based on addressing leaks reported by users (passive control), periodic surveys, or monitoring by zone or sector. Supervision generally depends on the expertise of the shift operator, and the precision of identification can be affected by the subjectivity of the official and that person's level of training. For this reason, AI-based applications have recently been developed to add value by establishing classification mechanisms with sufficient precision to detect water leaks based on the information collected (Mounce et al. 2010; Vanijjirattikhan et al. 2022).

This type of solution is being used by the state-owned company Servicio de Agua Potable y Alcantarillado de Lima (SEDAPAL) in Peru, which operates in the Metropolitan Area of Lima. In partnership with the IDB, the FEMSA Foundation, and the governments of Switzerland and Israel, this company has conducted a pilot that uses computation in the Cloud and AI models to manage water and wastewater treatment systems. With this pilot, the company was able to detect 7,000 events, including water losses, flow increases, failures in meters and telemetry, and changes in pressure (Brzezinski 2023).

Operation and Maintenance of the Systems

A determining factor in managing energy generation and distribution systems is to ensure efficient operation and maintenance in order to address the ongoing increase in demand and provide reliable electricity supply.

Efficient management of network capacity prioritizes generating energy that is the least costly both in monetary and environmental terms.[56] Likewise, energy management can focus on optimizing the capacity of local systems. Empirical studies have found that implementing a strategy to monitor consumption, together with a storage system that helps reduce consumption in the network at times of system stress, significantly reduces operational costs as well as CO2 emissions (Zhang et al. 2012). An example of using AI for this purpose is intelligent management systems that integrate administration of capacity and the use of energy storage systems with price and demand forecasting models, to determine the optimal times for charging and utilizing storage, whether for the distribution network or the battery system (Abdalla et al. 2021; Ahmad et al. 2022).

AI-based solutions can also help electricity service providers that are developing intelligent energy networks or *Smart Grids*, which use smart meters, advanced telecommunications technologies, and remote control systems to efficiently coordinate all of the network agents. These systems facilitate two-way communication between information systems and users, and produce information that strengthens models to administer demand. The aim is to develop applications such as maximum demand management, which administers consumption based on system load levels (Johannesen et al. 2019). In addition, AI-based applications based on the information collected in measurement devices are being developed to identify and monitor the topology and physical condition of energy distribution system networks in real time (Li et al. 2020), This optimizes their operation and control (Chung et al. 2023) and improves their reliability and resilience.

56 In general in the countries, to determine the energy that enters into the system, an optimization model with multiple restrictions evaluates capacity and the average cost of generation of the different plants, whether they are thermal (gas or coal), hydraulic, nuclear, solar farms, or wind parks. The aim is to identify the type of plant that is more efficient and meets with the system's energy security needs.

In France, a company designed an application[57] to analyze the level of energy consumption and send signals to users based on the system's stress level. The platform presents real-time information on both demand and wholesale prices, as well as predictive models to help consumers plan their electricity consumption during the course of the day. In countries with high loss levels – both technical and non-technical – the use of these types of networks has helped to effectively identify those losses and develop plans to prevent them (Levy et al. 2018).

Another example of solutions to improve efficiency and sustainability in operations are Building Energy Management Systems (BEMS), which include models to predict demand. These systems have been implemented to improve the planning and administration of energy consumption, optimize resources, and reduce the carbon footprint (Runge and Zmeureanu 2021). A British company developed an application that combines the information system on energy use in a building with meteorological information in order to optimize the use of energy in real time[58] through AI algorithms. This software is connected to smart meters and the main energy network, enabling administrators to optimize consumption based on wholesale prices. This has generated savings of nearly 10 percent in energy costs for buildings that have implemented the tool and an approximate reduction of up to 40 percent of carbon emissions.[59]

The main challenge for power companies is to detect energy losses, physical losses in networks (technical losses), or losses due to unauthorized consumption associated with theft or fraud (non-technical losses). In terms of non-technical losses, AI-supported solutions enable companies to predict the possibility of unauthorized consumption by certain clients, which makes it possible to optimize monitoring and inspection. A relevant case in the region is the *Energizados* tool developed by the IDB and implemented by power companies in Brazil, Guatemala, and Costa Rica. This tool analyzes historical consumption and uses machine learning models to identify connections with a high probability of fraud. For two companies in the region that use *Energizados*, the investment recovery index score (benefit-cost relationship) from audits was 2.9, while that score for the traditional method was 1.7. In addition, detection of electricity fraud by these two firms increased by 1.65 times on average (**Figure 8**).

57 Ecowatt. Available at https://www.monecowatt.fr/

58 Grid Edge. Available at https://gridedge.ai/ai-for-flexibility/

59 "Case Study: Artificial Intelligence for Building Energy Management Systems" (2019, 20 June). Available at https://www.iea.org/articles/case-study-artificial-intelligence-for-building-energy-management-systems

Figure 8. Description of Energizados

Energizados is a tool developed by the IDB that, using AI, identifies non-technical losses of electricity sector entities. The tool has been implemented in the Compañía Estatal de Energía Eléctrica de Río Grande del Sur in Brazil, the Empresa Eléctrica de Guatemala, and the Compañía Nacional de Fuerza y Luz in Costa Rica.

Description of the Solution

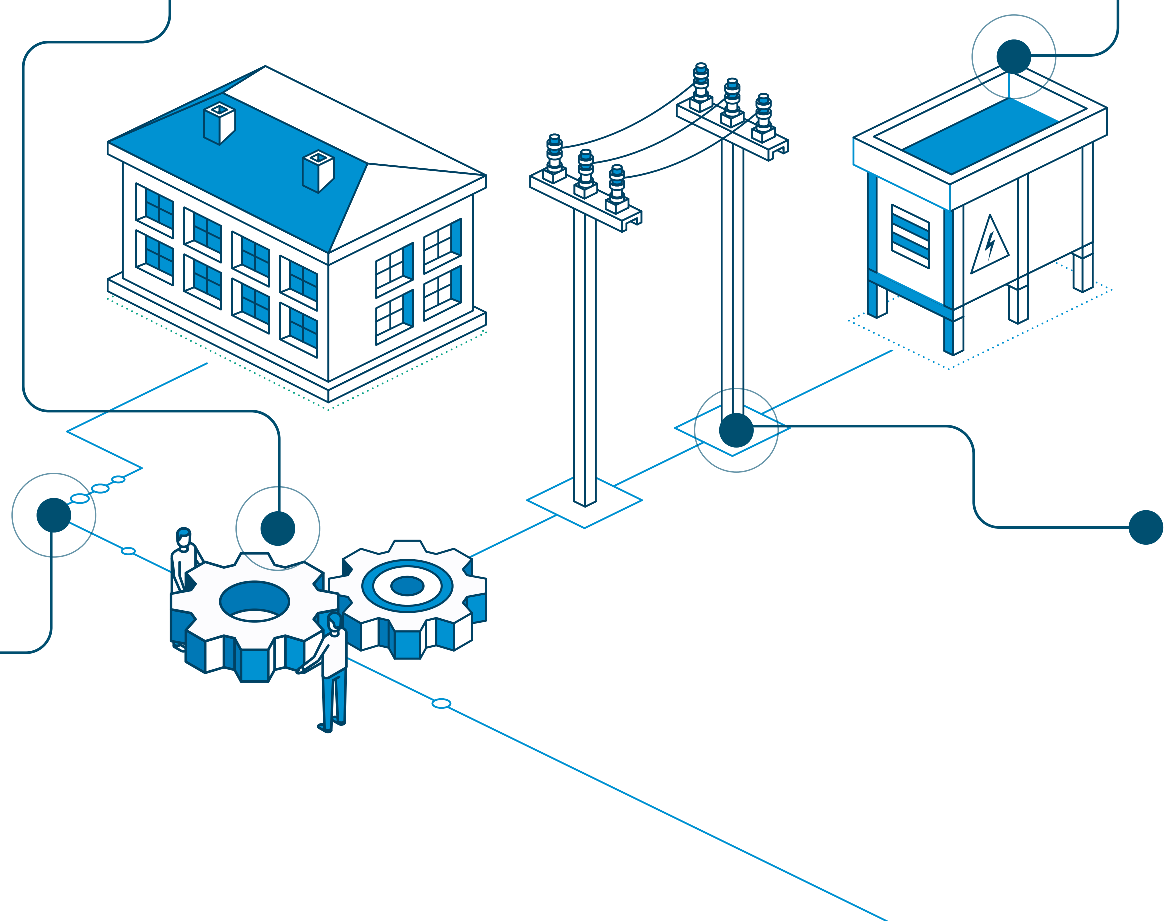
Energizados is an open-source solution that uses historical consumption data to identify connections with a high probability of being fraudulent. The tool employs AI such as supervised, semi-supervised, and analytical rule models. These models facilitate the analysis of the companies' electricity connections and the identification of anomalies and fraud, which have been subsequently verified by manual inspections that feed back into the models. In addition, Energizados presents the results through geographic visualizations that facilitate territorial analysis and support better decision-making by providing greater efficiency in the planning of inspections.

Results and Impact

For the two companies that use Energizados the investment recovery index through auditing (benefit-cost relationship) increased from 1.7 to 2.9. In addition, detection of electricity fraud through the use of the tool increased 1.65 times. For the Compañía Estatal de Energía Eléctrica de Río Grande del Sur in Brazil, adopting Energizados facilitated an increase in the identification of fraud from 17-23 percent to 28 percent. In short, in cases where Energizados has been implemented, it has helped increase the precision and efficiency of inspections and reduce their costs.

The Problem to Resolve

In Latin America and the Caribbean, the electricity sector faces losses of about 15% of the total electricity supply. Non-technical losses associated with energy theft, fraud, or measurement errors impact the financial sustainability of power companies, increase costs for the population, and are a health risk for communities in the case of illegal connections. Energizados aims to solve these problems by improving the operation of the electricity network and increasing the efficiency of electricity distribution.



Conclusions

According to those interviewed, Energizados is an example of a solution that transforms the energy sector through the use of AI, is affordable, and would be easy to implement in other countries of the region. It facilitates more precise inspections at lower cost and in less time. Among the success factors of this project are the availability of data, the commitment to innovation by company leadership, and the articulation between data scientists, product developers, and clients.
Source code:: https://github.com/EL-BID/Energizados

Sources: IDB; and interviews with the IDB project team.

The energy sector has also seen strong development and implementation of predictive models for wholesale prices used to design production plans for generators and design bidding strategies for marketers. This enables providers to improve their processes and reduce costs, which results in greater efficiency in the use of natural resources, better programing of consumption, and lower rates for final users (Pourdaryaei et al. 2024). For example, in the operation and maintenance phase, predictive models help optimize variability in the input flow of water for hydroelectric plants and reduce their losses (Arch et al. 2019). Similarly, in the field of commercialization, these types of models strengthen the automation of commercial offers, which increases the probability of closing contracts (Arch et al. 2019). In this context, in recent years the development of these models has incorporated components of AI that better address challenges such as analyzing non-linear shocks[60] related to the behavior of prices, inferring hidden relationships between variables, and developing learning capacities about the past in order to improve the precision of predictions (Castelli et al. 2020; Pourdaryaei et al. 2019).

60 The concept of the non-linear relationship between variables refers to the relationship involving complex dependencies that cannot be represented through a direct line and therefore require other forms for their representation, such as, for example, a quadratic or polynomial function or irregular patterns.

In the transport sector, there are different AI tools focused on traffic management known as Advanced Traffic Management Systems (ATMS).[61] These systems help reduce congestion, address roadways accidents in a timely manner, and reduce the accident rate, among other benefits.[62] ATMS are based on predictive traffic models that generate alerts for the authorities to solve problems related to existing infrastructure or increase capacity, as well as to evaluate the impacts of a possible intervention (Boukerche et al. 2020).

There are also solutions that generate value using machine learning models to predict road congestion. These models analyze images captured through security cameras, drones, or photos by inspectors to estimate traffic volume, speed, and trajectory.[63] This makes traffic management more efficient by evaluating possible road interventions and distributing transit agents in a way that maximizes human resources[64]. An example is the AI-based monitoring systems that analyzes images from surveillance cameras and model vehicle flows in order to improve the management of traffic lights in real time[65] and reduce traffic congestion.[66] These types of models have been used in cities such as Pittsburgh in the United States, Bengaluru in India, and Shanghai in China, among others.[67] Furthermore, the government of Singapore established a dynamic charge for the use of roads (Electronic Road Pricing - ERP) under which rates are established through machine learning models that simulate traffic and predict future congestion to calculate the optimal level that induces a reduction of actual traffic congestion levels. Toward this end, in 2020 the government installed sensors with GPS technology in vehicles (Lehe 2019).

Another key element to manage mobility systems is to identify the location of users, whether static or dynamic, which supports analysis of travel patterns and more efficient

61 Advanced Traffic Management Systems (ATMS).

62 U.S. Department of Transportation Federal Highway Administration (2023, August). Available at https://ops.fhwa.dot.gov/atdm/approaches/atm.htm

63 Inteia. Available at https://inteia.com.co/estudios-de-movilidad/

64 Ibid.

65 Adaptive Signal Control Technology (ASCT).

66 Lopez Conde, M. and Twinn, I. (2019), "How Artificial Intelligence Is Making Transport Safer, Cleaner, More Reliable and Efficient in Emerging Markets: Traffic Management Operations" (2019, November). Available at https://www.ifc.org/content/dam/ifc/doc/mgrt/emcompass-note-75-ai-making-transport-safer-in-emerging-markets.pdf

67 Ibid.

operation of the systems. This identification process is possible thanks to Global Navigation Satellite Systems (GNSS).[68] In Madrid, Spain, Romanillos et al. (2018), in coordination with the city's Compañía de Transporte Municipal, analyzed more than 250,000 routes of the city's public bicycle system (BiciMAD),[69] which allowed for conducting an in-depth study of users' travel patterns and obtaining information about activity on certain streets. The aim was to identify which streets could be used on certain dates by pedestrians and bicyclists. In addition, based on origin-destination matrices and information on trips, the authors identified options to expand exclusive bike paths (Romanillos et al. 2018).

Similarly, different predictive models of traffic accidents have been developed to identify safer road segments, patterns of location and mortality, and the probability of accidents. The information generated by these models is used by transport authorities to mitigate the causes of accidents (García De Soto et al. 2018) and prioritize the implementation of solutions (Sameen and Pradhan 2017; Santos et al. 2021). An example is a model based on deep learning developed by a group of researchers from MIT and the Center for AI in Qatar. The model predicts transit accidents with a high level of precision and has had good results in cities where it has been applied.[70] The model can be used to plan for the construction of new road infrastructure because it has the capacity to predict accidents in locations for which there is no historical record.[71]

There are also AI applications for vehicles that aim to reduce the number of transit accidents and their severity. The IDB supported the government of San Salvador in implementing a pilot system in public transport vehicles to automatically prevent collisions and accidents – the Collision Avoidance System (CAS). This system is comprised of a series of alarms, cameras, and sensors that raise an alert to drivers when pedestrians, vehicles, or other elements approach imminently.[72] The system also detects traffic signs and excess speed, controls lighting, defines secure distances between vehicles, and provides warnings about lane departures and possible head-on and side collisions with pedestrians and bicyclists.[73] After eight weeks of implementation, the percentage of drivers that reduced the generated alerts was higher than 40 percent. These types of systems help to reduce crashes between vehicles by up to 30 percent.[74]

Another key aspect of smart traffic management is the response to traffic accidents. Currently, tools are being developed to increase the automatization of responses to address these types of emergencies. One of them is real-time analysis of videos from security cameras using Convolutional

68 "The GNSS are satellite constellations coordinated to position devices in any part of the earth," with the most well-known being the Global Positioning System (GPS) in the United States. However, such systems have also been developed by other countries, such as, for example, China's BEIDOU, Russia's GLONASS, and the European Union's GALILEO, just to mention a few (Gutiérrez Puebla et al. 2020).

69 The study includes analysis of the distribution of trips, length of distances traveled, speed, and traffic network flows by hour and travel times, among others.

70 "Deep learning helps predict traffic crashes before they happen" (2021, October). Available at https://www.csail.mit.edu/news/deep-learning-helps-predict-traffic-crashes-they-happen

71 Ibid.

72 "¿Pilotos de innovación en el transporte público sin costo alguno para los países? Sí, es posible" (2018, September). Available at https://blogs.iadb.org/transporte/es/innovacion-en-el-transporte-publico-sin-costo-alguno-para-los-paises-si-es-posible/

73 Ibid.

74 Ibid.

Neural Networks (CNN) to detect objects in real time. Once the accident and its location are identified, an alert is sent to nearby emergency units. This significantly reduces response times and increases the effectiveness of interventions (Desai et al. 2021).

In the ports and logistics sector, AI models have been used to manage the traffic of freight vehicles in terminals, among other uses (Valenciaport 2020). Aerial images of the ports identify critical congestion and help to manage the speed with which vessels approach one another, mitigating congestion and reducing CO_2 emissions.[75] An example is the Port of Barcelona's use of a system to trace and manage the flow of containers in the port.[76] The containers have a code that is difficult to identify by personnel on land, since the containers can be in different positions and also because some of the codes are illegible.[77] To address this, port administrators use video analysis algorithms to obtain the container codes and in this way automatically control the flow.[78]

Finally, there is widespread concern about levels of pollution and the role of the transport sector in increasing the amount of suspended particles that affect the population. According to the IDB, at the global level 25 percent of annual greenhouse gas emissions are produced by the transport sector, which makes it the second largest contributor to this type of emission after the generation of electricity and heating (Calatayud et al. 2023). Therefore, monitoring the path of greenhouse gases is an important step forward to improve understanding of these pollution levels. Toward this end, the Applied Physics Laboratory (APL) of Johns Hopkins University developed a deep learning model that, through satellite images and public information about highways and roads, precisely estimates pollutant emissions produced by the transport sector in 500 cities with the most emissions worldwide.[79]

In the water and sanitation sector, efficient management of water resources plays a critical role in addressing the water shortages and the sustainability of sectors such as agriculture, public health, and environmental conservation. An important component of water management systems is treatment and distribution plants, as these ensure continuous supply to the community. Therefore, the distribution network requires continuous monitoring of flow to avoid leaks that generate water losses. Moreover, treatment plants require advanced processes to detect contaminants and separate residue (Nova 2023).

