Digital Transformation Enabler: Machine Learning

An Industry IoT Consortium Whitepaper

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This Digital Transformation Enabler (DXE) playbook provides a high-level description of digital transformation and of machine learning (ML) technology (artificial intelligence). The playbook offers examples and insights into ways this technology has been successfully deployed in industrial IoT environments to transform those businesses and their operations digitally. The document also provides technical guidance that helps organizations to uncover new and transformative ML-based solutions to deal with customer problems, enabling the creation of value-added services that drive new revenue streams.

ML technologies extend beyond the resolution of technical problems, into discovering and addressing unique challenges, providing new perspectives on current problems, and uncovering previously unconsidered use cases. The industrial disruption expands beyond the boundary of technology into the business realm—transforming the way companies think, operate and act.

Hence, this playbook is aimed at a wide range of stakeholders, such as the CXOs who are mainly concerned about digital transformation and how technology (in this case ML) enables it, and the system architects, engineers and implementors who are concerned with the practical aspects of design, implementation and operation of this technology as part of these systems.

1 About Digital Transformation Enablers

1.1 Digital Transformation

Organizations in industry are under pressure from a relentless barrage of emerging and emergent digital technologies that threaten to disrupt and transform their business and operations. Organizations that fail to act on these threats (and opportunities) risk significant disruptions to their business and operations, exposing them to pressures from nimbler and more innovative competitors threatening to make them obsolete.

Digital transformation (DX) is a catch-all term that refers to efforts by organizations to leverage disruptive technologies and transform the way they operate and deliver value to the market. The overall objective of DX is to deliver better outcomes to customers and shareholders and achieve better ROI, while maintaining compliance, security and trustworthiness throughout the transformation journey.

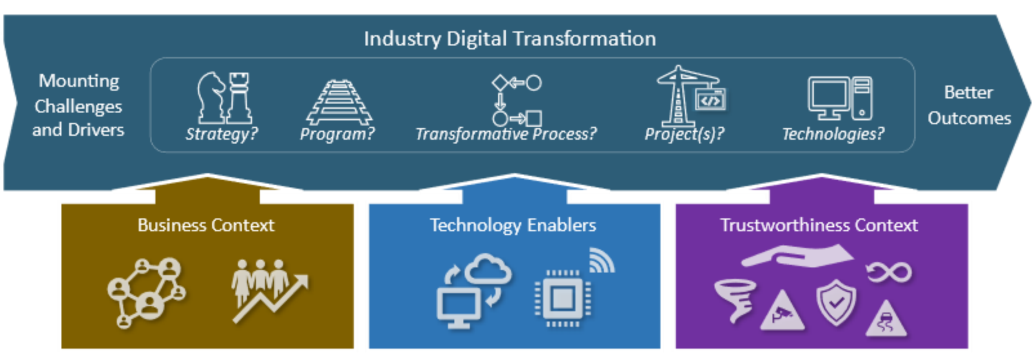

Figure 1-1: Digital transformation journey. Source: IIC.

The term *industry digital transformation* (IDX) reflects the digital transformation context within industry. IDX is primarily a business endeavor focused on the coherent and innovative application of emerging and emergent digital technologies in a principled manner, and the strategic realignment of the organization towards the improvement of business models, industrial models, and processes and ultimately the creation of entirely new ones.

One important aspect of IDX initiatives is that they involve sensor-driven IoT solutions that by definition incorporate a digital/physical boundary. This results in concerns about the IT/OT[1] divide and a potential convergence and integration between their respective operations. These concerns manifest themselves during the transformation journey and at multiple levels, including systems, procedures, best practices, compliance, organization structure and workforce.

Another perspective on digital transformation is that it covers three related areas: *digitization*, *digitalization* and *digital transformation*. *Digitization* deals with the conversion of analog operational data into digital form to facilitate the use of this data within operational processes. *Digitalization* deals with the ingestion and consumption of the digitized data into operational processes for the purpose of optimizing and integrating them. *Digital transformation* builds on the above and leverages disruptive technologies to create new and innovative business and operational and service delivery models and uncover new revenue opportunities and compete in new markets.

For further information about digital transformation, please refer to the "Digital Transformation in Industry paper"[2] and "Digital Transformation Journey in the Enterprise and its Leadership" Journal of Innovation article,[3] both published by the Industry IoT Consortium (IIC).

1.2 Digital Transformation Enablers

Digital transformation enablers (DXEs) are specific digital technologies that can enable or accelerate the transformative effects of core processes, the enterprise and its operations.