An important solution to make water management more efficient is the use of smart meters. On the one hand, these meters facilitate the inspection of networks

75 Quantil. Available at https://www.linkedin.com/posts/quantil-math_inteligencia-artificial-en-puertos-activity-7188503860242513920-lyPm?utm_source=share&utm_medium=member_desktop; and ORCA AI. Available at https://www.orca-ai.io/

76 "Caso de éxito: puerto de Barcelona." Available at https://www.allread.ai/es/casos-de-exito/puerto-barcelona-usan-inteligencia-artificial-identificar-contenedores-vagones/

77 Ibid.

78 Ibid.

79 Ibid.

by detecting unusual consumption; on the other, they help households and businesses manage their water consumption. Although smart meters are not themselves an AI application, they are a facilitator of these types of applications because they generate and collect the information necessary to conduct classification and prediction analysis. An example is the Empresa de Acueducto y Alcantarillado de Bogotá (EAAB) in Colombia, which launched the Medición Inteligente de Agua project to get the largest consumers to monitor their consumption and in this way obtain statistics and establish alarms to monitor their productive processes and even identify internal leaks in a timely manner.[80] Similar tele-measurement systems are being installed in different cities in LAC[81] primarily because they create value by strengthening digitalization of water distribution and treatment systems as well as by optimizing consumption by users.[82]

Similar to the energy sector, one of the biggest problems faced water utilities is losses in distribution networks, known as non-revenue water (NRW), due either to unauthorized consumption (theft or fraud) – known as non-technical losses – or to physical loses (Vanijjirattikhan et al. 2022) – known as technical losses.

A prominent AI application in this sector is the development and implementation of models to detect non-technical losses in water systems. A reference case in the region is *Aquadata*,[83] a solution developed by the IDB and implemented in 2023 by the Empresa Pública Metropolitana de Agua Potable y Saneamiento (EPMAPS) of Quito, Ecuador (**Figure 9**).

80 "Bogotá estrena la medición inteligente del agua (MIA)" (2022, October). Available at https://www.acueducto.com.co/wps/portal/EAB2/Home/general/sala-de-prensa/boletines/detalle/bogota+estrena+la+medicion+inteligente+del+agua+%28mia%29

81 "Análisis de participación y tamaño del mercado de medidores inteligentes de América del Sur y Central: Tendencias y pronósticos de crecimiento (2024-2029)." Available at https://www.mordorintelligence.com/es/industry-reports/south-and-central-america-smart-meters-market-industry

82 "La provincia de Neuquén instaló 300 medidores inteligentes de agua sobre red Sigfox." Available at https://www.grupodatco.com/neuquen-despliega-medidores-de-agua-inteligentes-con-tecnologia-sigfox/

83 BID fAIr LAC, Acuadata. Available at https://fairlac.iadb.org/piloto/acuadata. Interview with the EPMAPS and IDB project teams.

Figure 9. Description of Aquadata

Aquadata is a tool developed by the IDB and implemented by the Empresa Pública Metropolitana de Agua Potable y Saneamiento de Quito (EPMAPS) in Ecuador in 2023. The tool detects non-technical losses of water through Artificial Intelligence models and historical data.

Description of the Solution

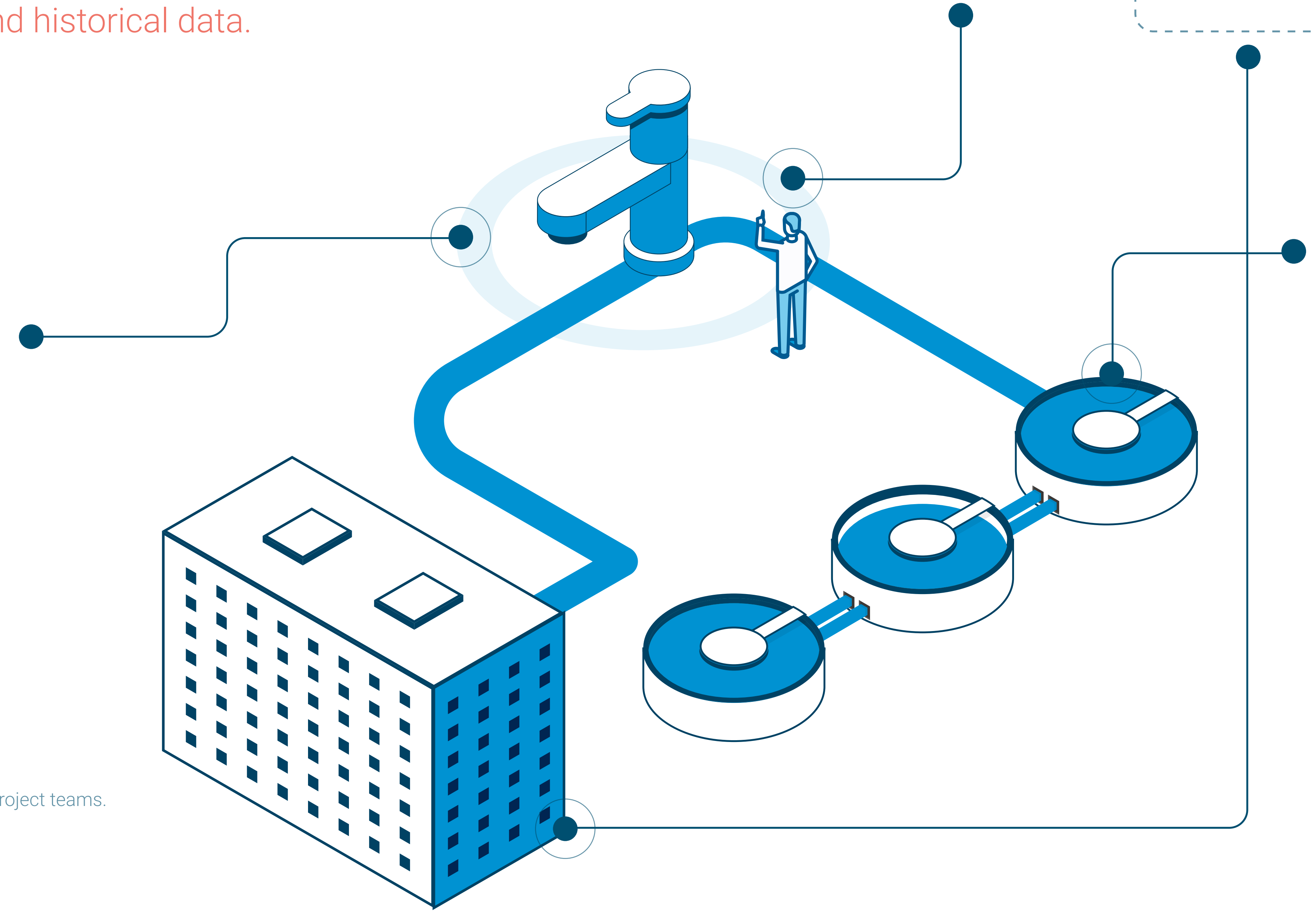
Aquadata uses machine learning models, specifically gradient boosting, a supervised classfication model, trained on data from 2010–2022 for a million clients in order to identify the likelihood of fraud. During testing, EPMAPS verified the tool's positive results through field audits.

Results and Impact

Aquadata has enabled EPMAPS to detect a large number of anomalies in water consumption with a confidence level above 90 percent. This has improved the effectiveness of field inspectors, whose assertion levels (imposition of fines) increased from 13 to 34 percent. It also helped in identifying breakdowns in more than 18 percent of water meters.

The Problem to Resolve

Aquadata aims to help reduce non-technical and commercial losses in water systems, which can reach 40 percent of the total water supply, and more effectively identify anomalies in water use with less need for control and inspections.



Conclusions

According to interviews with EPMAPS and IDB teams, this project has strengthened the entity's financial results and helped to preserve the city's water resources. The project's success factors include training, the transfer of knowledge, and the work of multidisciplinary teams. The challenges the project has faced include initial skepticism, and difficulties associated with the collection and formatting of the data, as well as their storage, in compliance with the local regulation.

Source: IDB; and interviews with the EPMAPS and IDB project teams.

One of the main problems faced by treatment plants is high contamination levels of the water, which is generally caused by bacteria, parasites, drugs, fertilizers, insecticides, and pesticides, among others. The contaminants can be difficult to classify in the treatment phase, in part because they do not permanently alter the color of the water and are not easy to see by the human eye (Maroju et al. 2023). To address this problem, different studies have focused on using machine learning algorithms to identify the elements of contamination in the water. For example, researchers at the University of Chicago used AI to create chemical probes capable of detecting and eliminating harmful substances in the water.[84]

There are also businesses responsible for promoting and implementing automatization systems in water treatment plants. Performance is monitored through a digital model of a treatment plant, which helps improve its functioning and provide information about maintenance needs.[85] These types of systems also adapt wastewater purification processes to new technologies, for example, through classification algorithms to detect foreign bodies in water sources and eliminate the waste through biological treatment.[86]

Granata et al. (2017) developed a predictive model to determine the level of wastewater contamination through certain drainage characteristics based on information from 65 communities in the United States between 1992 and 2002. The researchers found that when used correctly, the machine learning model[87] predicted the level of contamination of wastewater, and can be used in other treatment plants. It can also be used effectively in plant management systems with information from sensors in real time (Granata et al. 2017). The government of Singapore used a control tool in the Ulu Pandan treatment plant implement predictive models both for wastewater and water quality.[88] The software uses machine learning techniques to model the wastewater flow and load, as well as the levels of oxygen and certain chemicals within the bodies of water of the plant.[89] An advantage of this tool is that it is driven by data on the functioning of the plant. In this way, the model keeps learning, constantly increasing its precision.[90]

Finally, AI contributes to improving the management of solid waste. A use case is the recognition of images that detect potential or existing dump sites and facilitate classification of waste. For example, the Argentine foundation Bunge y Born AI used satellite images to develop a system that identifies open-air informal dump sites to prevent their spread and their negative impact on the environment and public health (Fundación Bunge y Born, n.d. and 2021).

84 "Artificial Intelligence Applied to the Treatment of Municipal Wastewater" (2021, May). Available at https://www.bluegold.es/es/inteligencia-artificial-aplicada-al-tratamiento-de-aguas-residuales-municipales/

85 "Managing Sustainable Water Treatment with Intelliflux." Available at https://ifctrl.com/industries/water/

86 Ibid.

87 In this case, the authors used decision trees and support vector regression, as this latter method obtained the best results.

88 IWA (2020), "Digital Water, Artificial Intelligence Solutions for the Water Sector: Predictive Wastewater Treatment Plant Control." Available at https://iwa-network.org/wp-content/uploads/2020/08/IWA_2020_Artificial_Intelligence_SCREEN.pdf

89 Ibid.

90 Ibid.

Relationships with Clients

The use of AI in the energy sector helps improve the relationship of businesses and clients by providing relevant information and facilitating communication. AI can induce savings for clients by providing access to information about energy costs, optimal times to use energy, and the quantity of energy generated through renewable sources (Engelhardt, McClelland and Collet, n.d.). In addition, AI tools such as bots support the processing of email and chats on digital platforms. These can solicit information that users lack, inform them of service interruptions or anomalies, help them optimize their consumption based on their needs and prior consumption, and provide them with responses in less time. This improves the user experience and satisfaction, while at the same time promoting loyalty of clients to the companies that serve them.[91]

An example of AI that generates value for users are applications that optimize the operation of transport systems and help reduce congestion. Predictive traffic models that use AI[92] help develop applications to provide citizens with better information for their transport decisions. Such is the case of the TIMON Project, directed by a research team from the Universidad de Deusto in Spain, which optimizes travel routes for users according to their needs by, for example, predicting traffic levels[93].

There are also AI applications for users that provide relevant information for efficient use of public transport. Through an application provided by the Metropolitan Transport Authority (MTA),[94] subway and bus riders in New York City access information in real time on the occupation levels of vehicles, schedules, status of service, anomalies in routes, and average wait times, among other topics (Calatayud et al. 2022). This information is provided through AI models that process data generated by sensors located in the transport infrastructure (buses, trains, and stations) (Calatayud et al. 2022). Some empirical studies have shown that these types of applications increase user satisfaction because of their positive impact on the reliability and robustness indicators of the system (Chan et al. 2020).

Another example of this type of tool is the application developed by the IDB for Santa Cruz de la Sierra Airport, Viru Viru, in Bolivia. This application provides persons with visual disabilities greater independence to move around the airport.[95] Through images, the application determines where the user is and compares in real time the image captured with a collection of images of the airport that exist in the

91 Visor AI (2021); Microsoft – Streebo Inc. (2024); Infosys BPM (2024); Wipro (2019); Talbott (2024); and Sergiienko (2024).

92 Despite good results that are being obtained in the precision of the prediction with machine learning models compared with statistical time series models, it is important to mention that the system is still not progressing in reducing the structural complexity of the models, which in turn increases the computational complexity, which requires more resources.

93 TIMON, “Inteligencia Artificial que predice las congestiones de tráfico” (2019, January). Available at https://www.spri.eus/es/teics-comunicacion/timon-inteligencia-artificial-que-predice-las-congestiones-de-trafico/#:~:text=El%20objective%20de%20TIMON%20es,inteligencia%20artificial%20y%20big%20data.

94 For more information, see: https://new.mta.info/

95 “El aeropuerto de Viru Viru en Bolivia apuesta por la accesibilidad universal y la inclusión” (2023, October). Available at https://blogs.iadb.org/transporte/es/el-aeropuerto-de-viru-viru-en-bolivia-apuesta-por-la-accesibilidad-universal-y-la-inclusion/

Cloud. Through voice indicators, it guides the user throughout the terminal.[96] To help the user get to certain locations, places are grouped by category – for example, airlines, bathrooms, ATMs, and restaurants, among others.[97] This type of application helps individuals with visual impairments navigate critical infrastructure such as airports,[98] while also optimizing airport operational resources by providing personalized assistance and facilitating contact with responsible personnel when users require support.

Also important to planning and managing transport system capacity is incorporating the gender perspective in the design of the different public transport systems and when evaluating the impact of implementation. Some empirical work has used machine learning models, such as Bayesian Networks (BN), to analyze demand for public transport modes in order to identify the characteristics that must be improved to consolidate a gender perspective in public transport systems. One study that analyzed information from public rail transport and the bicycle system, among other services found that to achieve a more just railway system and increase demand by women, it is necessary to improve the availability of seats to reduce social interaction, increase personal space, integrate shared mobility services for last-mile connections, install assistance points in case of assaults or other needs, announce means of contact for assistance, and promote campaigns to reduce incidents (Molero et al. 2021). The study also found that improving the shared bicycle system requires focusing on reducing routes with a certain level of incline, including electric bicycles, putting in place means of protection from the rain, and including child seats, among other measures (Molero et al. 2021).

To improve safety at transit stations, especially for women, machine learning models are being developed in different places to analyze videos in real time from installed security cameras and report possible aberrant behavior. An example is the software being developed by the University of Wollongong in Australia to detect behavior such as fights and harassment in public transport stations that can indicate occurences of insecurity. To identify such incidents, the model emits alerts so that authorities can intervene in a timely manner. [99]

As it does in the energy sector, adopting AI in the water and sanitation sector generates value by improving the relationships of companies with their clients. Through AI, the companies understand their clients' consumption, enabling them to personalize services at low cost, detect anomalies in demand, and inform clients about service interruptions and failures. This generates savings in water resources and improves the user experience.[100] A water and sanitation company that has used AI toward this end is the Dubai Electricity and Water Authority. It developed *Rammas*,

96 Ibid.

97 Ibid.

98 According to the IDB's *Moviliblog*, tourism accounts for 4.6 percent of GDP in Bolivia and more 320,000 direct and indirect jobs. One of the main locations for tourism in the country is the Santa Cruz de la Sierra Airport, Viru Viru. It is considered the country's most important airport because it is where large numbers of passengers and goods enter and leave the country.

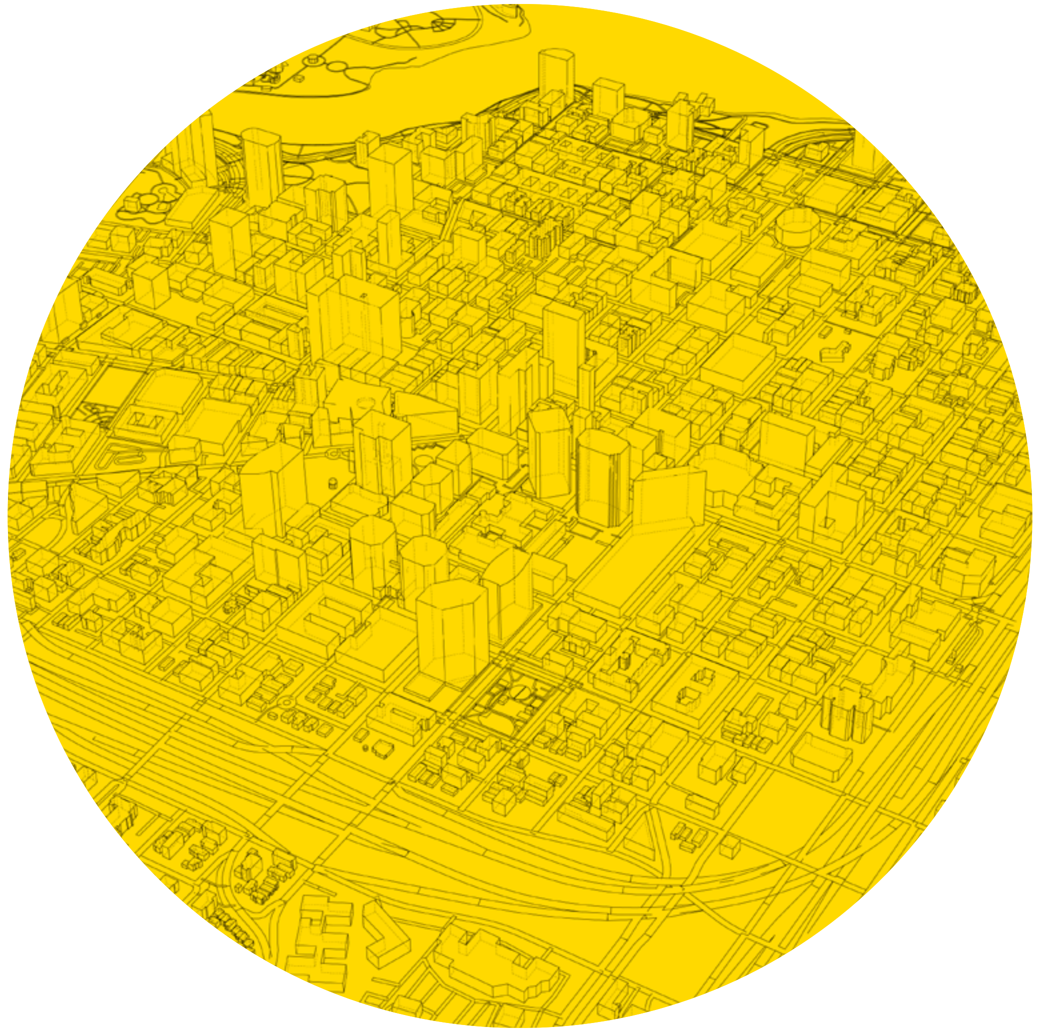
99 University of Wollongong Australia, "AI Research to Aid Women's Safety on Public Transport." Available at https://www.uow.edu.au/media/2020/ai-research-to-aid-womens-safety-on-public-transport.php

100 Nestor (2023), Talbott (2024), Wipro (2019), and Tempest (2023).

a chatbot that resolves questions among the different actors involved, such as clients, providers, potential workers, and contractors through the use of an application developed by the organization as well as other digital platforms (Deloitte 2023). An advantage of this tool is that it functions permanently in two languages, which facilitates interaction with clients.