A DXE playbook provides a description of a DXE (focused on a particular technology) and includes examples of the use of this technology in real-world applications, the issues that had to be considered and the concerns that had to be dealt with, and how. The document can also help a stakeholder understand ways in which this technology can transform a core process and ultimately a business, ranging from strategies and policies to frameworks, standards and technologies. DX efforts are driven by business initiatives that are often motivated by pain points,

[1] Operational Technology

[2] *https://www.iiconsortium.org/pdf/Digital_Transformation_in_Industry_Whitepaper_2020-07-23.pdf*

[3] *https://www.iiconsortium.org/news/joi-articles/2021-November-JOI-The-Digital-Transformation-Journey-in-the-Enterprise-and-its-Leadership.pdf*

such as difficulties in uploading software to automobiles or the high costs associated with unscheduled maintenance.

Some DXEs apply to a specific set of application verticals, although many can be employed more widely. However, since adopters can generally understand examples pertaining to their own industry better than examples in other industries, DXE playbooks will include multiple examples to foster deeper understanding. The DXE playbook supplements associated frameworks by providing guide points rather than a map of the technical and architectural capabilities and considerations related to the technology.

1.2.1 Relationship With IIC's IIRA and Existing Technology Frameworks

Each DXE playbook is aligned with the viewpoints of the IIoT as defined in the IIC Industrial Internet Reference Architecture (IIRA[4]). It is also aligned with the specific technology frameworks that are regularly published by the IIC–for example, the Industrial Analytics Framework[5], the Industrial IoT Artificial Intelligence Framework[6] and Industrial Internet Security Framework.[7]

1.3 How to Use a DXE Playbook

The following diagram highlights the steps involved in using a digital transformation enabler:

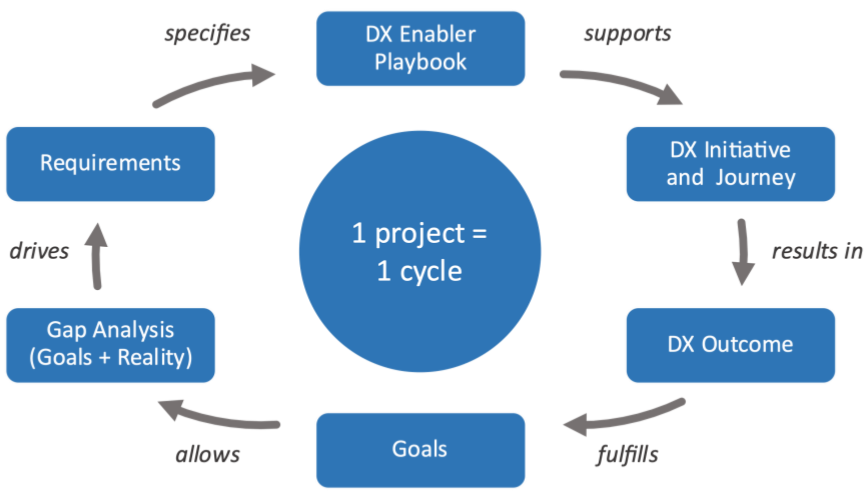

Figure 1-2: Steps involved in using the DX Enabler. Source: IIC.

These steps are typically executed in the following order:

- The reader reads the DXE playbook.

[4] *https://www.iiconsortium.org/pdf/IIRA-v1.9.pdf*
[5] *https://www.iiconsortium.org/pdf/IIC_Industrial_Analytics_Framework_Oct_2017.pdf*
[6] *https://www.iiconsortium.org/pdf/Industrial-AI-Framework-Final-2022-02-21.pdf*
[7] *https://www.iiconsortium.org/pdf/IIC_PUB_G4_V1.00_PB-3.pdf*

- With the knowledge gained, the reader's organization begins ML-specific tasks (design, implementation, operation) that support the DX journey.
- This transformation enables the organization to achieve a transformative outcome.
- The organization is now equipped to fulfill new goals in a way that were not possible before the transformation.
- The reader can now perform a gap analysis to see in which ways the organization can be improved.
- This analysis drives the creation of new requirements.
- New requirements may call for the deployment of a new technology that has not yet been previously considered.
- The reader obtains another DXE playbook focused on this new technology and restarts the process again at the first step.

2 DX Enabler: Machine Learning Technology

2.1 Machine Learning Background

Industrial artificial intelligence is the application of AI, machine learning in particular, to IoT applications in industry, in areas like smart manufacturing, robotics, predictive maintenance, diagnosis of infectious disease and autonomous vehicles. With the ever-increasing amount of internally and externally sourced data available to organizations, ML has been identified as a critical tool for leveraging this data in transformative ways:

- helps uncovering insights from data intensive environments,
- acts an enabler of digital transformation and
- acts an agent for future proofing the organization.

ML provides analysis capabilities and enables continuous monitoring to provide a deeper understanding of the data and can improve this understanding over time with minimal human involvement or knowledge of the process. ML can also continually inspect incoming data to gain new insights and then issue recommendations based on those insights. The general process can be described as follows:

- digitize, extract, transform raw data for analysis, sharing, archiving or distribution,
- analyze the data—typically to identify anomalies,
- tune parameters to find an optimum point/output,
- generate acceptable solutions,
- prescribe the next course of action,
- use historical data to predict the likelihood of future events and
- identify an appropriate action given a condition.

Perhaps more than any other technology, ML plays a significant role in disrupting the organization and empowering its digital transformation journey. ML enables new areas of innovation since it can be applied in many different ways. For example, predictive analytics and process optimizations allow new thinking about design, operation, and management that have not been possible before. The Industrial IoT AI Framework referenced earlier provides further examples of the transformative nature this technology.

ML complements big data, composable architectures and decision intelligence practices. It provides radical new ways of solving existing problems, such as process optimization, as well as addressing new problems, such as logistics problems caused by COVID-19. With these new perspectives and new proposed solutions, ML encourages novel ideas and insight about business operations.

Gartner lists five key ways that ML can deliver business value[8]:

- innovation,
- exploration,
- prototyping,
- refinement and
- firefighting.

Of these, the business effect of innovation and exploration are in clear alignment with digital transformation goals, with main objectives that focus on disruption of current business practices and the exploration of new ideas. As ML hunts for patterns in an organization's vast data reservoir and uncovers novel insights, it stimulates new perspectives for achieving business goals, and new methods of addressing business challenges emerge.

ML can be especially compelling when deployed in the form of managed services that adapt to the evolving needs of a customer. By disrupting current thinking, ML can transform business practices and assist with decision-making in ways that may not be possible by human actions alone. These managed services have uses across industry—in design, manufacturing, operations, workplace management and in other applications.

ML excels in advanced decision making and process optimizations. By driving the discovery of new business ideas, assisting with governance practices, enriching customer experiences, accelerating productivity increases and simplifying prioritization of business objectives, ML has emerged as a key enabler of organizational digital transformation and the associated new business outcomes.

[8] *https://www.gartner.com/en/doc/431403-five-ways-artificial-intelligence-and-machine-learning-deliver-business-impacts*

2.2 CONTACTS

For further information about the topics discussed in this DXE playbook, you can contact the following groups at the Industry IoT Consortium:

IIC Group	Contact
DX Working Group	*dxwg@engage.iiconsortium.org*
Industrial AI Task Group	*ai-team@engage.iiconsortium.org*
Industry Working Group	*industrywg@engage.iiconsortium.org*
Technology Working Group	*tech@engage.iiconsortium.org*

Table 2-1: IIC Working Group contact information.

2.3 STAKEHOLDERS

The stakeholders for this document comprise both CXOs, for whom the IIC Digital Transformation Framework is directed, and architects, engineers and implementors of the system(s) being led by the CXO(s). CXOs should share this document with other pertinent stakeholders within their organization to provide insight into how others have deployed this technology and have achieved successful digital transformation in their environment.

2.4 STRATEGY FOR APPLYING THE DXE TO ACHIEVE BUSINESS TRANSFORMATION

The IIC *Industrial IoT AI Framework* provides extensive descriptions of the strategic, tactical—and practical—business, usage, functional and implementation considerations related to the design, implementation and operation of ML-powered systems. It describes the transformational impact ML technology can have on systems and enterprises.

Business viewpoint: Maximize value to the organization and its ecosystem through a direct improvement of the RoI (such as improving production throughput or reducing operational costs) and indirect improvements related to societal aspects (such as increasing the accuracy of disease diagnosis).

Usage viewpoint: Enable new capabilities and types of solutions such as predictive maintenance, automation of factories, fault detection and fleet logistics. This requires consideration of the trustworthiness, ethical and societal concerns related to AI technology and its implementation.

Functional viewpoint: Focus on the functional components in an industrial AI system, its structure and interrelations, and the relation and interactions of the system with external elements to support the development, training, usage and operation of the system.

Implementation viewpoint: Consider the different aspects of design and integration of an ML system into an IIoT system, such as scope, response time, reliability, bandwidth and latency, capacity, security, big data properties and portability and reusability.