The IDB, through the Fuente de Inovación partnership,[101] has implemented pilot projects that apply smart waste technologies to improve management of domestic solid waste. One of the projects is being carried out with the Consorcio Intermunicipal del Valle Medio de Itajaí (CIMVI) in Brazil. This pilot aims to improve communication with final users and the collection and analysis of data to generate management indicators and support decision-making. CIMVI's waste-sorting plant in Brazil has integrated the Greyparrot technology, which uses computer vision and AI to analyze recyclable waste. The system automates the auditing and analysis of 100 percent of the waste processed, which identifies 89 types of waste in 13 categories, including more than 35 types of solid and flexible plastics.

The technology provides real-time data on the composition of the waste, and this information is presented in control panels with relevant information about the types and quantities of waste. This digitalization initiative enables CIMVI to access reliable and timely data, which improves decision-making and communication with interested parties and ultimately improves its waste management services.



101 Fuente de Inovación is a partnership between the IDB Group and external partners that promotes innovative solutions in the basic water and sanitation sector in LAC to achieve intelligent, inclusive, and sustainable services. Source: https://www.iadb.org/es/quienes-somos/topicos/agua-y-saneamiento/iniciativas/fuente-de-inovacion

4 CONSIDERATIONS FOR THE ADOPTION OF ARTIFICIAL INTELLIGENCE IN INFRASTRUCTURE SECTORS

4.1 Agile Development Methodology for AI-based Solutions

As indicated in Chapter 3, AI-based solutions have the potential to generate value and significantly impact the performance of infrastructure sectors such as energy, transport, water and sanitation, and solid waste. In particular, it is a tool to strengthen planning and design, construction, and management and maintenance of assets to optimize operational efficiency and improve the relationship with users.

The incorporation of AI can become a transformational factor, involving changes to processes, systems, interdepartmental relationships, and, in some cases, the adoption of new operational and business models. Therefore, it is important that infrastructure organizations implement methodologies for AI development and innovation that are robust, aligned with their objectives, and in line with best practices. Successfully developing and implementing these types of solutions means adopting technical, ethical, legal, mathematical, managerial, cultural, and project management considerations. This requires a holistic understanding of the problem and the solution, for which it is necessary to implement flexible methodologies that effectively incorporate these considerations. In addition, the use of AI models generally means incorporating change management strategies. Adopting AI solutions therefore requires a responsible government that considers aspects of communication, transparency, inclusion, equity, security of information and systems, reliability of results, and accountability.

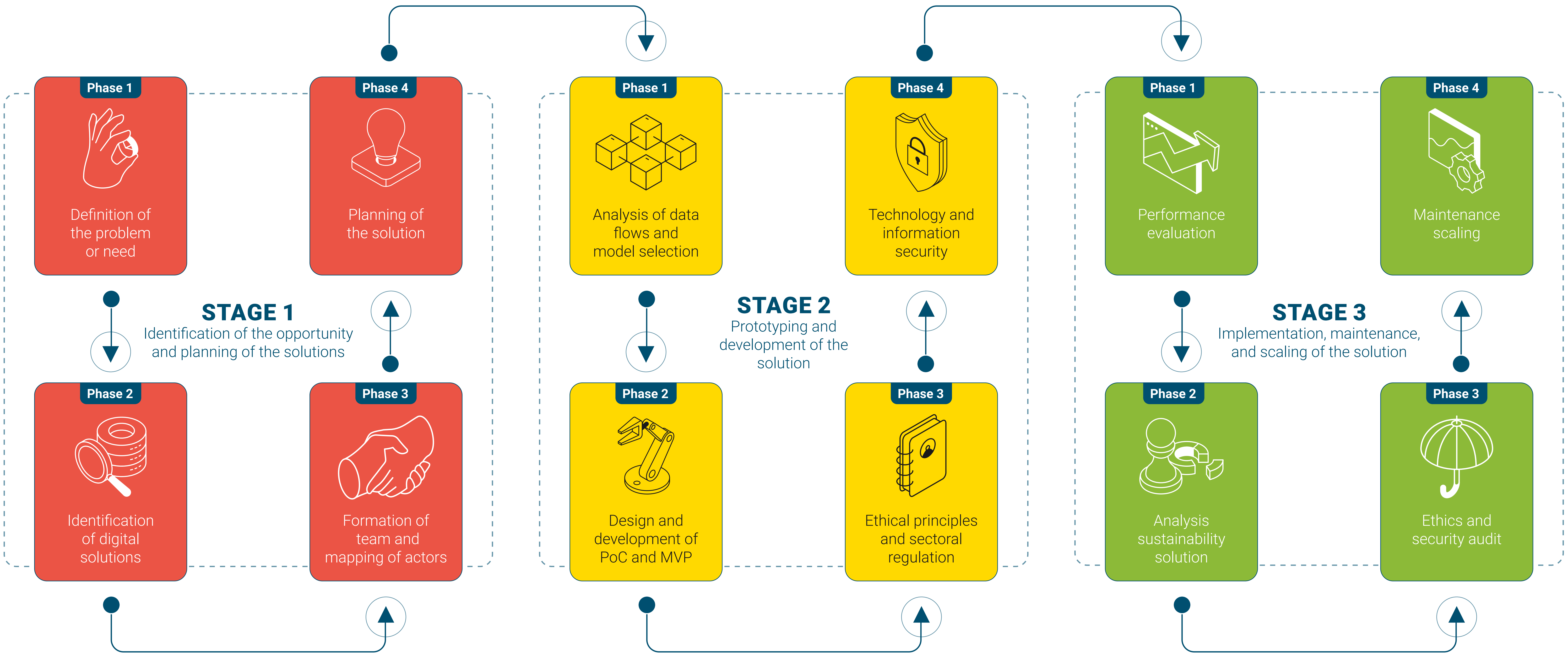
The experience of the IDB in promoting and developing AI-based solutions in infrastructure sectors has led to concluding that the agile development and innovation approach,[102] which is commonly used in entrepreneurship and technological innovation processes, is also pertinent to developing and adopting these solutions in the infrastructure sectors. As its name indicates, this approach focuses on the flexibility of the processes, adaptation capacity, experimentation, and ongoing feedback from the user or client. In addition, it considers continuous iterations throughout the system's production chain in order to carry out timely modifications in the structure of the model. For that purpose, it usually involves developing prototypes and pilots to experiment with functional variations of the product. This incorporates flexibility into the process, as in any development stage a different solution can be redesigned as a consequence of experimentation involving real users (Minatta et al. 2022).

The agile approach enables organizations that manage critical infrastructure to iterate through their models and systems, continually incorporate comments and new ideas, and make adjustments in real time. This is crucial to guarantee operational continuity, improve security, and ensure that the infrastructure can be rapidly adapted to new demands or emerging risks. In addition, by using prototypes and pilots in the development process, organizations identify and mitigate possible failures before they impact the overall system.

Taking this all into account, the agile development and innovation approach generally consists of three main stages: (1) identification of the opportunity and planning of the solution; (2) prototyping and development of the solution; and (3) implementation, maintenance, and scaling of the solution (**Figure 10**).

102 The term "agile" refers to the set of frameworks and principles that codify a software development method. This concept describes projects that prioritize simplicity, collaboration, and interaction of the team and the client with frequent deliveries and creation of self-organized teams with the capacity for adaptability that reflects and prioritizes client satisfaction. This methodology is characterized by being iterative and differs from the traditional methodology in several aspects. The term "agile" is currently used to refer to diverse development and innovation practices and is even used in other areas of knowledge different from software development. Sources: Agile Alliance, "¿Qué es Agile?" Available at: https://www.agilealliance.org/agile101/; and Dingsoyr (2009), "What Do We Know about Agile Software Development? IEEE Software."

Figure 10. Agile Development and Innovation Approach



Source: Prepared by the authors.

As shown in **Figure 10**, the framework is iterative between stages, and each stage maintains a continuous cycle of improvement. This is intended to reflect the model's flexibility and adaptability, as changes can be introduced at any point in the cycle without significantly affecting its development

The sections that follow present a set of key considerations that the IDB recommends be taken into account by designers and implementers of AI solutions in infrastructure sectors throughout the process of developing and implementing these solutions. These considerations have been identified through the review of cases and international practices, as well as the IDB's experience and the lessons it has learned in supporting countries of the region in adopting these technologies. These considerations are key to ensuring that the integration of AI is carried out effectively and aligned with strategic objectives, and that the benefits for critical infrastructure are maximized.

Stage 1: Identifying the Opportunity and Planning the Solution

The first stage of the agile development and innovation approach is ***identification of the opportunity and planning of the solution.*** Its objective is to define and delimit the problem, as well as establish the decision elements in order to implement an AI solution. It generally includes four main phases.

Stage 1, Phase 1

Defining the problem or need:

The organization defines a specific problem that needs to be solved or identifies a need, such as strengthening decision-making or innovation in products, services, or processes.

A good definition of the problem is generally clear and concise and makes reference to a solvable situation. To do this, it is important to ask the following questions: What are the causes and consequences? Why is it important to resolve it? What happens in the absence of intervention? What interest groups are affected? What are the indicators that establish the existence of the problem? Why has the problem not yet been solved? For problem definition, it is essential to gather as much information and available evidence as possible, so that the formulation is based on concrete data and facts rather than assumptions.[103]

Stage 1, Phase 2

Identification of possible digital solutions:

This refers to the definition of alternative solutions that would be most appropriate to resolve the problem identified and to determine the relevance of using AI in the solution. This constitutes a filter to prevent the risk of developing AI projects based on the technology itself rather than on the problem to be solved (Pombo et al. 2020).

To assess the relevance and necessity of implementing an AI-based solution, it is important to first understand the problem before considering how to solve it. Working groups often start with the contrary causal relation. That is, they select the AI solution that they want to implement and then decide where to apply it. In the experience of the IDB, specifically

103 IDB Infrastructure and Energy Sector (INE), "Guía de desarrollo de productos digitales." PowerPoint presentation, IDB.

in infrastructure sectors, successful projects are those that start by identifying a problem, delimiting it in order not to lose the focus, and then deciding on the tools required to solve it.[104] In this phase it is best to pose the following questions: Why is a digital solution necessary to solve the problem? What are the different aspects offered by the digital product compared to some other solution?

Analyzing the methods of existing solutions

It is a priority to understand the possible solution methods and their feasibility, as well as to identify the theoretical and empirical foundations of the initial approaches to a potential solution. It is therefore best to proceed with a market study of the solution methods and the existing solutions. This means moving forward with an analysis of the technological tendencies and available use cases. Moreover, part of the analysis of the possible solution methods usually considers the complexity of development (technical viability), the costs associated with each option, and the types of skills and capacities required for implementation.

It can occur that the same sector or other sectors have adopted AI-based solutions similar to those that are being considered for implementation in the case at hand. In this case, the solutions already developed, as well as the lessons derived from their development and implementation, will be useful for designing the new solution. As part of this, open source code can help save time and incorporate best practices from previous projects. An example are the applications developed by the IDB in infrastructure sectors,[105] which have public repositories that can be used for the designers and implementers of solutions, including BA *Obras, Caminos of the Villa, VíaSegura, Cycle de Movilidad, Distancia2, Energizados, Pavimenta2* and *Congestiómetro*, to mention a few.

Making use of solutions previously developed by startups or technological partners can be a useful and efficient strategy to address similar problems. Drawing on the experience of these companies through processes of open innovation, partnerships, or exchanges of knowledge allows for exploring new ideas and possible solutions.[106] To maximize the impact of these collaborations, it is crucial to define objective decision-making criteria that enable the selection of existing solutions with the greatest potential and alignment with the organization's goals.

In addition, this strategy opens up opportunities to develop local solutions that are adapted to the particular needs of the region and comply with international standards. This not only promotes transparency, equity, and responsibility in the implementation of AI, but also strengthens regional ecosystems. Initiatives such as fAIr LAC+, promoted by the IDB Group, develop frameworks, tools, and best practices. fAIr LAC+ offers consultancies, training, and tools to support the countries and entrepreneurs in the ethical and effective adoption of the AI. Tools such as fAIr LAC 3S and fAIr Venture promote building a portfolio of regional solutions and solid ecosystems.

104 Ibid.

105 For more information, see https://code.iadb.org/es/herramientas

106 IDB Infrastructure and Energy Sector (INE), "Guía de desarrollo de productos digitales." PowerPoint presentation, IDB.

Stage 1, Phase 3

Formulating the team and mapping the actors:

In this first stage it is useful to define a project management structure and the interdisciplinary team with the capacity to incorporate the technical, legal, and business knowledge to develop and implement the solution. It is also useful to identify interested actors and possible strategic partners.

Identifying the actors is important because it contributes to framing and delimiting the problem and the possible solution. It also allows for understanding the actors' motivations and interests, as well as their potential influence on the product to be designed and implemented. It is especially important to identify the actors that will benefit from AI and those that will need to change their operation or behavior once it is adopted.[107] Similarly, it is useful to identify possible strategic partners and project sponsors in order to evaluate the viability of the respective partnerships or the support that they could contribute to successful project implementation.

For example, in transport projects such as implementing an AI-based traffic management system, the interdisciplinary team needs to include experts on urban planning, transport technology, and mobility regulations, in addition to operators and final users, in order to ensure that the solution is adequately integrated with the existing infrastructure and responds to the specific needs of the urban environment.

On the other hand, for an energy project such as optimizing electricity networks through the use of AI, it is essential to involve specialists in electrical systems, cybersecurity, energy sector regulators, and experts in sustainability. The interaction with different actors is critical, since energy projects usually face unique challenges related to the stability of the network, regulatory compliance, and public acceptance of new technologies.

Stage 1, Phase 4

Planning the solution:

It is also important to analyze possible alternatives and consider the criteria to choose the most appropriate solutions. Valuable elements include analyzing existing solutions, reviewing available data and possible models, identifying the technological tools needed, identifying the skills and capacities needed, and formulating ethical, information security, and sectoral regulation considerations.

Analyzing alternatives and evaluating criteria are essential in infrastructure sectors because of the complexity and long-term impact of the projects. Selecting the best solution means considering many factors, including operational efficiency, sustainability, and resilience.

The evaluation of technological tools is crucial to ensure the adaptability of the infrastructure to future innovation. Ethical and security considerations, along with compliance with sectoral regulations, are indispensable to minimize risks and ensure the long-term success of the projects.

107 Ibid.

Type of data and possible models to develop

In this phase it is crucial to identify and analyze the characteristics of the data to be used, such as their origin and availability – that is, whether they are structured[108] semistructured[109] or non-structured,[110] and whether they are open, personal, or reserved. Other factors to consider are the volume of the data[111] and its representativeness and quality,[112] as well as the variability of categories, relationship between variables, dimensionality, equilibrium in the categories,[113] source and update frequency, and ways to extract and capture the data. Additionally, the sensitivity level of the available information should be assessed. For example, as mentioned in the ethical considerations phase—regarding data privacy and cybersecurity—it is necessary to determine whether the input data is private or has ethical implications. In such cases, it may be necessary to apply transformations during development stages to protect privacy or mitigate potential biases or ethical risks. Thus, in this stage, the type of information is categorized to assess risks and thereby determine the appropriate data handling measures in terms of both security and data volume for processing

Identifying and analyzing the characteristics of the data to be used is an important step prior to implementation in the prototyping and development of the solution stage described in Section 4.1.2. As mentioned in the description of this stage, a key element in model selection is the analysis and implementation of the project's data flow. This consists of a series of articulated steps through which the data are extracted, processed, and transformed from raw data to an optimal condition for model training and evaluation.

Identifying and understanding the solution

Based on the analysis of existing solutions and identification of the data to be used and potential models to be developed, the most suitable type of solution is determined, along with its various components.To define the ideal solution to address the problem or need identified, the different solutions are evaluated based on criteria such as effectiveness to solve the problem, technical and financial viability, operational efficiency, procurement implications, needs for partnerships or in-house development, the time horizon required, and impacts on sustainability and resilience, among others.

In addition, once the solution is identified, it is advisable to develop a thorough understanding of it in aspects such as its alignment with the business strategy and operation, relevant regulations that must be taken into account, its advantages compared with other types of solutions, relevant contextual factors-political, social, or infrastructure-related- and its objectives and expected outcomes, among others aspects.

108 These types of data have defined aspects such as attributes, length, and size, and their storage is presented in related databases, spreadsheets, and table formats (Vélez et al. 2022).

109 These are labeled data that have no formal structure, such as the data presented in a database (Vélez et al. 2022).

110 Data that have no structure and can be stored in Word or PDF documents, videos, images, social network chats, and email, among others (Vélez et al. 2022).

111 The quantity of data necessary varies according to the type of model, the complexity of the problem, and the number of parameters required (Vélez et al. 2022)..

112 If they are incomplete, disorganized, without metadata and with serious indications of errors (Vélez et al. 2022).

113 Especially with problems of classification, it is important that the different classes and categories within a variable are balanced in a way that does not reproduce biases in the training (Vélez et al. 2022).

Technological tools

In this phase it is useful to also consider the requirements that will arise in terms of the technological tools needed to develop and implement the identified solution.

The data infrastructure to develop AI solutions is divided into two functions: storage and processing. These two functions involve the interaction of (i) the data infrastructure, (ii) the environment for development of the AI model, and (iii) the supporting technological infrastructure

The data infrastructure is related to the form in which the information is organized; that is, if it is structured in relational tables[114] or non-relational tables.[115] The infrastructure is also composed of the data engineering model that is used, whether it is Extract, Transform and Load (ETL)[116] or Extract, Load, and Transform (ELT);[117] and the data storage infrastructure, which can be a data warehouse,[118] data lake,[119] or a combination of the two known as data lakehouse.[120]

In terms of the development environment of the AI model, decisions generally should be taken in terms of processing capacity and speed at which the models will be trained. Infrastructure projects that use images generally have Graphic Processing Units (GPUs)[121] to support sessions to train the AI models being developed. The development of these GPUs has enabled significant advances in machine learning models, mainly in processing speed, compared with the speed of traditional CPUs; greater energy efficiency, since GPUs offer better performance per watt compared with CPUs; and the possibility to implement parallel processing, since the architecture is designed to carry out multiple tasks simultaneously.[122]

In addition, it is crucial to consider supporting technological infrastructure which consists of a physical or virtual place where data will be stored and processed. It is key to define whether this space will be constructed in the Cloud (whether private, public or a hybrid), or housed in local infrastructure (servers). This choice

114 Relational databases are those that store information in tables, known as relational tables, where each one is a collection of data organized in files (records) and columns (attributes). See "¿Qué es una base de datos relacional (sistema de gestión de bases de datos relacionales)?" Available at https://www.oracle.com/co/database/what-is-a-relational-database/

115 This system of databases does not follow a rigid scheme; instead of files and columns it uses different data storage and recovery models, which facilitates improvement in terms of scalability with regard to relational types of databases. See "Qué es NoSQL?" Available at https://aws.amazon.com/es/nosql/

116 Consists of combining data that come from different sources and applying rules of business, validation, and statistics in order to clean and order them with the aim of storing them in a centralized repository. See AWS, "¿Qué es extraction, transformation and carga (ETL)?" Available at https://aws.amazon.com/es/what-is/etl/

117 According to AWS, "the ELT approach loads the data as they are and transforms them in a prior stage, according to the use case and the analysis requirements." Available at https://aws.amazon.com/es/compare/the-difference-between-etl-and-elt/>

118 According to AWS, a data warehouse "is a central information repository that can be accessed for analysis for informed decision-making." Available at https://aws.amazon.com/es/what-is/data-warehouse/

119 This refers to a centralized repository dedicated to the storage of structured, semi-structured, and non-structured information of any magnitude, without the need to transform it previously in a pre-defined scheme. See "What Is a Data Lake?" Available at https://aws.amazon.com/what-is/data-lake/

120 This is a conjugation of data warehouse and data lake that combines information storage without processing with the benefits of the control and management of structured data offered by the data warehouse model. Source: Google, "What Is a Data Lakehouse? Available at https://cloud.google.com/discover/what-is-a-data-lakehouse#:~:text=data%20management%20features.-,What%20is%20a%20lakehouse%3F,organized%20sets%20of%20structured%20data).

121 A Graphics Processing Unit (GPU) is a processor specialized in graphics and the rendering of images. However, as it has a high processing capacity, it has been used to carry out intensive mathematical calculations and parallel processing, facilitating the work of the computation of complex machine learning training models. See "What Is a GPU?" Available at https://www.intel.com/content/www/us/en/products/docs/processors/what-is-a-gpu.html#:~:text=What%20does%20GPU%20stand%20for,video%20editing%2C%20and%20gaming%20applications.

122 NVIDIA, "Why GPUs Are Great for AI (2023, December). Available at <https://blogs.nvidia.com/blog/why-gpus-are-great-for-ai/>; and "What Is a GPU? Available at https://www.intel.com/content/www/us/en/products/docs/processors/what-is-a-gpu.html#:~:text=What%20does%20GPU%20stand%20for,video%20editing%2C%20and%20gaming%20applications.

will impact development time, costs, security, and the team competencies required.

In this regard, there are two main options: the use of computation services in the Cloud, or the use of a solution based on local infrastructure, which is also referred to as "on-premise." Cloud computing refers to the on-demand delivery of scalable and virtualized IT resources over the Internet through a pay-as-you-go model. These services, typically supported by servers distributed across the globe, rely on the sharing of underlying physical resources, enabling the rapid and flexible provision of storage capacity, processing power, information management and access, application execution, and content or service delivery.[123]

Just as there are different modalities to develop computation in the Cloud, there are also different business models for contracting its services. The most common options are Infrastructure as a Service (IaaS); Platform as a Service (PaaS); and Software as a Service (SaaS).[124] IaaS is the infrastructure service, that is, the operation of virtual machines, storage capacity, processing, and networks allowing clients to configure them according to their needs. PaaS focuses on offering access to the necessary environment to develop, manage, and launch applications based on the use of the respective support infrastructure. Finally, SaaS offers end-user solutions as a service according to client needs, without it, clients would have to manage the back office, maintenance, and supporting technological infrastructure (World Bank 2022; García and Iglesias 2022).

For projects related to energy, transport, water, sanitation and solid waste, there are certain advantages to developing AI solutions in the Cloud:[125]

- **Accessibility:** Storage of and access to information from any terminal or geographic location.
- **Scalability and flexibility**. The Cloud supports an increase in traffic and users relatively easily and, similarly, adjusts to reductions, which is why it is an infrastructure that adapts to the application.
- **Agility for development of the product**. This allows for carrying out experiments regarding traffic – such as increasing and decreasing use of the application – and the functionalities of the solution.
- **Reduction of costs**. Good administration and planning of resources for storage, processing, and execution of applications in the Cloud significantly reduces costs compared to a solution based on local servers, in the sense that you only pay for what you are actually using, avoiding costs associated with unused infrastructure. Another aspect to consider is the environmental sustainability of the solution. According to Microsoft Cloud estimates, cloud computing can be between 22 and 93 percent more energy-efficient than on-premise solutions.[126] At the start of 2024, Google Cloud reported that it met 100 percent of its annual demand for electricity with renewable

123 "¿Qué es la nube?" Available at https://azure.microsoft.com/es-es/resources/cloud-computing-dictionary/what-is-the-cloud; and "¿Qué es la computación en el nube?" Available at https://aws.amazon.com/es/what-is-cloud-computing/

124 IBM, "What Are IaaS, PaaS and SaaS?" Available at https://www.ibm.com/topics/iaas-paas-saas#:~:text=IaaS%2C%20PaaS%20and%20SaaS%20are,types%20of%20cloud%20service%20offerings.

125 Ibid.

126 "Sustainability with On-Prem and Cloud Simulation" (2022, October). Available at https://softwaresim.com/blog/sustainability-with-on-prem-and-cloud-simulation/

sources, while Microsoft Azure has reported being carbon-neutral since 2012.[127]

- **Data storage capacity:** The Cloud offers practically unlimited storage capacity adaptable to the needs of the application. In contrast to local infrastructure, where space can be limited and expensive to expand, the Cloud allows for scaling storage simply and according to demand. This facilitates management of large volumes of data without worrying about the underlying infrastructure. This is especially relevant for the effectiveness and precision of AI solutions, since in these cases it is necessary to manage massive volumes of data for the development and training of models.

For its part, the on-premise model refers to infrastructure and resources where the applications deployed are the property of the entity and located in its facilities.[128] This allows for complete control of the hardware; that is, the organization is responsible for the server, assembly, storage, cooling of the equipment, UPS,[129] administration of access, and safeguarding of the information, among other responsibilities.[130] This alternative is generally used to process sensitive data that have special protection, as in certain cases the regulation prohibits housing those data outside of the country.[131] However, it is important to take into account that, although the on-premise model has direct control of the infrastructure, it requires constant operation and maintenance and has limited capacity, since its growth requires buying more servers, which implies more space, energy consumption, and cooling needs.

Another important decision in terms of technology is whether to develop the AI solution within the organization or contract it to a third party. The first option (development in-house) offers greater control, better adaptation to the particular needs of the project, and generally lower costs. However, it requires that the organization have the necessary knowledge and skills. For its part, external development can prevent the organization from having to develop and incorporate knowledge and skills that it does not have. However, the cost of external development is usually higher and in all cases requires an internal team with relevant responsibilities such as project management, procurement of information, design of an appropriate strategy for integration of systems, and subsequent updating of the model.

127 Hive, "Who Has the Greenest Cloud? The Most Sustainable Cloud Tech in 2024" (2024, February). Available at https://www.hivenet.com/post/who-has-the-greenest-cloud-the-most-sustainable-cloud-tech-in-2024

128 TIC Portal (on-site) (December, 2023). Available at https://www.ticportal.es/glosario-tic/on-premise

129 UPS (Uninterruptible Power Supply) is a device that provides support to electrical facilities when the main source of power fails. See USAID, "Uninterruptible Power Supplies." Available at https://www.usaid.gov/energy/powering-health/system-components/uninterruptible-power-supplies

130 TIC Portal (on-site) (December, 2023). Available at https://www.ticportal.es/glosario-tic/on-premise

131 Ibid.

Finally, in terms of the technological tools to develop an AI-based solution, there are additional considerations regarding the organization's level of preparation to use and make the most of these tools. The considerations include (i) the level of maturity of businesses and processes for the adoption or use of technologies, (ii) the risks associated with their adoption, including legal and ethical aspects, (iii) existing barriers to adoption, and (iv) the standards or regulations related to these technologies that must be taken into account in developing and implementing the solution.

Identifying required skills and capacities

As shown in the description of phase 3 of this stage, it is useful for the organization to assemble an interdisciplinary team with the skills and capacities to incorporate the technical, technological, business, and legal knowledge needed to successfully develop and implement the solution. Once the solution to be implemented is identified, the specific technical skills required to build and apply the models can be determined.

Although their construction is occasionally outsourced, the use and maintenance of the models falls to internal personnel who, if not prepared, may underutilize the potential of the solution or even not use it, which compromises the sustainability of the model. The experience of the IDB in developing AI solutions in infrastructure highlights the importance of including in the team professionals with knowledge of data science, machine learning, and information technologies, as well as an understanding of the business. This will allow for evaluating, starting from the design stage, whether the model responds to the organization's needs, and for receiving feedback about the model's functions and results in the sectoral context in which it is being developed.

Ethical, privacy, and information security considerations

It is recommended that a matrix of the risks associated with implementing the future solution be developed that incorporates ethical, reputational, regulatory, and environmental, social and governmental (ESG) risks. The matrix should also examine possible impact and the organization's mitigation plan. Likewise, as mentioned earlier, it is important to identify whether the model's input data are of a personal nature in order to employ some type of transformation, such as anonymization, in order to protect their privacy.

Although not the case in most development of AI in infrastructure sectors, it is important to analyze whether the model's training information includes sensitive variables such as nationality, gender, or ethnicity. If such variables exist, it may not be advisable to simply remove them from the model, as there could be other variables in the dataset that are correlated with them and may still preserve existing biases (Mehrabi et al. 2022). In these cases, it is not uncommon to use special methodologies for the treatment treatment of these variables[132] in order to mitigate the

132 Some of these are (i) differential privacy techniques, such as anonymization of the data (Ponomareva et al. 2023); (ii) adjustments in terms of the loss, resampling, or weighting of the data; and (iii) adversarial debiasing, which consists of training a model in such a way that an adversary (another model) cannot predict a sensitive attribute through learned representations. See Mahmoudian, H., "Using Adversarial Debiasing to Reduce Model Bias" (2020, April). Available at https://towardsdatascience.com/reducing-bias-from-models-built-on-the-adult-dataset-using-adversarial-debiasing-330f2ef3a3b4

possible biases identified. Moreover, it is useful to employ indicators related to algorithmic equity, described in Section 4.1.3, as a reference.

It terms of security, it is recommended to evaluate breaches that could occur during the development activities. As this is still the initial stage, when prototyping has not yet started, this exercise is useful for internalizing the cybersecurity measures that should be implemented.

Stage 2: Prototyping and Developing the Solution

Prototyping and developing the solution opens the way for experimentation through functional testing of the product, which facilitates learning and interaction with the real world and the users. This stage is a central component of the agile development and innovation approach in that it is through trial and error that the final solution is shaped and strengthened.

Stage 2, Phase 1

Analyzing the data flow and selecting the model:

Analyzing the data flow

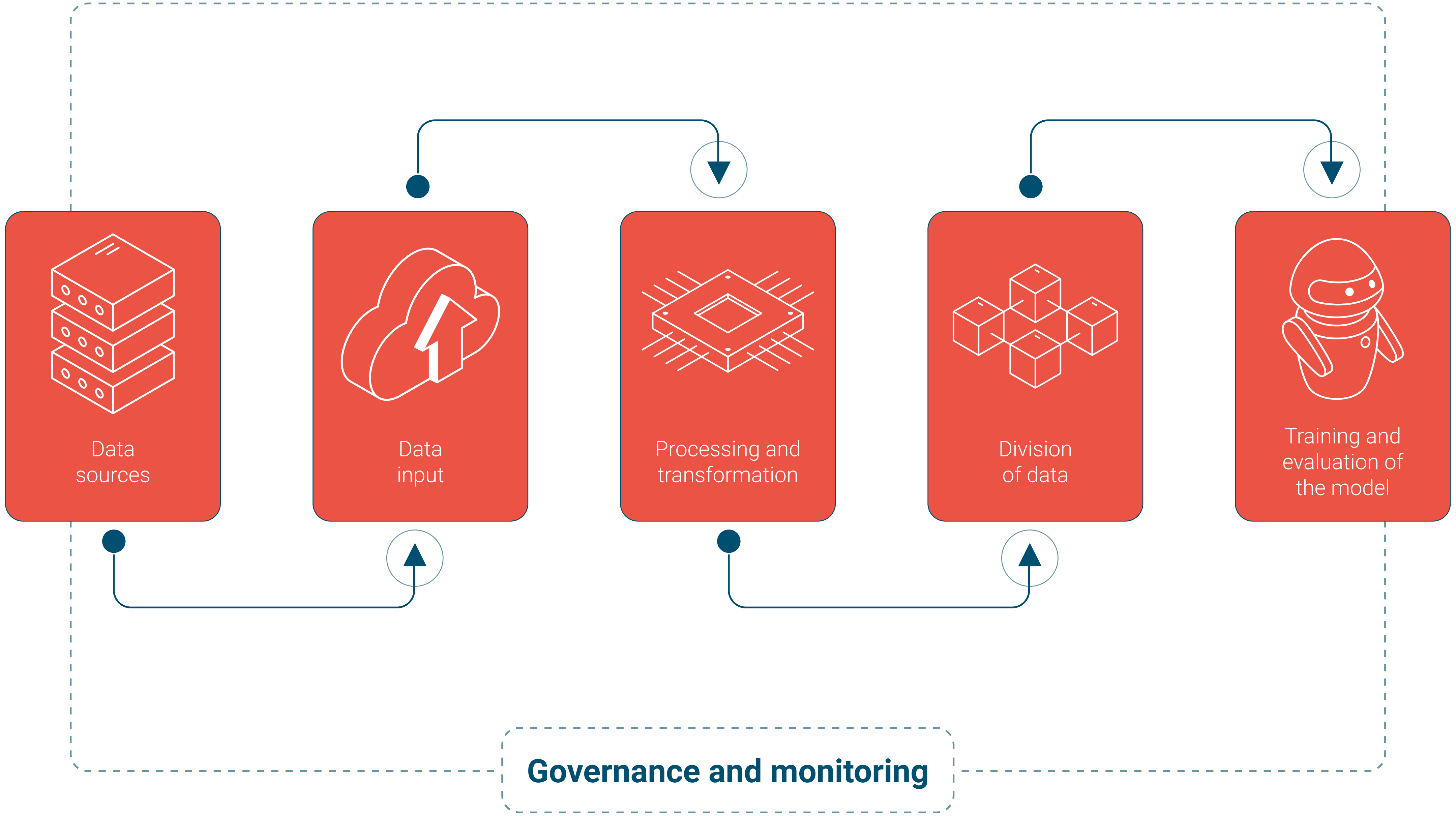
In this stage, once the solution has been established, a key element in selecting the model to be developed is the analysis of the project's data flow. This flow consists of a series of articulated steps during which those data are extracted, processed, and transformed from their raw form into an optimal condition to train and evaluate the model. The objective of implementing this type of flow is to prepare the data for training the model and putting it into production. In the process of managing the data, the different tasks of identification, collection, cleaning, training, and evaluation of the model interact, known as the data flow or pipeline. **Figure 11** shows the pipeline with its main phases.

In energy, water, solid waste, and transport projects, the **collection of information** is crucial to building AI models. Diverse technologies are used to do this, such as IoT sensors that monitor energy consumption, water levels, and traffic flows in real time, together with infrastructure management systems that record historical data on climate, user behavior, and maintenance patterns. Drones and satellites are also used to capture geospatial images and data.

The process known as the ***input of data*** consists of collecting data in order to later transfer them to a single centralized database where they can be accessed, stored, and analyzed.[133] The collection of the data can be done through different mechanisms: (i) data generated through internal information systems, (ii) data acquired from external sources, (iii) data obtained from open-access public sources, and (iv) a combination of the above. Generally, in this phase it is also determined whether the entity will adopt an ETL or ELT type model. The storage and management infrastructure for the data is also determined; for example, whether it will be a data warehouse, data lake, or data lakehouse.