2.5 POLICIES FOR APPLYING THE DXE TO ACHIEVE BUSINESS TRANSFORMATION

The Industrial IoT AI Framework has identified a wide range of requirements that relate to policy, compliance and the application ML technology. Below is a sample list of these requirements. Please refer to Section 3 for further details:

- trustworthiness of AI: security, privacy, confidentiality, explainability, controllability,
- ethical and societal concerns: ethics, bias, safety,
- effect of ML on labor and
- regional and industry-specific policy considerations.

2.6 STANDARDS

Below is a list of standards that are relevant to this DXE playbook:

Standard	Related Document
IEC 61508: Functional safety of electrical, electronic, programmable electronic safety systems	*https://bit.ly/3iTNPEF*
IEC 61511: Instrumented systems for the process industry sector	*https://bit.ly/3yXLWfC*
IEC 62443: IEC Technical Committee 65 (TC 65) for operational technology in industrial and critical infrastructure	*https://webstore.iec.ch/publication/7030*
ISO/IEC 27000: Family of Standards for IT systems	*https://webstore.iec.ch/publication/62675*
ISO/IEC DIS 23894: Artificial intelligence—Risk management	*https://bit.ly/3Dl7pRb*
ISO/IEC JTC 1/SC 42: Information Technology (including AI)	*https://www.iso.org/committee/45020.html*
ISO/IEC/IEEE 42010:20115: Systems and software engineering—Architecture description	*https://www.iso.org/standard/50508.html*

Table 2-2: Standards relevant to the DXE playbook.

2.7 SUPPORTING ENABLING TECHNOLOGIES

The rapid emergence of ML and its convergence with other transformative technologies in industry, such as IoT, digital twins, edge, XR, 5G and distributed ledger, promise to unleash a new generation of highly distributed systems that are personalized, contextualized, feature real-time human-to-machine and machine-to-machine interactions and new human machine interfaces.

This will empower a new generation of transformational capabilities in organizations in virtually every industrial sector, with ML acting a main catalyst for such disruptive IIoT solutions.

Technology	Description	Related Documents	How is it used?
Edge	Distributed computing performed near the boundary between the pertinent digital and physical entities, delineated by IoT devices.	*Introduction to Edge Computing in IIoT* (IIC)	ML is often tasked with the processing of significant amounts of sensor data. This places high demand for analytics to be performed on edge devices in close proximity to the physical devices where the data is created.
5G	Hyper-connectivity technology that enables ultra-reliable low-latency communications (URLLC), enhanced mobile broadband (EMB) and massive machine type communications (mMTC).	*Industrial 5G Devices* (5GACIA)	The connectivity aspects of modern IIoT systems and the demands for AI-driven (ML) intelligent operation “beyond line-of-sight” are placing high demands on systems in terms of more autonomy and agility, lower latency and higher bandwidth.
Digital Twin	Virtual representations of real-world entities and processes synchronized at a specified frequency and fidelity in industrial settings, connect the virtual and physical worlds enabling new opportunities and efficiency through digital transformation.	*Digital Twin Interoperability Framework* (DTC)	Digital Twins often include AI systems (ML) to analyze the real-world data with computation models based on first-principles, data-driven, and hybrid approaches. This provides insights for decision making.

Table 2-3: Use of ML with selected transformative technologies.

2.8 HEADWINDS AND TAILWINDS

Headwinds are influences and challenges that inhibit progress. Headwinds for ML technology tend to be specific to the application of that technology. *Tailwinds* are influences that advance progress towards improved conditions. Tailwinds for ML technology also tend to be specific to the application of that technology. Please refer to section 3 for details.

2.9 Architecture Frameworks and Models

Sections 4 and 5 of the Industrial IoT AI Framework provide information about the functional and implementation aspects of ML technology, such as:

- functional: architecture objectives, data concerns, learning techniques and system of systems issues and
- implementation: scope, response time, reliability, bandwidth and latency, capacity, security, data properties, interoperability and portability to other systems.

3 DXE Example: Steel Grade Evaluation Service

The steel manufacturing industry is the business of processing iron ore into steel and turning that metal into partially finished products, or recycling scrap metal into steel.

3.1 Overview/Strategy

Toshiba has been selling MetalSpector, a leading-edge steel inspection equipment, to several major steel companies for the past few years. In 2020, Toshiba released a new steel grade evaluation service, designed to reduce steel inspector's workload while assuring steel quality data integrity. The key approach is to understand how the product is used rather than just how it works. Understanding the customer's environment is necessary to move to a subscription-based business model.

3.2 Use Cases

In the quality assurance department of a steel manufacturer, samples of the outgoing steel are extracted, and metallography is applied to assure product quality using a microscope. The inspectors perform the measurement for its grade judgment based on the steel industry standards ASTM E-45, and JIS G-055.

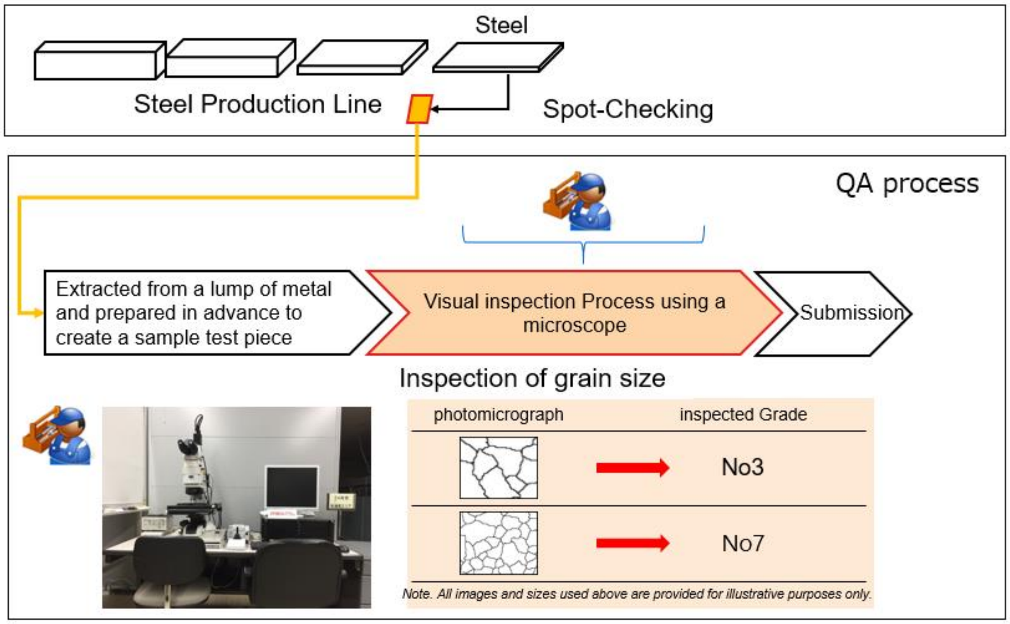

Figure 3-1: Current steel inspection process. Source: Toshiba.

3.2.1 Measurement System

The non-metallic inclusion measurement system automatically measures non-metallic inclusions in steel samples using an auto-focus optical microscope, X-Y stage, color area sensor camera, and an image processor. The sample holder with the test piece set is moved to a predetermined position on the X-Y stage and image input is performed.

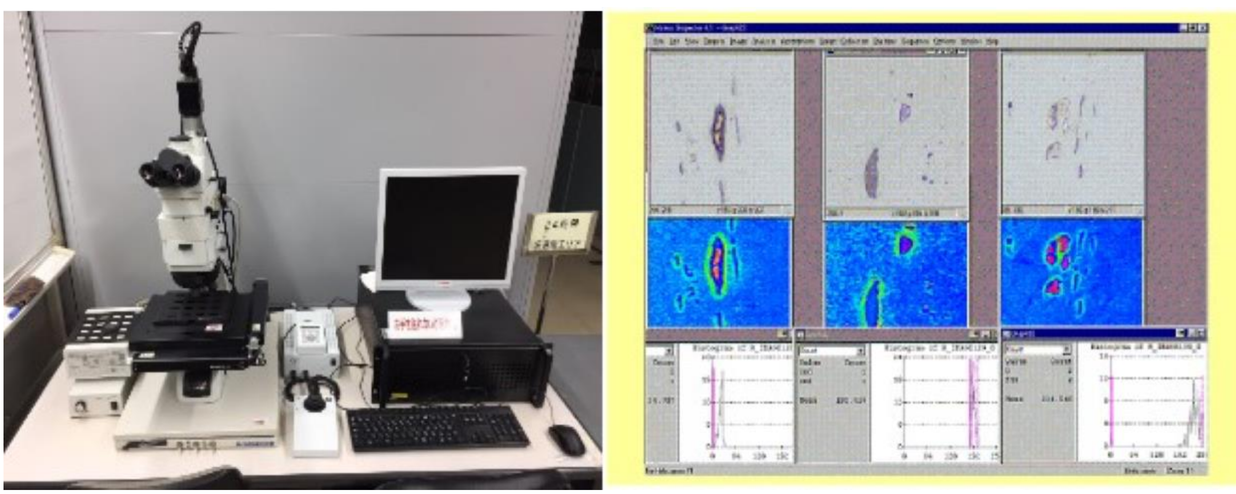

Figure 3-2: Non-metallic inclusion measurement system (Microscope). Source: Toshiba.