133 Astera, "¿Qué es la ingestión de datos?" Available at <https://www.astera.com/es/type/blog/data-ingestion/#:~:text=La%20ingesti%C3%B3n%20de%20datos%20es,lotes%20o%20en%20tiempo%20real; and Cognizat, "Ingesta de datos." Available at <https://www.cognizant.com/es/es/glossary/data-ingestion

Figure 11. Data Pipeline



Source: Adapted by the authors based on: *A Guide to Data Pipelines (and How to Design One from Scratch)*. Available at https://www.striim.com/blog/guide-to-data-pipelines/

During the ***processing and transformation*** of the information, anomalies, duplications, atypical or missing data, and problems of scale (standardization and normalization) are identified. In addition, the combination of variables, smoothing of data, creation of dichotomous variables, descriptive, univariate, bivariate, multivariate analysis, and the representation of the variables through visualization models are performed.[134] Activities related to cleaning the information include detecting and imputing missing data, standardizing variables, unifying names of columns, and treating atypical data.[135] The anonymization[136] or pseudonymization[137] of the information can also be carried out to comply with privacy regulations and standards in the event that these apply.

134 Zhong, S., "Mastering Exploratory Data Analysis (EDA): Everything You Need to Know" (2024, April). Available at https://medium.com/data-and-beyond/mastering-exploratory-data-analysis-eda-everything-you-need-to-know-7e3b48d63a95

135 Patel, H., "Feature Engineering Explained." Available at https://builtin.com/articles/feature-engineering#:~:text=Apr%2029%2C%202024-,Feature%20engineering%20is%20the%20process%20of%20selecting%2C%20manipulating%20and%20transforming,used%20in%20a%20predictive%20model.

136 Anonymization of the information is processing personal data so that they cannot be attributed to specific individuals. Source: European Union, Agencia Española de Protection de Datos (2020), 10 misunderstandings related to anonymisation.

137 The pseudonymization of the information involves processing personal data so that they cannot be attributed to specific individuals. Source: European Union (2016), Reglamento General de Protección de Datos (GDPR). Artículo 4.

As indicated in Chapter 2, a constant problem in classification models is the imbalance of the classes. This occurs when one class has much more data than another, which can result in good performance of the model in general but deficient performance in predicting the minority class, which has less data. In these cases, the model evaluation is only considering the performance of the majority class (Ávalos et al. 2021). Some solutions to this problem include applying undersampling to the dominant class (adjusting the cases upward to avoid calibration errors), duplicating the minority class, or modifying the weighting of each class in order to balance the influence of each one, among other solutions (Ávalos et al. 2021).

Selecting the model

In this phase, **training and evaluation of the models** are generally carried out in order to select the one that best adapts to the objectives of the project. For this, one starts with a basic model and increases its complexity until the optimal model is identified. This process considers factors such as the type of problem, availability of the data, technological requirements, time restrictions, and budgetary limitations.

A good practice is to begin with the simplest model and gradually increase its complexity. However, greater complexity of the model reduces understanding of the decision-making processes of humans, a capacity known as ***explainability***.[138] Nevertheless, in diverse AI applications, complex models such as neural networks usually obtain significantly better results,[139] so it is useful for the team to focus on the performance objectives and evaluation process of the solution that is described later on.

Another element to consider in choosing the model is the nature of the problem. As discussed in Chapter 2, the problems addressed by machine learning models can be condensed into three large categories, according to Rebala et al. (2019): (i) classification, which identifies the category or categories to which each element that is being analyzed pertains; ii) clustering, which identifies similar characteristics between the elements in order to group them; and (iii) prediction, which uses historical information to predict the future behavior of the target variable. Algorithms such as Support Vector Machines (SVM), decision trees, random forest, neural networks, and Convolutional Neural Networks (CNN) can be used for the first category. For the second category, algorithms such as, K-means, K-medoids, DBSCAN, Clustering hierarchy, and Gaussian Mixture Models (GMM) can be used. For problems of prediction, logistic regression, polynomial regression, random forest, LSTM, and Xgboost (Extreme Gradient Boosting) algorithms, among others, are usually used.[140]

The ***type, quantity, and quality of the information*** available are equally important factors in selecting the model. It is important to quantify the volume of information available, which implies understanding how this information is stored, the access mechanism, and the collection processes. Whether the data are structured or unstructured, and whether they are qualitative or quantitative, is also analyzed.[141]

138 Hosni, Y., "Brief Guide for Machine Learning Model Selection" (2021, December). Available at https://medium.com/@yousefhosni/brief-guide-for-machine-learning-model-selection-a19a82f8bdcd

139 Ibid.

140 Rebala (2019); McMillan and Varga (2022); Betanzos (2020); Smola and Vishwanathan (2008); Nevala (2027); and McKinsey Analytics (2018).

141 Hosni, Y., "Brief Guide for Machine Learning Model Selection" (2021, December). Available at https://medium.com/@yousefhosni/brief-guide-for-machine-learning-model-selection-a19a82f8bdcd Op.cit.

An additional criterion for selection of the model is the computational capacity required to train it. This criterion is known as ***computational time and capacity***. This refers to the quantity of the resources needed, as well as the time required to train the model.[142] For example, it can be quicker and easier to train a logistic regression model than a five-level neural network model. The complexity of the model is directly proportional to the processing resources needed for its training.

Performance indicators and equity metrics are two important elements when choosing the best possible model. The first type of indicators inform how well the model is interpreting the data provided, and thus the quality of the response that it is producing to the problem presented.[143] The second type of metrics assess the nonexistence of biases at the group and individual level.

142 Ibid

143 Btd., "20 Key Criteria for Optimal Machine Learning Model Selection" (November, 2023). Available at https://medium.com/@baotramduong/machine-learning-criteria-for-model-selection-bca4b9742405

In order to ***implement the selected model,*** the information that will be used model training is defined. Although there is a specific rule to dividing these data, in general 80 percent of the data are used to train the model and 20 percent to validate it. To the extent possible, it is ideal that the model be tested with external information in order to understand its level of generalization.

The type, quantity, and quality of the information available are equally important to selecting an appropriate model. It is important to quantify the volume of information available, which means understanding how this information is stored, the access mechanism, the collection processes, and whether the data are structured or unstructured, or are qualitative or quantitative.[144] In other words, phases 1, 2, and 3 of the data pipeline described in Figure 11 should be carried out.

144 Hosni, Y., "Brief Guide for Machine Learning Model Selection" (December, 2021), Available at https://medium.com/@yousefhosni/brief-guide-for-machine-learning-model-selection-a19a82f8bdcd Op.cit.

Stage 2, Phase 2

Designing and developing the Proof of Concept and Minimal Viable Product

Once the initial validations have been carried out and any doubts resolved about how the possible solution will function, it is customary to proceed with the prototype preparation phase. Prototypes are used to represent how the product would function. Generally, functionality and usability aspects are tested with users in a way that the feedback allows for carrying out iterations that improve the robustness of the product.[145] As part of this, Proof of Concept (PoC) is an exercise that validates the technical viability of the idea in a way that demonstrates from the technical perspective that the proposal is achievable or at least has a theoretical or empirical basis.[146]

145 Ibid.

146 IDB Infrastructure and Energy Sector (INE), "Guía de desarrollo de productos digitales." PowerPoint presentation, IDB.

This exercise allows for quickly learning which aspects of the solution must be revised or modified. These tests are carried out in a controlled environment with the support of technical or administrative resources, as needed.[147]

Some examples of PoC in critical infrastructure projects include those that can be implemented to develop initiatives such as real-time monitoring of intelligent electricity networks to manage energy consumption and detect failures early; optimization of the distribution of potable water through network sensors to identify leaks; and predictive maintenance of transport infrastructure through drones that inspect and prevent wear. PoC examples also encompass cybersecurity control networks; the use of monitoring platforms to detect threats; and intelligent waste management in cities through the use of containers with sensors that optimize collection routes. These pilots test the viability of innovative technologies prior to their large-scale implementation. The IDB has carried out several PoCs in infrastructure related to vehicle counting, the use of edge technology, and the use of satellite images to determine road transitability and to estimate distributed power generation from solar panels. Some of these ideas have yielded satisfactory results, while others have encountered challenges in being converted into a Minimum Viable Product (MVP).

Once the technical feasibility has been assessed based on the PoCs, the process moves to the prototyping phase, where in some cases specific functional versions—such as the user platform—are tested to evaluate the user experience (UX) and/or service design. The aim is to identify in a timely fashion the key functions that users and other groups of interest will require or prefer.[148] Key to this process is that team members who develop the model and team members from the business side who participate in this development have a clear understanding of their project role. For example, it is advisable for the Product Owner (PO) to participate in all stages of the process, since they will be able to ensure that the development cycle remains aligned with the actual needs of end users.

The next phase, construction of the solution, involves developing what is known as the Minimal Viable Product (MVP). In this phase, a basic but functional and stable version of the product is developed – in this case a model trained with real data to test hypotheses and evaluate results in terms of both the model's performance and how it meets users' expectations and needs. A point to highlight in the process of developing the MVP is its utility for adapting the solution to changes in the environment, since this product validates hypotheses relatively quickly and efficiently. This makes it possible to develop functional products that continually iterate based on knowledge of the market that is obtained from exposure to users. Moreover, it is useful to verify that the tools, images, and content used in this product

147 Proof of concept (POC). Op.cit.

148 IDB Infrastructure and Energy Sector (INE), "Guía de desarrollo de productos digitales." PowerPoint presentation, IDB.

comply with all the respective licenses and to review whether they have associated costs that must be considered.

Finally, when the MVP is developed by an external provider, it is useful to verify the delivery of all the related components, such as wireframes, user interface elements, design systems, and detailed flows. Likewise, in applicable cases, the same should be done with access and control over the data, the source code, and the models used.

Stage 2, Phase 3

Ethical principles and sectoral regulations:

During the prototyping and solution development stage, consideration must be given to design principles associated with transparency, accountability, and important ethical aspects. This allows for developing AI solutions within existing risk management frameworks[149] as well as promoting greater confidence in their use.

149 Ibid

Moreover, AI systems interact with the environment, which is why their processes must comply with sectoral regulations. During this stage, an analysis is conducted of the applicable sectoral regulations, the relevant legal aspects of the technological systems to be used, the existing regulations on privacy and data protection, and any specific regulations on AI, if applicable

As mentioned earlier, one of the risks associated with developing AI models is that they can replicate existing biases in society and, as such, their results can have impacts on specific population groups. One form of impact can occur through algorithmic bias.[150] These biases include processing, confirmation, and exclusion biases. The first bias refers to distortions that can be introduced in the data before they are used to train the model. Confirmation biases are produced when AI solutions corroborate previous stereotypes or beliefs; exclusion biases refer to what happens when certain population groups are systematically excluded from the training set.[151]

150 This refers to systematic and repeatable errors of an AI system "that create unfair results, such as privilege to an arbitrary group of users over others." Awan, A.A., "¿Qué es el sesgo algorítmico?" (April, 2024). Available at https://www.datacamp.com/es/blog/what-is-algorithmic-bias

In this context, ethical oversight is conducted by identifying and mitigating biases and also by applying behavioral principles. The principle of *transparency* in AI solutions refers to the capacity to understand how and why an AI model makes certain decisions. The principle of *responsibility* also must be taken into account. It refers to the capacity to attribute actions and decisions of an AI-based solution to a specific person in charge, who takes responsibility for the possible effects of these biases and incorporates mitigation measures.

151 Op. cit.

Another aspect to highlight is related to the treatment of personal or reserved information. When there is information with these characteristics, an anonymization[152] or pseudonymization[153] exercise can be undertaken to train the model without infringing on existing regulations on personal data. An example is the treatment of the information used to develop and implement the Distancia2 tool, a technology platform developed by the IDB that was implemented in 46 cities in LAC during the COVID-19 pandemic. Its objective was to mitigate the risk of contagion in areas with large urban agglomerations. This solution uses video footage recorded by cameras installed in the cities and, through AI algorithms, estimates the distance between individuals for purposes of analysis and to generate public health alerts. During the design and development of this tool, a requirement was that it neither use the private information of individuals nor analyze their particular features or unique characteristics. In this way, the model implemented is limited to detecting persons anonymously and estimating the distance between them.[154]

Stage 2, Phase 4

Security of technology and information:

AI models face a series of security challenges. The risks include the generation of malicious input data or security breaches in the frameworks used in production of the models.[155] To prevent these attacks or vulnerabilities, it is recommended that a security-by-design approach be adopted that integrates preventive security measures from the design stage of the model.[156]

Infrastructure sectors include critical assets with high levels of interdependence, which makes them vulnerable to cyber attacks that can unleash systemic crises. The organizations that apply AI solutions in their processes must therefore understand the fundamental importance of cybersecurity.

It is essential to incorporate a focus on security starting in the design stage that integrates cybersecurity in the model's entire production chain. This approach ensures a secure project, a privacy protocol for the data, secure architecture, training and awareness about these vulnerabilities, and continuous security testing.[157] In terms of the latter, a common practice is to carry out penetration, fuzzing, and adversary attack testing in test models and in the pre-production and production stages of the model.[158]

152 In the process of anonymization of data, a unique and new set of data are created. Independent of the analysis that is done with this, it is not possible to identify personal characteristics of the observation. Agencia Española de Protección de Datos (AEPD), "Anonimizatción and seudonimización" (October, 2021). Available at https://www.aepd.es/prensa-y-comunicacion/blog/anonimizacion-y-seudonimizacion

153 During the process of pseudoanymization two sets of data are created to revert the process that will need to comply with all the applicable standards. Agencia Española de Protección de Datos (AEPD), "Anonimization and seudonimization" (October, 2021). Available at https://www.aepd.es/prensa-y-comunicacion/blog/anonimizacion-y-seudonimizacion

154 Source: IDB, Distancia2. Available at https://fairlac.iadb.org/piloto/distancia2

155 "Riesgos de la inteligencia artificial en ciberseguridad." Available at https://globalt4e.com/riesgos-de-la-inteligencia-artificial-en-ciberseguridad/

156 Ibid.

157 National Cyber Security Centre, "AI and Cyber Security: What You Need to Know." Available at https://www.ncsc.gov.uk/guidance/ai-and-cyber-security-what-you-need-to-know#section_5

158 National Cyber Security Centre, "Guidelines for Security AI System Development." Available at https://www.ncsc.gov.uk/collection/guidelines-secure-ai-system-development

Stage 3: Implementing, Monitoring, and Evaluating the Solution

Implementation, maintenance, and scaling of the solution generally includes four phases: (i) evaluation of performance; (ii) sustainability of the solution; ((iii) ethical and security audit; and (iv) updating of the model.

Stage 3, Phase 1

Evaluating performance:

This phase analyzes the performance of the developed AI model. This generally involves defining and implementing a set of indicators to evaluate the performance of the solution and promote confidence in its results. These types of metrics estimate the effectiveness of a model in performing its specific task and achieving the expected results. These indicators serve various purposes, such as measuring accuracy, adjusting hyper-parameters, facilitating interpretability, and identifying overfitting and underfitting, among others.

The evaluation indicators depend as much on the characteristics of the data that are being used as on the type of problem that is being solved. The performance indicators most frequently used for classification problems[159] are Accuracy,[160] Precision,[161] Sensitivity,[162] F1 Score[163], ROC-AUC and PR-AUC, and the Confusion Matrix.[164] The most common metrics for regression problems[165] are Mean Absolute Error (MAE),[166] Mean Squared Error (MSE),[167] Room Mean Squared Error (RMSE),[168] Coefficient of Determination (R^2),[169] Mean Absolute Percentage Error (MAPE),[170] and Adjusted Coefficient of Determination (adjusted R^2) [171].

159 Halder, N., "Decoding Machine Learning Success: Evaluating Performance Metrics with Python" (February, 2024). Available at https://medium.com/gitconnected/decoding-machine-learning-success-evaluating-performance-metrics-with-python-2f98a452bbc4

160 **Accuracy**: This refers to the "proportion of observations correctly predicted with respect to the total." It is an intuitive metric and offers a simple measure of the effectiveness of the model, although, when there is an imbalance in the data it can cause errors (Halder 2024).

161 **Precision:** This refers to the "proportion of positive observations predicted correctly with respect to the total of positive predictions." This is a very useful metric when the cost of a false positive is not low (Halder 2024).

162 **Recall:** This refers to the "proportion of positive observations predicted correctly with respect to all observations of the real class." This is a very useful metric when there is a high cost associated with obtaining a false negative (Halder, 2024)

163 **F1 Score**: This refers to the average weighting of the *Precision* and *Recall* indicators. This metric is appropriate when there is a balance between the two indicators outlined, especially in unbalanced categories (Halder 2024).

164 The **Confusion Matrix** is a tabular representation of the predicted and real categories that allows the researcher to relatively easily identify the types of errors committed by the model. In this type of matrix, the following components can be identified: true positives (TP), which are the cases correctly identified as positive; true negatives (TN), which are the cases correctly identified as negative; false positives (FP), which are negative cases incorrectly identified as positive; and false negatives (FN), which are positive cases incorrectly identified as negative. In general terms, the rows represent real categories or classes, columns represent classes predicted by the model, the main diagonal shows the correct predictions, and the elements outside of the diagonal refer to the errors. For more information see https://www.sciencedirect.com/topics/engineering/confusion-matrix#:~:text=A%20confusion%20matrix%20represents%20the,by%20model%20as%20other%20class.

165 Halder N., "Decoding Machine Learning Success: Evaluating Performance Metrics with Python." Available at https://medium.com/gitconnected/decoding-machine-learning-success-evaluating-performance-metrics-with-python-2f98a452bbc4

166 **Mean Absolute Error (MAE):** This is the "average of the absolute differences between the predicted and real values." This metric allows for getting an idea of the deviation of the predictions (Halder 2024).

167 **Mean Squared Error (MSE):** This is the average of the square of the differences between the predicted and real values. The MSE sanctions large errors more than the MAE does, which can be either an advantage or disadvantage depending on the case (Halder 2024).

168 **Root Mean Squared Error (RMSE):** This is the squared root of the MSE, which allows for having an indicator on the same scale as the original values (Halder 2024).

169 **Coefficient of Determination (*R^2*)**: This represents the proportion of the variance of the objective or dependent variable that is explained by the independent predictors or variables. It corresponds to the goodness of the fit of these predictions (Halder 2024).

170 **Mean Absolute Percentage Error (MAPE):** This measures the average of the absolute errors between the predictions of the model and the real values, expressed as a percentage of the real values.

171 **Adjusted Coefficient of Determination (*adjusted R^2*):** This corresponds to an adjustment of the ***R^2*** in accordance with how many predictors there are in the model. Source: Investopedia. Available at https://www.investopedia.com/ask/answers/012615/whats-difference-between-rsquared-and-adjusted-rsquared.asp#:~:text=Adjusted%20R%2Dsquared%20is%20a,model%20by%20less%20than%20expected

It is not customary to use a single parameter to determine the effectiveness of an AI model, although the minimum expected performance is precision greater than 50 percent. When evaluating the performance of a model, its cost function is usually taken into account, which measures the distance between the model's results and reality.[172] Usually the objective is to minimize that distance, which is generally done with an algorithm known as gradient descent. It is recommended to optimize the model from random data points and adjust the learning rate during training ensure that the results obtained are consistent.[173]

172 "Understanding Cost Functions in Machine Learning: Types and Applications" (2023). Available at <https://medium.com/@anishnama20/understanding-cost-functions-in-machine-learning-types-and-applications-cd7d8cc4b47d>; "Machine Learning Fundamentals (i): Cost Functions and Gradient Descent" (2017, November). Available at https://towardsdatascience.com/machine-learning-fundamentals-via-linear-regression-41a5d11f5220; and "Gradient Descent for Dummies" (2021, May). Available at https://raed-asdi.medium.com/gradient-descent-for-dummies-1eda90f269b. For more information, see https://www-sciencedirect-com.ezproxy.uniandes.edu.co/topics/engineering/gradient-descent

173 Ibid.

Depending on the type of problem that the model is addressing, performance metrics are selected to identify the strengths and weaknesses of the algorithms used. It is therefore recommended that more than one indicator be used in order to have a more robust and detailed evaluation of the model.

Stage 3, Phase 2

Strategy to sustain the solution:

This phase refers to the set of actions that should be adopted so that the solution, once developed, is used and continually updated by the organization. In this regard, a key factor for successful implementation of AI is institutional willingness to ensure the sustainability - understood as the capacity to adopt the solution- of the solution, considering sustainability to be the capacity to adopt the solution, integrate it into existing processes, and ensure the human, technological, and financial resources required for its ongoing use. In some cases this requires a change in the institutional culture in relation to developing and adopting technological innovations.

It is useful during this phase to conduct a communications campaign about the existence of the tool, how it works, and the results that it generates. It is also useful to evaluate and communicate the return on investment related to the adoption of the solution in order to provide feedback for the development and implementation process and promote adoption and continuity. Furthermore, it is important that the different areas within the company understand that AI helps reduce investment and operational costs; in this way, the costs of the project will be considered as an investment, and future flows can be secured to ensure an adequate budget for its maintenance and continuous improvement.

In this same vein, it is useful to create or strengthen a culture of experimentation and continual learning in the organization that facilitates innovation with an agile approach and helps to ensure sustainability in the adoption of the solution. Controlled experiments together with direct feedback from users iterate quicker and ultimately produce results with a greater impact.[174] Errors at the end of the project have a higher cost than growth with small experiments, not only from the perspective of time

174 IDB Infrastructure and Energy Sector (INE), "Guía de desarrollo de productos digitales." PowerPoint presentation, IDB.

and resources, but also in terms of the motivation of the team. In this regard, implementing a knowledge transfer program is key for the project to continue iterating, to adjust the model in its different stages, and to ensure that the different areas of the organization take ownership the solution. Training the team will enhance the effective use of the project and its continued adoption, as well as support future updates.

Stage 3, Phase 3

Ethics and security audit:

This component is based on the ex post evaluation of the solution to identify possible vulnerabilities in information security and ensure that the results do not perpetuate social stereotypes that can be discriminatory towards certain population groups. Having automated decision-making systems generates ethical and moral challenges in defining the rules that the system follows. As a consequence, it is necessary to have adequate control mechanisms in place, such as algorithmic auditing (Villagrán 2022). Although most models used in the infrastructure sector do not usually have sensitive data, it is a good practice to conduct ethical and security audits, mainly in cases where possible alerts are identified regarding biases or the treatment of sensitive information.

One mechanism to monitor and comply with the ethical standards established from the model's design stage is "group equity," which refers to the identification of population groups that could be harmed by the results of the model.[175] This concept, which aligns with best practices, is quantified through disparity metrics that examine and compare the behavior of groups using different performance indicators based on proportions or differences.[176] Similarly, there are general group-level bias metrics,[177] such as Demographic Parity (DP),[178] Equality of Opportunities (EO),[179] or Statistical Parity (SP);[180] and individual-level bias metrics,[181] such as the indicators of Equality of Probabilities (EOdds)[182] and Calibration,[183] among others.

Finally, in algorithmic auditing processes it is recommended that, in addition to documenting the procedures and registering the individuals involved, intervention protocols be adopted for the model when they fail the algorithmic fairness evaluations (Pombo et al. 2020; Torres et al. 2021; Villagrán 2022).

175 Microsoft, "Rendimiento and equidad del modelo" (February, 2024). Available at https://learn.microsoft.com/es-es/azure/machine-learning/concept-fairness-ml?view=azureml-api-2

176 Ibid.

177 Gomede, E., "Fairness Metrics in Machine Learning" (September, 2023). Available at https://medium.com/the-modern-scientist/fairness-metrics-in-machine-learning-8c3777b48a9c

178 Which verifies "whether the probability of a positive prediction is equal in all demographic groups" (Gomede 2023).

179 This determines whether in all the groups the rate of true positives is equivalent, which targets a reduction in the quantity of false negatives (Gomede 2023).

180 This ensures that there is an equitable distribution of the positive results expected (Gomede 2023).

181 Gomede, E., "Fairness Metrics in Machine Learning" (September, 2023). Available at https://medium.com/the-modern-scientist/fairness-metrics-in-machine-learning-8c3777b48a9c

182 It is assured that in all groups the rates of true positives are equivalent to those of false positives (Gomede 2023).

183 This indicator evaluates whether the predicted probabilities exactly reflect the probability that an occurrence is produced. Given that a poorly calibrated model tends to reproduce biased decisions, calibration is an element to consider (Gomede 2023).

Stage 3, Phase 4

Maintenance, updating, and scaling of the solution:

This phase refers to the activities associated with additional developments, updates, and maintenance of the model based on existing needs. Scaling the model can enhance its impact in the organization. Changes in the environment, in users, and in the data that feeds the model, generate the need for it to be revised, require adjustments to its parameters, or that it be retrained with new information.

Over time, the developed and implemented model can gradually lose precision due to structural changes in the market or society. Milder changes can also occur in the behavior of the variables that feed the model and in its statistical properties, and even in the channels to collect information, which makes it necessary to retrain the model with new information.[184]

This phenomenon is known as model drift, as it may lead to a degradation in the performance of the deployed machine learning model.[185] To keep track of this phenomenon, it is important to have in place a continuous process for quality control and monitoring of the model's performance that detects deviations from the indicators that were obtained in the early stage of production,[186] as well as for facilitating the incorporation of new input data to anticipate changes in the environment.

Likewise, it is important to maintain documentation of the changes both to the model and the interface through which users interact. Version control enables collaboration between the different developers, facilitates the traceability of the modifications, allows for navigating with relative agility between versions to recover part of a previous solution, contributes to resolving conflicts between simultaneous changes to the code, and fosters algorithmic auditing, among other benefits.

Finally, in projects that involve machine learning, scalability is understood to be the capacity of the system to incorporate significant increases in data volume, increase its efficiency and effectiveness, and support larger workloads without its performance being affected.[187] Therefore, scalability of an AI solution involves different dimensions, among which are the data, model, and infrastructure.[188] In regards to the information

184 "Understanding Data Drift and Model Drift: Drift Detection in Python." Available at https://www.datacamp.com/tutorial/understanding-data-drift-model-drift

185 Nicoomanesh, A., "Model Drift: Identifying and Monitoring for Model Drift in Machine Learning Engineering and Production" (2024). Available at https://medium.com/@anicomanesh/model-drift-identifying-and-monitoring-for-model-drift-in-machine-learning-engineering-and-0f74b2aa2fb0>

186 Ibid.

187 Censius, "ML Scalability." Available at <https://censius.ai/wiki/ml-scalability#:~:text=Machine%20learning%20scalability%20refers%20to,users%20residing%20at%20global%20locations.>; and OpenTeams, "Scalable Infrastructure for MLOps: Ensuring High Performance and Efficiency" (2023, June). Available at https://www.openteams.com/scalable-infrastructure-for-mlops-ensuring-high-performance-and-efficiency/

188 Ibid.

dimension, to the extent that the application evolves, the quantity of information increases, meaning there will be more data to retrain, validate, and test the new versions of the model.[189] The model can also vary in its size and complexity, and thus require greater computing capacity. This leads to the need for scalable infrastructure to meet the growing demands for storage (ever more information) and processing (more complex models with more parameters).[190] The scalability of the solution will be achievable through actions such as implementing a performance monitoring system that provides alerts when the model is becoming outdated, using cloud computing to scale technological platforms as needed, using parallel processing,[191] or executing tasks in Docker-type containers[192] to improve operational efficiency of the models.[193]

189 Ibid.

190 Ibid.

191 For more information, see "Parallel Processing." Available at https://www.techtarget.com/searchdatacenter/definition/parallel-processing#:~:text=Parallel%20processing%20is%20a%20method,time%20to%20run%20a%20program.

192 "¿Qué es Docker?" Available at https://aws.amazon.com/es/docker/

193 Census, "ML Scalability." Available at https://censius.ai/wiki/ml-scalability#:~:text=Machine%20learning%20scalability%20refers%20to,users%20residing%20at%20global%20locations.; and OpenTeams, "Scalable Infrastructure for MLOps: Ensuring High Performance and Efficiency" (2023, June). Available at https://www.openteams.com/scalable-infrastructure-for-mlops-ensuring-high-performance-and-efficiency/

4.2 Main Recommendations to Develop AI Solutions

Finally, based on the considerations presented in the previous section, and taking into account the advantages of the agile development and innovation approach to implementing AI solutions in infrastructure sectors, it is recommended that the following set of nine principles be considered throughout the process of developing and implementing solutions:

- **Understanding the problem and the relevance of AI to solve it:** This principle is based on the idea that it is preferable to first understand the problem before thinking about how to solve it. This highlights the importance of defining and delimiting the problem or need in a way that is clear, concise, evidence-based, and refers to a solvable situation. Once the problem is identified and understood, when identyfing alternatives, it is critical to evaluate the relevance of using AI in the solution based on the benefits, costs, and implications for the organization of using this technology. The focus of AI project should be on solving the specific problem at hand, rather than on the technology itself.

- **Design and development based on the user**: This principle is based on placing the user at the center of solution development. This means understanding the characteristics of the individuals or entities that will be the main users of the model, the primary use cases, their motivations, and in which processes the results of the model will be integrated, among others. This will require interacting with users throughout the product creation process to identify their needs, motivations, and expectations.

- **Agile development**: This principle refers to the ability to create projects in a dynamic and iterative manner, adapting the products in response to change. this includes a set of frameworks[194] and methodologies[195]

194 Some examples are Scrum, Kanban, and Extreme Programming (Agile Alliance).

195 Some examples are pair programming, test-driven development, and sprint planning

that enable product development through iteration, experience, and collaboration that can be adapted relatively easily to changes involving users, the market, and the business itself.[196]

- **Leveraging the data**: This principle goes beyond using information in the processes, and requires a transformation of the organization[197] to analyze, manage, and communicate its productive processes by maximizing the information available. This demands quality information,[198] that is, information that is complete in terms of being consistent and accurate. Otherwise, the results of the model will lack reliability and robustness.

- **Use of open standards and innovation**: This principle is based on the creation of knowledge in community. It is based on the premise that an open approach to development and innovation maximizes resources and the impact of the solutions that are implemented.[199]

- **Use of open-source foundational models:** As indicated, Foundational Models (FM), also known as pre-trained or general-purpose models, are neural networks that perform deep learning trained with large quantities of data and composed of a significant number of parameters, that carry out general tasks, such as generating text and images, understanding different human languages, and holding natural language conversation, among others.[200] Some of the advantages obtained from using these types of models[201] within the development of the system include reduction of development time, optimization of resources, adaptability through fine-tuning, horizontal and vertical scalability, and community-driven growth, among others.[202]

- **Importance of ethics, privacy, and security:** This principle refers to three main concepts. The first involves the application of ethical principles in the design and structuring of AI models. Second, solid

(Agile Alliance).

196 Agile Alliance, "What Is Agile?" Available at <https://www.agilealliance.org/agile101/#:~:text=Agile%20is%20the%20ability%20to,an%20uncertain%20and%20turbulent%20environment.; and Microsoft, "¿Qué es el desarrollo de Agile?" (October, 2023). Available at https://learn.microsoft.com/es-es/devops/plan/what-is-agile-development

197 For this it is important as a first step to identify the organization's maturity level in terms of data analysis, given that implementation of the project must be carried out step-by-step.

198 Problems with the quality of information can be due to multiple factors, such as human error, technical error, or mistakes in collection of data.

199 On the one hand, there are the open-source platforms such as Qgis or R. On the other, there are projects already implemented that decide to share their repository, including libraries and the source code, such as what the IDB does through its "Code for Development" Initiative.

200 "¿Qué son los modelos fundacionales?" Available at https://aws.amazon.com/es/what-is/foundation-models/

201 Some examples are Bidirectional Encoder Representations from Transformers (BERT) (https://github.com/google-research/bert); Generative Pre-trained Transformer (GPT) (https://github.com/openai/gpt-2); A Robustly Optimized BERT Pertaining Approach (RoBERTa) (https://github.com/facebookresearch/fairseq/tree/main/examples/roberta); Text to Text Transfer Transformer (T5) (https://github.com/google-research/text-to-text-transfer-transformer); XLNet (https://github.com/zihangdai/xlnet); and You Only Look Once (YOLO) (https://github.com/ultralytics/yolov5).

202 "3 Ways to Adapt a Foundation Model to Fit Your Specific Needs." Available at https://kili-technology.com/large-language-models-llms/three-ways-to-adapt-an-llm-model-to-suit-your-ml-needs

model design must ensure that user data is managed safely and data privacy is respected, avoiding misuse or unauthorized access. Finally, the third concept involves system security. This means mitigating cybersecurity risks that may occur when AI models are applied to critical infrastructure, as is the case for the energy, transport, and water and sanitation sectors.

- **Scalability**: This principle is prospective and consists of designing and implementing a system that has the capacity to grow as needed. The scalability of the system should depend on aspects such as the quantity of data that the model requires, processing and storage capacity, and the type and frequency of interactions with users.

- **Sustainability:** Finally, this principle highlights the importance that the implemeted AI solutions be effectively adopted in the organizations, they generate relevant impact, and that they guarantee the continued use of the resources in the mid and long term.

5 CONCLUSIONS AND RECOMMENDATIONS

Artificial Intelligence is a general-purpose technology comparable to historic milestones such as the steam engine, electricity, information technology, and the Internet because of its capacity to profoundly transform multiple sectors and dimensions of society. Its development and adoption offer significant opportunities for digital transformation in key infrastructure sectors such as energy, transport, water and sanitation, and solid waste. As those sectors involve complex systems organized in networks, multiple actors, and high intensity in physical capital and data, they have great potential to benefit from the transformative impact of this technology. Considering the opportunities offered by AI in the infrastructure sectors, it is given important for organizations to implement robust development and innovation methodologies that are consistent with their objectives and with best practices.

The IDB has supported governments and organizations in areas of infrastructure in the design, prototyping, development, and deployment of AI solutions that have helped improve the performance of processes, regional integration, and the quality of citizen services. The IDB's Infrastructure and Energy Sector has been a leader in the use of AI, helping its clients pilot and adopt solutions developed both by the public entities themselves as well as the private sector. In turn, together with IDB Lab, it has promoted the creation of innovative solutions in the region's entrepreneurial sector in order to improve public service delivery and create development opportunities.

Taking into account the review of international practices in this document, this section presents a set of recommendations for the successful development and implementation AI-based solutions in infrastructure in LAC. These recommendations are directed towards those that design and implement these solutions, public policymakers in the region, and entrepreneurs or teams that innovate in this field.

General Recommendations

- When implementing digital solutions in infrastructure sectors, focus on the problem to solve rather than on the technology itself. This means defining and delimiting the problem or need in a way that is clear, concise, and evidence-based, and that makes reference to a solvable solution. Once the problem is identified and understood, evaluate the appropriateness of using AI in the solution, based on the benefits, costs, and implications of the use of this technology for the organization. It is recommended that the use of AI in these solutions be directed to cases or components where its use is appropriate, useful, and viable from the operational, financial, and legal perspective.

- Implement agile AI development and innovation methodologies to facilitate rapid iterations, continuous adjustments, flexible adaptation to changes, and improvements in the models and in the requirements of the processes and users.

- Incorporate Proof of Concept, prototypes, and pilot projects within the development methodology in order to test the solution prior to its large-scale implementation. This will allow for identifying and incorporating specific technologies and functions based on concrete needs and requirements.

- Develop organizational schemes that facilitate the adoption of technological solutions based on AI. The success of their development and implementation will depend to a great degree on the commitment and support of senior management, the existence of internal leaders or "champions" who drive the process, and the consolidation of a culture open to innovation, change, experimentation, and teamwork. Furthermore, the participation and commitment of the entire operational team is critical to ensure the sustained and continuous use of the tool over time.

- Diagnose the capacity of personnel to understand the opportunities and risks of AI, manage the data, and participate in developing and implementing solutions based on this technology. As part of these diagnostics, design and implement programs for training and the transfer of relevant knowledge.

- Examine the financial viability of adopting AI-based solutions, taking into account the associated costs, especially for training the models and processing data, as well as the possible evolution of those costs depending on the project phase. Also, consider the costs associated with implementing AI projects, including costs related to change management, development of skills, and sustainability of the models over the long term.

- Identify and define the return on investment (ROI) of adopting AI-based solutions to justify their implementation. This means evaluating the tangible and intangible benefits, such as reduced operating costs, increased efficiency, improved decision-making, and optimized processes. Establishing indicators of success that are measurable and linked to the strategic objectives ensures that the technological solutions contribute real and sustained value over the long term, facilitating their scalability and acceptance.