Issues include:

- labor-intensive QA process,
- long inspection hours caused by increasing number of samples,
- lack of consistency in grading judgement depending on inspector,

- skill transfer from veteran inspectors to junior inspectors and
- product quality data fraud.

The latest ML technology can be deployed to assist in the inspection accuracy, speed and operator training using an as-a-service model. The service provides traceability and automated logging to protect against unauthorized access and data fraud.

3.3 Solution Architecture Descriptions Or Patterns

The steel inspection process is changed to a service that connects the microscope image to a data management system and data-center-based steel-inspection model. The system operates as follows. It:

- captures steel images using a digital microscope and then transfers and stores the images to a historian database,
- transfers image data with a sequence number to a service for feeding an AI model estimator,
- stores steel-grade result estimated by the ML model with a sequence number to the log and
- inspectors determine final quality decision by referring to the estimated steel grade.

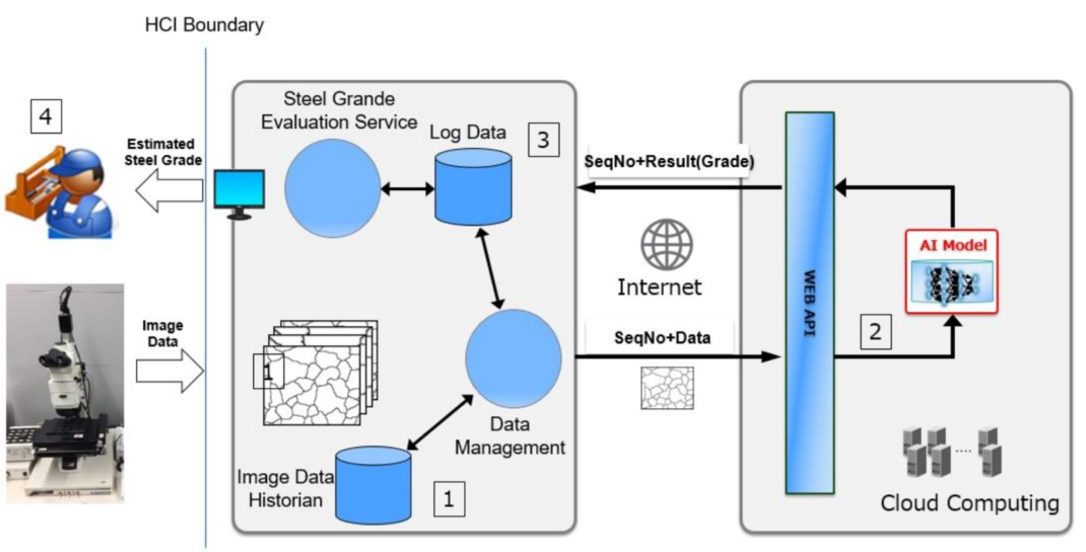

Figure 3-3: Steel inspection as-a-service. Source Toshiba.

3.4 Transformations Achieved

By proving the value of the ML image estimation and data auditing, the customer became receptive to providing customer data as part of a subscription contract. In turn, this allowed a new set of services to be realized, based on training the customer's inspectors.

Because the AI imaging service found success in a real-world scenario, the value of similar business opportunities was recognized. Image inspection is highly relevant to other manufacturing applications, and new image inspection services can be provided to customers with similar needs.

From Toshiba's perspective, the following transformations were achieved:

- mindset focus changed from product-function oriented to product-usage oriented,
- revenue stream changed from fixed purchase to as-a-service,
- solution focus changed from performance-focused and hardware-oriented solutions to user-focused products and services and
- business opportunities changed from highly customized integrations to modular services that can be adapted to specific customer needs.

From the customer's perspective, the key objectives of productivity and data integrity were fully satisfied, providing the following transformations:

- data integrity is assured by storing in a secure database, which eliminates data fraud,
- workload efficiency so that inspectors can focus on the more difficult inspection samples and train junior inspectors,
- the ML model can be improved over time, providing continuous improvement and
- once the ML model-training is complete, it can be used for junior-inspector education, which enables improved transfer of skills to the next generation.

3.5 Considerations for IT/OT Integration

Key considerations are based on the difference between the support periods of the MetalSpector equipment and that of the service platform on which the inspection service runs. It is an important design consideration to avoid managed services specific to a data-center-service provider as much as possible, since the equipment support lifetime is expected to be much longer than the service platform's support lifetime. Data-center-provider dependencies should be eliminated to allow migration to other platforms and support future improvements.