- Pay special attention to ethical, privacy, and security aspects from the initial stages of the design of AI-based solutions. This means incorporating ethical principles such as transparency, equity, and responsibility in the development of the models to ensure that the solutions neither perpetuate biases nor discriminate against certain groups. In addition, ensure the protection of personal data, comply with current privacy regulations, and establish robust security mechanisms that minimize risks such as unauthorized filtrations or access. Implementing these measures from the start not only strengthens confidence in the technology, but also protects the organization from possible long-term legal and reputational risks.

- Document and disseminate lessons learned and successful case studies that promote understanding of AI in the public sector and help convince more policymakers of the opportunities offered by this technology.

- Examine the experiences of other regions with implementation of AI solutions in infrastructure sectors in order to gain knowledge and input to strengthen the planning and execution of policies and projects that promote the adoption of AI.

Recommendations for Stage 1: Identifying the Opportunity and Planning the Solution

- If they are not already defined, define the data needed, available sources (sensors, smart meters, video cameras, SCADA systems, and transport or distribution networks, among others), and establish optimal data architecture and governance schemes. Those elements ensure the adequate collection and management of critical data, such as data for traffic flows, water or energy consumption, and the condition of infrastructure. Paying special attention to the quality, security, and availability of the data during development and implementation is key to achieving an efficient and sustainable operation, optimizing decision-making, and complying with sectoral regulations. Furthermore, differentiate from the start the use of data of systems and networks without privacy implications from the data of users and other individuals where the protection of data and cybersecurity are critical.

- Identify and evaluate from the design stage the requirements for technological tools and data infrastructure to develop AI solutions, especially in relation to storage and processing capacity. Avoid exclusive arrangements with specific providers and consider the value offered by computation services in the Cloud, given their efficiency, flexibility, agility, and scalability.

- Evaluate and identify the optimal operational scheme to develop the AI solution. "In-house" development implies lower costs and keeps institutional knowledge within the organization. On the one hand, arrangements involving external teams bring in the technical expertise and experience needed to develop the solution efficiently, often resulting in shorter development times. In addition, connecting with specialized firms can bring the benefit of access to a diverse team with multiple skills. On the other, working with internal consultants allows for close and personalized collaboration.

- Analyze the possibility of collaborating with technology startups, which represent a valuable option to develop AI-based solutions for infrastructure sectors. In LAC, there is a growing ecosystem of startups specializing in water, solid waste, transport, and energy that offer innovative solutions adapted to local challenges. Working with these firms can provide agility, new perspectives, and vanguard technologies, as well as facilitate implementation of more personalized and flexible solutions. This collaboration reduces development times while at the same time fostering the growth of the regional entrepreneurial ecosystem.

- In assembling the teams, consider professionals with the skills necessary to successfully develop and implement the solution. As part of this process, evaluate the existence of skills in data science, machine learning, and design and management of technological architecture. Furthermore, incorporate professionals with knowledge of the business; who will be able to validate from the design stage that the model responds to the needs of the organization; and who can provide valuable feedback about the functionalities and results in the specific context of the sector.

- Identify the interest groups that will be relevant to successful adopt the solution. As part of this process, it is useful to connect potential partners or sponsors that can contribute to the viability of adoption. Similarly, local governments and regulators are important actors to promote adoption of the solutions and achieve a greater impact through their use.

- Examine from the start the ethical, reputational, and regulatory risks, among others, associated with developing and adopting the solution. Evaluate the possible impact of the risks, and establish a plan for their mitigation. In the case of using sensitive information, evaluate implementation of methodologies for special treatment of this type of variable and the equity algorithm indicators discussed in Chapter 4.

Recommendations for Stage 2: Prototyping and Developing the Solution

- Analyze the project's data to ensure that they are adequate, clean, and ready for use in training and production of an AI or machine learning model. This process identifies possible problems with the sources of information, ensuring that it is efficiently incorporated, and optimizing the stages to process and transform the data. By correctly structuring the flow of data, the quality of the model is improved, errors are minimized, and the time and costs associated with previous corrections are reduced, which increases the probabilities for success in implementing the solution.

- Assess the representativeness of the population in the datasets, and evaluate whether consent is required for their processing. In cases where there is not sufficient data, evaluate the adoption of techniques such as increasing the data in order to effectively train AI models.

- Study the criteria proposed for selection of the models – the nature of the problem, the type and quality of the information, computational capacity, performance indicators, and explicability, among other criteria. Start with simple models and increase their complexity as needed. This will facilitate design, development, and experimentation; enable changes in how performance information and user feedback are collected; and help avoid the waste of computational resources.

- Understand the importance of developing Proof of Concept, prototypes, and Minimum Viable Product as spaces for experimentation, learning, and feedback to continually improve the solution.

- Place a strong emphasis on the development of user-friendly interfaces that facilitate use of the applications by members of the organization, including, if necessary, non-specialized personal.

- Implement permanent ethical and security surveillance processes from the design stage. This means continuously monitoring use of the data, ensuring the privacy of users, and preventing possible biases in the models. In addition, establish robust security measures to protect sensitive information from cyber attacks or unauthorized access.

Recommendations for Stage 3: Implementing, Monitoring, and Evaluating the Solution

- Define and implement performance indicators such as those outlined in Chapter 4 to evaluate the performance of the solution, as well as the effectiveness of the model in executing its specific task and achieving the expected results.

- Advance algorithmic audits that provide important information to ensure that the models perform as expected, and that they do not generate results with undesired ethical implications. In this regard, it is useful that validation of the models include response mechanisms for cases in which the responses are not what was expected.

- Place importance on the explicability and transparency of the models. The capacity to explain how the models function and on what basis decisions are made is essential for the accountability of and confidence in AI solutions. This is especially critical in the public sector in terms of the use of State resources, accountability requirements, and the implications of the solutions implemented for the well-being of the population.

- Implement communications strategies regarding the existence of the tool, how it functions, and the results that it generates for the organization.

- Evaluate and communicate the return on investment related to adopting the solutions so that this feeds back into the development and implementation process, and promotes the adoption and continuity of the solutions. All areas of the organization need to understand that AI is a big help in evaluating hypotheses about the market and reducing investment and operational costs. This can ensure future flows that allow for an adequate budget for maintenance and continuous improvement.

- Consolidate a culture of experimentation and continuous learning that facilitates innovation in any area of the organization, and that contributes to ensuring sustainable adoption of the solution. In this regard, implementing a knowledge transfer program is key for the project to continue iterating, to adjust the model in its different stages, and to ensure that different areas or the organization related to the problem appropriate the solution.

- Have in place a continuous quality control and monitoring process for performance of the model that detects deviations in the results and facilitates incorporation of new input data to anticipate changes in the environment.

- Document the changes both to the model as well as the user interface. This ensures clear follow-up of the modifications, facilitates collaboration between teams, and contributes to rapidly identifying the impact of the adjustments on system performance and the user experience. To ensure effective documentation, it is recommended that version controls be used that record and track each change made to the code. In addition, collaborative platforms can be employed to create a centralized knowledge base where teams can describe in detail updates and improvements to the changes, and justifications for them. It is important to structure the documentation in clear sections that include dates, versions, and technical descriptions in a way that any member of the team can easily consult and understand the history of the modifications.

- Ensure technical and organizational flexibility that allows for adapting solutions to changes in the environment, as well as to new applicable regulations.

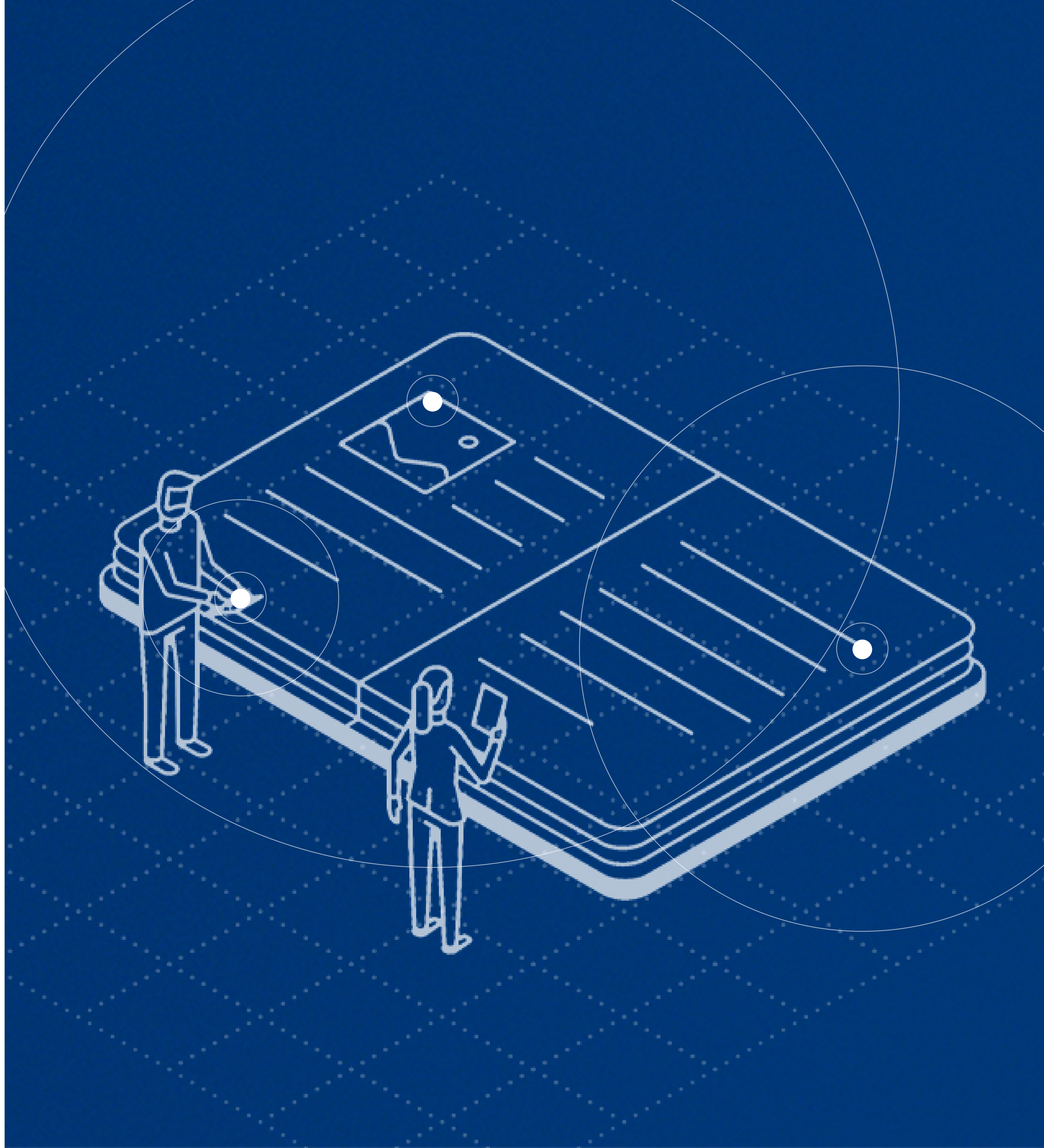
- Take actions that facilitate the scalability of the solutions, such as implementing a performance monitoring system that provides alerts when the model is outdated, using computation in the Cloud to scale platforms in a timely manner, and use technological options to make operation of the models more efficient.

Organizations in the critical infrastructure sectors in LAC have a unique opportunity to advance the adoption of Artificial Intelligence as a means to accelerate their digital transformation and achieve better results in operational efficiency, productivity, user satisfaction, sustainability, and contribution to the countries' economic and social development. To attain these benefits, it is vital that decision-makers fully understand the potential and the implications of AI, as well as the opportunities offered by real use cases and solutions to existing problems. In addition, it is advisable that these leaders familiarize themselves with the methodologies recommended for AI development and innovation, and that they consider the key aspects for development and adoption of these types of solutions.

6 ANNEXES

Annex 1.
Review of AI Regulatory Frameworks in Latin America and the Caribbean

An important element to consider for successful implementation of AI-based solutions in infrastructure sectors is the applicable regulatory framework. This annex presents a review of regulatory frameworks in LAC related to developing and adopting these technologies. Specifically, a comparative analysis is carried out of the main elements of data protection regulations in the region and of specific developments in the countries in terms of regulations and guidelines on the development and adoption of AI.



By adopting standards and regulations on AI, each country can influence the level of development of these technologies at the national level (TMG 2020). In fact, the regulatory frameworks determine the possible opportunities that can be brought to bear by early and timely adoption of AI for individuals, businesses, and society, as well as the risks associated with privacy and possible discriminatory practices, among others. In addition, regulatory frameworks can prioritize putting into practice some of the principles considered as fundamental to AI, such as impartiality, privacy, responsibility, and transparency.

The objective of this annex is to present a review of AI and data protection regulatory frameworks in 11 countries of the region that covers aspects with possible implications for developing solutions based on this technology in infrastructure sectors. The countries analyzed are Argentina, Brazil, Chile, Colombia, Costa Rica, Ecuador, Mexico, Panama, Peru, Dominican Republic, and Uruguay. As discussed in this section, most of the regulatory developments related to AI implemented in countries of the region have been implemented in the data privacy and protection component. Moreover, some governments have addressed the ethical implications of the use of this technology through the design of principles, guidelines, or recommendations, rather than through the issuance of specific regulations. In addition, a common public policy practice in the region is to design national plans or strategies that enable the adoption of this technology in governments and different economic sectors.

Regulatory Frameworks for the Protection of Data in AI

A regulatory area that is critical for the development and implementation of AI-based solutions relates to the data protection regimes of each country. These systems define the standards for data generation, access, collection, management, storage, and processing (TMG 2020), which constitute an important input for AI-based development. Table 1 presents a summary of the main elements of existing regulatory frameworks for data protection in the 11 countries of the region analyzed. Some of the elements considered, which can be determining factors for the development of AI-based solutions, include requirements related to data subjects' consent, database registration, third-party data processing, privacy impact assessments, restrictions on international data transfers, and data localization requirements,

Table 1. Data Protection Data Regulatory Frameworks in Latin America

Country	Main Data Protection Law	Consent of the Data Holder	Record of Databases	Processing of Data by Third Parties	Obligations for the Evaluation of the Impact on Privacy	Restrictions on International Transfers of Data	Requirement for the Location of Data
Argentina	Law 25.326 of 2000	Yes	Yes	Yes	No	List of countries	Financial, accounting, and labor sectors
Brazil	Law 13.709 of 2018	Yes	No	Yes	Yes	List of countries	State, public, and financial information
Chile	Law 19.628 of 1999 Law 20.575 of 2012	Yes	Yes	Yes	No	Not specified	Banking sector
Colombia	Law 1.581 of 2012	Yes	Yes	Yes	No	List of countries	Defense sector
Costa Rica	Law 8.968 of 2011 Regulation 37.554-JP of 2013 to the Law	Yes	Yes	Yes	Yes	No	Not specified

Country	Main Data Protection Law	Consent of the Data Holder	Record of Databases	Processing of Data by Third Parties	Obligations for the Evaluation of the Impact on Privacy	Restrictions on International Transfers of Data	Requirement for the Location of Data
Ecuador	Organic Law of 2021	Yes	Yes	Yes	Yes	List of countries	Data reserved for the State and for national security (Fintech Law)
Mexico	New Federal Law DOF 05-07-2010	Yes	No	Yes	Yes	Not specified	In cases of national security and public information
Panama	Law 81 of 2019	Yes	No	Yes	Yes	List of countries	Not specified
Peru	Law 29.733 of 2011	Yes	Yes	Yes	No	List of countries	No
Dominican Republic	Law 172 of 2013	Yes	No	Yes	No	List of countries	Not specified
Uruguay	Law 18.331 of 2008	Yes	Yes	Yes	Yes	List of countries	For risks of central administration and sectoral regulation such as banking

Sources: EY (2023); IAPP Research and Insights (2024); Centro LATAM Digital (2022); Baker McKenzie (updated between December 2023 and January 2024); and Asamblea Nacional República de Ecuador (2022).

As can be seen, the 11 countries examined have data protection regimes expedited through national laws. The first countries to implement these types of regimes were Chile and Argentina in 1999 and 2000, while Ecuador is the country that implemented the regime most recently, in 2021. In all of these countries, the regimes require the consent of the owner of the data as a protection measure. However, there are circumstances under which consent is not necessary in these countries. Some are associated with the data being of public access or anonymized, or with because the data processing cmplies with legal requirements, among other reasons (EY 2023).

In 7 of the 11 countries analyzed, the databases must be registered with the respective authorities and related reports must be periodically delivered to them (EY 2023). The countries with this requirement are Argentina, Chile, Colombia, Costa Rica, Ecuador, Peru and Uruguay. In the case of Chile, registration is required for information collected by public entities.

Another of the aspects analyzed in the data protection regulatory framework is authorization for the processing of data by third parties. In all of the 11 countries analyzed, such processing is permitted. In some countries, such as Argentina and Costa Rica, aspects such as the finality of and compliance with certain conditions are key, while in others such as Ecuador the scope of the processing must be determined contractually (EY 2023).

The data protection regulatory frameworks also take into account the requirement to implement Privacy Impact Assessments. This requires that the agent or supervisor in charge of treatment of the data conduct an evaluation of the protection of the data in terms of risks associated with such aspects as rights and liberties (European Commission 2012). This requirement exists in 6 of the 11 countries of the region analyzed: Brazil, Costa Rica, Ecuador, Mexico, Panama, and Uruguay.

Finally, data protection regulatory frameworks in the region include elements on international transfers of data, and in some cases there are certain requirements regarding the location of data in national territories. At least 8 countries of the region have incorporated restrictions on international transfers of data. The restrictions are consistent in requiring that that those data transfers only be carried out with countries with similar or higher data protection levels (EY 2023). Towards that end, countries have established lists of countries with which data can be transferred. While Chile and Mexico have no such specifications, Argentina, Brazil, Chile, Colombia, Ecuador, Mexico, and Uruguay have requirements for the localization of data in specific sectors such as the financial sector, defense, or in relation to state data. Peru has no such restrictions, while in Costa Rica, Panama, and Dominican Republic the laws do not specify these types of restrictions.