3.6 Systems and Product Lifecycle Concerns

Steel inspection systems have a lifecycle of decades, and maintenance support is required for the life of the system. The as-a-service model provides the means for providing continuous system support, including general maintenance, software updates, security patches and performance upgrades.

3.7 Relevant Standards for This Use Case

- ASTM E45, Standard Test Methods for Determining the Inclusion of Steel
- ASTM E768-99(2018), Standard Guide for Preparing and Evaluating Specimens for Automatic Inclusion Assessment of Steel
- JIS G-0555, Microscopic testing method for the non-metallic inclusions in steel

3.8 Tie to IIC Frameworks

The Industrial Internet Reference Architecture and the Industrial IoT Artificial Intelligence Framework frame system concerns into four groups, called *architecture viewpoints*.

For this steel grade evaluation service, the key system concerns can be organized as follows:

Business viewpoint:

- provide complete audit trail of inspection results, including the tracking of:
  - original sample image,
  - image processing result,
  - inspector grade result and
  - AI estimation grade result,
- reduce Inspector workloads,
- minimize downtime for system updates and
- provide ML estimation-grading as-a-service.

Usage viewpoint:

- automate common user actions,
- minimize additional user processes,
- prevent user from editing prediction results and audit material and
- provide similar look and feel of existing inspection system.

Functional viewpoint:

- system must operate even during data-center-service outages,
- system must operate with existing installed hardware,
- image processing must be performed on-site,
- data-center services must not prevent on-premises or edge equipment from functioning, and
- data-center services must secure audit trail and estimation data.

Implementation viewpoint:

- use the three-tier architecture pattern from the IIRA,
- deploy as modular microservices and
- communicate with existing equipment using standard industry protocols.

MetalSpector is part of the Toshiba SPINEX IIoT service family. All Toshiba SPINEX services use the Toshiba IoT Reference Architecture (TIRA), which is based on the IIRA three-tiered architecture pattern.[9]

[9] *IIRA three-tiered-architecture*

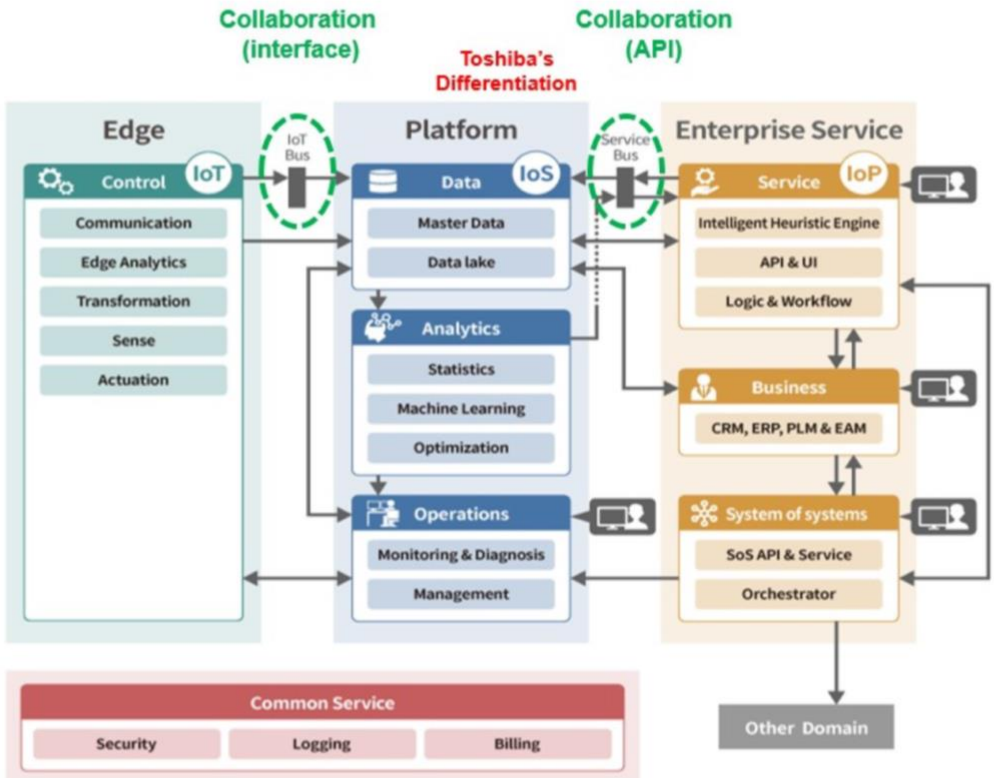

Figure 3-4: Toshiba IoT Reference Architecture (IIRA three-tiered architecture pattern). Source: Toshiba.