AI Regulatory Frameworks

The second set of regulatory frameworks reviewed involves AI in the region.[203] In particular, a review is presented of standards or guidelines specific to AI that countries have implemented. **Table 2** presents the results of the review for the 9 countries where such specific standards or guidelines have been identified. The existence of the standards or guidelines demonstrates the extent to which efforts are under way to find an equilibrium between the innovation that AI brings about and the possible risks associated with it (IAPP Research and Insights 2024).

203 Review by the authors based on Accessnow (2024), OECD-CAF (2022), and TMG (2020).

As shown in the table, standards and guidelines related to ethical aspects of AI were identified in 6 of the 9 selected countries: Argentina, Chile, Colombia, Costa Rica, Mexico and Peru. Each of these countries has standards and guidelines focused on the ethical aspects of AI. There are also documents dedicated to ethical aspects, such as *Formulación ética de proyectos en ciencia de datos* in Chile, and the *Marco ético para la AI* in Colombia, as well as a document prepared by INTEL and the IDB on the importance of having ethical guidelines on AI in Costa Rica. Finally, Peru issued a decree with a section on the ethical use of AI. Other guidelines have sections on ethical elements, with ethics proposals or ethical requirements for bidding in countries such as Argentina, Chile, Colombia, and Mexico.

In 6 countries, specific standards and guidelines on protection of data for AI solutions were identified that are in addition to those mentioned in the regulatory frameworks for the protection of data in AI (**Table 1**): Argentina, Brazil, Chile, Colombia, Mexico, and Uruguay. In the case of Argentina, Brazil, Chile, and Mexico, those documents are annexes to a regulation, specific sections with guidelines and suggestions with official documents, or publications of the entities responsible. Other types of documents issued by countries such as Brazil, Colombia, Mexico, and Uruguay include participatory processes, documents prepared by civil society, and sandboxes associated with the protection of data.

Standards and guidelines on transparency for AI solutions were identified in 3 countries of the region: Argentina, Chile, and Colombia. A specific document for the transparency program was identified only in Argentina, while in Chile these guidelines are part of an overall set of general guidelines, and in Colombia the reference to aspects of transparency is part of a section on the AI roadmap.

Finally, standards and guidelines specific to AI were identified in 8 countries of the region. Specifically, in Brazil, Chile, and Peru, AI strategies have been elevated to the level of standards – ordinance in Brazil, decree in Chile, and law in Peru – while in the other 5 countries these strategies and roadmaps are consigned to policy documents.

Tabla 2. Marcos regulatorios de IA en Latinoamérica

Country	Regulations Guidelines for Different Aspects of AI Solutions			
	Ethical Aspects	Protection of Data	Transparency	Specific AI Policies and Regulations
Argentina	*Recommendations for Reliable AI* (Jefatura Gabinete y Secretaría de Innovación Pública, 2023)	*Program for Transparency and Protection of Personal Data in the Use of AI – Annex to the Resolution* (Agencia de Acceso a la Información Pública, 2023)		*National Artificial Intelligence Plan* (Presidencia de la Nación, 2019)
Brazil	n.a.	*Preliminary Analysis Project of Law 2338* (ANDP,[1] y CAF, 2023) *Public Consultation Regulatory AI Sandbox* (ANDP and CAF, 2023)[1]	n.a.	*National AI Strategy* (Ordinance, 2021)
Chile	*Ethical Design of Data Science Projects* (División Gobierno Digital Chile, Universidad Adolfo Ibáñez, and IDB Lab, 2022) *Bases for the Type of Bidding for AI Projects with the Required Ethics* (Dirección de Compras y Contratación Pública – ChileCompra, 2023)	*Guidelines for the Use of AI Tools in the Public Sector* (Ministerio Secretaría General de la Presidencia and Ministerio de Ciencia, Technología, Conocimiento y Inovación, 2023)		*National AI Policy* (Decree, 2021)

Country	Regulations Guidelines for Different Aspects of AI Solutions			
	Ethical Aspects	Protection of Data	Transparency	Specific AI Policies and Regulations
Colombia	*Marco Ético para AI* (Government de Colombia, CAF and IDB, 2021) *Roadmap for Development and Application of AI* (Minciencias, 2024)	*Sandbox Privacy in AI Projects* (SIC[2], Government of Colombia and the Consejería Presidencial para asuntos económicos y transformación digital, 2020)	*Roadmap for Development and Application of AI* (Minciencias, 2024)	*National Policy for Digital Transformation and Artificial Intelligence* –CONPES Document (DNP, 2019)
Costa Rica	*Support for the Responsible and Ethical Use of AI* (MICITT, CINDE, IDB, and INTEL, 2021)	n.a.	n.a.	n.a.
México	*Initiative for the Regulation of AI PAN – in process* (Ignacio Loyola, 2023)	*Recommendations on the Treatment of Personal Data in AI* (INAI[3], 2022)	n.a.	*AI-MX Strategy* (Coordinación de Estrategia Digital Nacional, 2018)
	National Mexican Artificial Intelligence Agenda (Coalición IA2030MX, 2020)			

Country	Regulations Guidelines for Different Aspects of AI Solutions			
	Ethical Aspects	Protection of Data	Transparency	Specific AI Policies and Regulations
Perú	*National AI Strategy* (Secretaría de Gobierno y Transformación Digital y Presidencia de Consejo de Ministros, 2021) *Digital Confidence Framework – Ethical Use of Technologies and Data* (Decree, 2020)	n.a.	n.a.	*Law that promotes the use of AI in support of development* (Law, 2023)
República Dominicana	n.a.	n.a.	n.a.	*National AI Strategy* (OGTIC, Dirección Ejecutiva Gabinete de Innovación y Desarrollo y Digital, 2023)
Uruguay	n.a.	*AI and Data Strategies – public participation in process* (AGESIC, CAF and UNESCO, 2023–2024)	n.a.	*AI Strategy of Digital Government* (AGESIC, Presidencia, 2019)

Sources: Accessnow (2024); OECD-CAF (2022); and TMG (2020).

Note: Does not include legal projects.
[1] ANDP: Autoridad Nacional de Protección de Datos de Brasil; CAF: Development Bank of Latin America.
[2] SIC: Superintendencia de Industria y Comercio de Colombia.
[3] INAI: Instituto Nacional de Transparencia, Acceso a la Información y Protección de Datos Personales de Mexico.

Policy Recommendations

Policymakers in LAC play a significant role in consolidating policy and regulatory frameworks that facilitate and promote the adoption of AI in infrastructure sectors. This section presents five main lines of action through which governments of the region can make progress on consolidating these frameworks. These lines of action are based on a review of international experiences, interviews with experts about the development and implementation of these types of solutions, and a comparative review of AI regulatory frameworks in LAC, the main results of which are presented in this annex.

Modern, Efficient, and Stable Regulatory Frameworks for Data and AI

The regulatory frameworks of the countries for data protection and AI set up regulatory environments that can facilitate or inhibit the development and adoption of this technology in economic sectors, including infrastructure sectors. In general terms, these frameworks are configured as facilitators when they simultaneously succeed in promoting the achievement of different and apparently contradictory policy objectives, such as the privacy and security of sensitive information, on the one hand, and the advance of technological innovation as a factor of competitiveness, productivity, and digital transformation, on the other. Robust regulatory frameworks allow for attaining a balance in which both objectives can be achieved simultaneously, thereby guiding societies toward improved states of well-being

There are data protection regimes in most countries of the region. It is important that the countries make progress on modernizing those regimes without incorporating additional restrictions on the processing of data that are not supported by the evidence, such as requirements for the localization of data beyond sensitive or national security cases. This can create barriers to adopting Cloud services for the development and implementation of AI solutions in economic sectors, including infrastructure.

Furthermore, to the extent that the widespread adoption of AI in economic sectors is a relatively recent phenomenon, it is useful for governments to develop spaces for learning and experimentation with regard to the regulatory implications of AI adoption before defining specific and rigid legislative or regulatory frameworks that can constrain the adoption process. It is therefore a good practice, and one that has been implemented in most countries of the region, to have an initial “soft law” focus based on formulating guides and guidelines for responsible implementation of this technology. Another practice to consider is the implementation of spaces for regulatory experimentation (sand box regulations) for AI adoption – as has been done in multiple cases at the international level for the financial sector – in highly regulated sectors, which includes some infrastructure sectors.

Sectoral Regulatory Frameworks that Facilitate Innovation

To make progress in the adoption of AI in infrastructure sectors, regulatory frameworks for these sectors should not incorporate elements that can restrict or disincentivize innovation directed towards advances in efficiency and productivity, or the incorporation of new business models. For example, in sectors with the presence of public utilities (energy and water and sanitation), rigid tariff regulations can generate disincentives to implement initiatives to reduce costs. In the transport sector, traditional regulations can create barriers that cover new service modalities, such as those based on technology platforms. It is therefore recommended that policymakers in those sectors consolidate flexible policy frameworks that recognize technological innovation as a factor in sectoral development.

Effective Policies for the Development of Human Capital and Sectoral Capacity

As has been indicated throughout this document, developing capacities is key for adoption of AI in infrastructure sectors of the region. Some organizations in traditional sectors such as transport and water and sanitation have been late adopters of technological innovations, so they face cultural and technical capacity challenges to developing and implementing AI-based solutions. In general, organizations in infrastructure sectors will need to develop new capacities and skills, and make cultural changes, to be able to adopt and take advantage of the opportunities offered by an emerging technology such as AI that is now broadly used. It is thus vitally important that governments implement effective human capital and capacity development policies to help close the gaps for the adoption of this technology. To achieve this, the support of higher education, public-private collaboration to develop capacity, and national programs to prepare the workforce for the adoption of AI will have an important impact on these sectors.

Promotion of Ecosystems for Technological Innovation

The adoption of AI in economic sectors such as those in infrastructure is also driven by local ecosystems for technological innovation. These include different actors such as entrepreneurs, technology companies, the private sector, academia, and government, as well as the interrelationships between them, which accelerate dynamics of innovation that drive the development of AI-based technological solutions. Governments have an important role in promoting these ecosystems by defining and implementing public policies that address the determinants of the development of these ecosystems in such aspects as regulation, financing, human capital, technological infrastructure, and trade, among others.

In addition, through the implementation of new modalities such as innovative public purchasing programs, the State has a facilitative role in technological innovation as a purchaser of technology. These programs can also be extended to utilities with the participation of State capital.

Communication of Opportunities, Best Practices, and Success Stories

Finally, governments of the region promote the adoption of AI in sectors, including infrastructure, through policies and initiatives that communicate and inform economic actors about existing opportunities to improve productivity, competitiveness, and well-being by adopting AI, as well as about existing best practices and successful cases in the countries and at the international level. Likewise, the existence of modern regulatory frameworks for digital security and guidelines for the responsible use of AI and its related ethical aspects will contribute to consolidating the confidence of these actors and of citizens in the use and adoption of this technology.

Annex 2.
Methodology for the Interviews

Types of interviews	Objective and scope	Duration	Medium	Profile of those interviewed	Number of interviews	Date of the interviews
Semi-structured.[204] Followed the *Interview Guide* presented below. Additional questions were posed according to the particularities of each interview and the profile of each interviewee.	Understand the perspective of interviewees regarding the potential of AI for the infrastructure sectors, and the main considerations and recommendations for successful adoption of this technology in those sectors in LAC. Moreover, understand the lessons learned from the experience of the interviewees in specific cases of the development of these solutions.	30–60 minutes	Virtual with the presence of IDB personnel.	Members of IDB technical teams, clients, and external actors with experience in the development and implementation of solutions using emerging technologies and AI.	17	March and April 2024

204 Longhurst, R. (2003), Semi-structured Interviews and Focus Groups. *Key Methods in Geography.*

Interview Guide	
Information about the case analyzed	• What is the problem/need for which you are looking for the solution to resolve, and how was the process of understanding and diagnosing that problem/need? • What does the solution implemented consist of, and what are its main objectives and characteristics? • What type of AI model(s) were implemented in developing the solution and with what type of data? How were the decisions taken regarding the choice of the model(s) and the data to be used? • What advantages/disadvantages would you like to highlight from the AI model used in terms of its attributes (e.g., usability, scalability, testability, interpretability, adaptability, precision/performance, security)? • Briefly describe the process of developing and implementing the solution. • What external and internal IDB actors have intervened in developing and implementing the solution, and how has the interaction been with/between them? • What advances or results have been achieved to date in implementing this solution? What level of ownership or engagement have the beneficiaries demonstrated? • What challenges or difficulties did the team face in developing and implementing the solution and how were they addressed/solved? • What are the main lessons learned through the development and implementation of this solution that will be useful to strengthen the processes of developing and implementing AI solutions in this sector in the future?
Understanding the potential of AI in infrastructure	• In your opinion, what are the main opportunities and advantages that could be brought about by adopting AI in infrastructure sectors in LAC? • In addition to the solution discussed previously, do you know about other AI developments or solutions in the (Transport, Energy, Water or Sanitation) sector at the global level or in LAC that have high potential? What are they?

Interview Guide	
Considerations for adopting AI in infrastructure	• From your experience, what are the main success factors in the development and adoption of AI solutions in the (Transport, Energy, Water or Sanitation) sector in LAC? • From your experience, what are the main groups of interest that should be considered in the development and adoption of AI solutions in the (Transport, Energy, Water or Sanitation) sector in LAC, and how should they be effectively linked into these processes? Additional optional questions: • From your experience, what are the main considerations in terms of ethical aspects that should be taken into account in the development and adoption of AI solutions in the (Transport, Energy, Water or Sanitation) sector in LAC? • From your experience, what are the main considerations in terms of legal, regulatory, or institutional aspects that should be taken into account for the development and adoption of AI solutions in the (Transport, Energy, Water or Sanitation) sector in LAC? • From your experience, what are the main considerations in terms of technical aspects, data processing, and security that should be taken into account in the development and adoption of AI solutions in the (Transport, Energy, Water or Sanitation) sector in LAC? • From your experience, what are the main considerations in terms of the development of capacity that should be taken into account in the development and adoption of AI solutions in the (Transport, Energy, Water or Sanitation) sector in LAC?
Recommendations for policymakers	• What do you consider to be the main bottlenecks that the countries of LAC must address to successfully develop and implement AI in infrastructure projects? • What are the main recommendations you would make to policymakers to promote the successful development and implementation of AI projects in infrastructure sectors?

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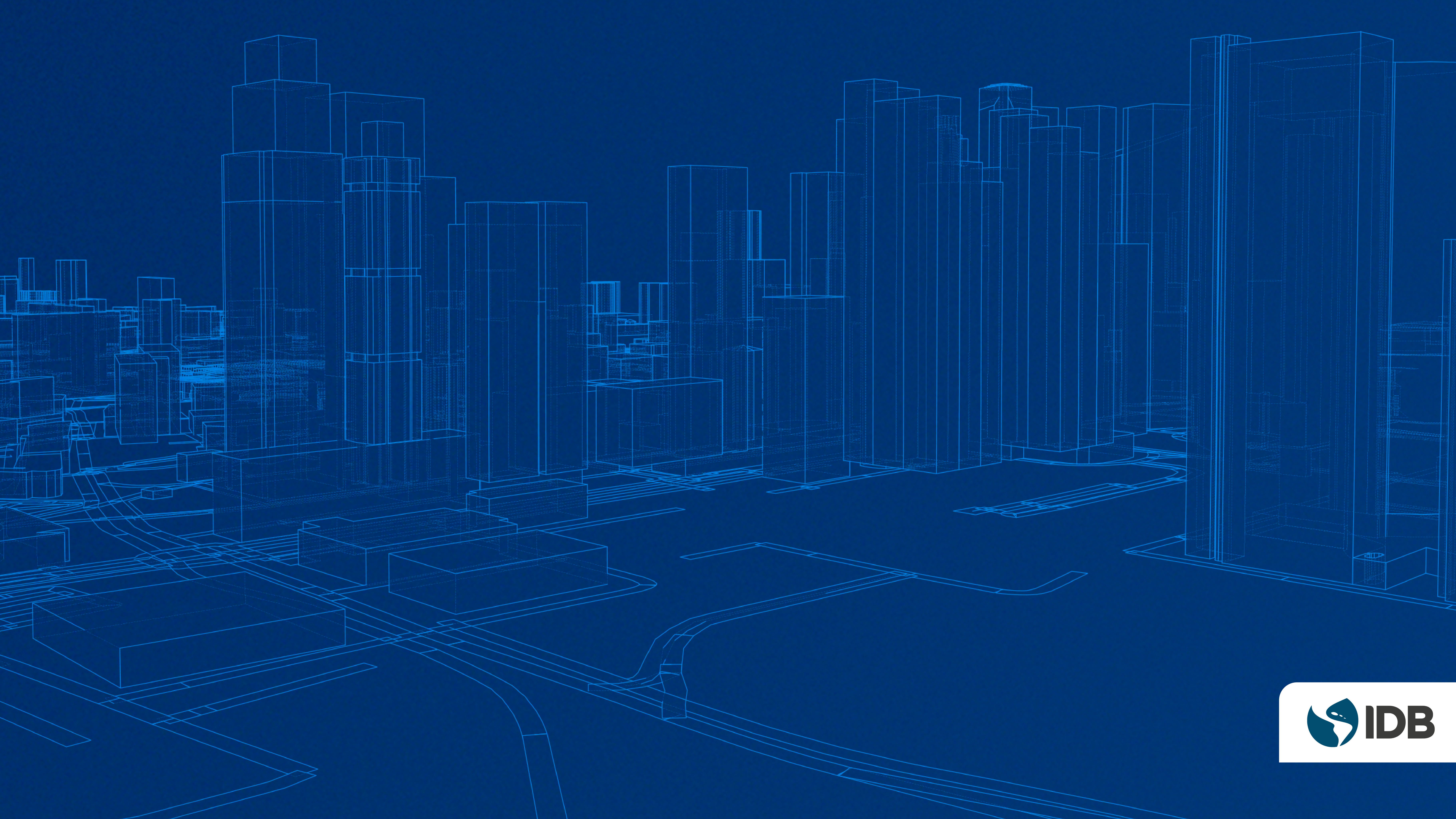

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