3.9 Challenges and Opportunities (Headwinds)

The biggest ongoing challenge is support of multivendor systems. Currently, the ML inspection service is only available for Toshiba MetalSpector systems. Multivendor support is a logical extension. To address this challenge, standards for both semantic and syntactic exchange of steel inspection data may be needed.

Because the successful deployment of MetalSpector helped validate the managed services approach at the business level, new opportunities for image-inspection services are being developed in other areas of manufacturing and infrastructure applications. For example, Toshiba has created a new managed service for the pharmaceutical industry, measuring surface defects in press-through-packaging (PTP) sheets. Similar managed services are also being developed for the inspection of film materials, paper, and non-woven cloth. Because these use cases also involve sample inspection, many of the image analysis components developed for MetalSpector can be applied to these inspection cases too.

4 Applicability to Other Verticals and Use Cases

Reserved for future use for additional use cases.

5 Appendix: DXE Reference Model

The diagram below provides a visual presentation of a Digital Transformation Enabler Playbook, including the typical components that would be found in a DXE playbook.

> Note: While each class description "defines" the class, these descriptions are intended to be colloquial in nature and not definitive. Other definitions may be more precise.

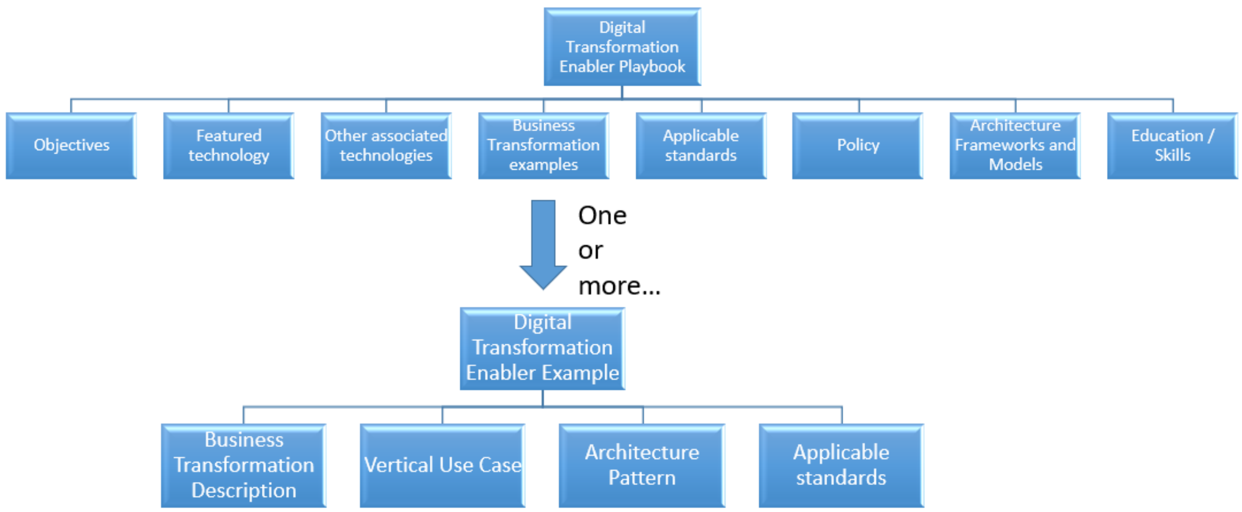

Figure 5-1: Visual representation of a Digital Transformation Enabler playbook.

A DXE playbook is a document bundle that provides context for understanding how to employ a given technology in a business setting to accelerate digital transformation.

A *digital transformation enabler* is a technology that can be employed in the industrial internet and to enable transformational outcomes across industries, such as over-the-air updates, machine learning, deep learning, big data, ubiquitous connectivity, cheap sensors and actuators. A digital transformation enabler has several subtypes described below.

A *strategy/mission* is the goal of the organization in question in this context. It could be to reduce downtime or invent new business models.

A *policy* is a stated intention for an approach to achieving the goal. It may be prescriptive—do this—or constraining—don't do that.

A *technology* is a software or hardware technology, such as connectivity, machine learning, big data or smart sensors. It will be included in the eventual system.

A *framework* is a reference document describing how to build something such as an architecture or a trustworthy system. The IIC has published several.

Relevant standards are standards (de facto or de jure) that can be applied in the implementation of the DXE.

6 AUTHORS & LEGAL NOTICE

This document is a work product of the Industry IoT Consortium's Industry Working Group chaired by Daniel Young (Toshiba America); and the Digital Transformation Working Group, chaired by Marcellus Buchheit (WIBU-Systems AG) and Bassam Zarkout (IGnPower).

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