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DIGITIZATION PRINCIPLES FOR APPLICATION SCENARIOS TOWARDS DIGITAL TWINS OF ORGANIZATIONS

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Abstract. In today's agile business ecosystems, digital twins (DTs) and especially digital twins of organizations (DTOs) allow for adaption through dynamically evolving models depicting organizational aspects such as production processes, data flows, human actors and interactions. A hybrid modelling approach is utilized, as the establishment of such DTOs either considered on their own or as part of a DT ecosystem is not trivial. Meta modelling and meta model merging patterns are applied to integrate heterogeneous perspectives and domain models. Two main research questions with respect to digitization towards digital twinning are discussed: First, which digitization principles/patterns are appropriate for DTOs? Patterns ranging from "counting" to "estimation" are introduced to fill digital models serving as a foundation for DTs with data. As a starting point, potential digitization principles for relevant characteristics of BPMN – "Modelling Method for Business Processes" and KPI – "Modelling Method for Key Performance Indicators" models are considered. Second, which principle/pattern is appropriate for which organizational structure? In order to ease the selection of suitable patterns for specific application scenarios, those will be associated with organizational structures like but not limited to construction processes, assembly processes or production processes each of them with domain-specific characteristics. A prototype consisting of three phases – use case requirements collection, model design and digitization assistance – builds upon (a) physical experimentations in the OMiLAB Innovation Corner using physical assets such as edge devices or sensors, (b) domain specific services considering software related aspects such as timeseries databases or simulation algorithms, and (c) modelling methods enabling the integration of physical and digital components. The paint production pilot from the European Change2Twin project serves as an application scenario evaluation use case. A notion of what the use case company intends to achieve by digital twinning and what is possible by introducing digital services is touched. The outlook presents how artificial intelligence may be introduced for the prototype to leverage the paint production use case and further application scenarios.

1 INTRODUCTION

According to Deloitte [1] digital technologies can accelerate reaching enterprise goals by 22%. This paper focuses on digital twinning – especially DTOs [5] – promising when dealing with digitization during digital transformation. A recent study [2], estimated the global DT market at 3.1 billion USD in 2020 and projects a growth to 48.2 billion USD in 2026. Nevertheless, only 30% of digital transformations [3] achieve the objectives, due to barriers [4] related to technologies, competencies or strategies. Hence, the transparent identification of appropriate digitization concepts enabling DTs to leverage industrial application scenarios – accelerating DT in an organizational context [6] – is considered critical. Especially, DTOs and their models evolve dynamically depicting processes, data flows or interactions for instance.

In general, digital transformation may be seen as a process [7] where digital technologies create disruptions triggering strategic, organizational responses considering both, value creation as well as change management including organizational barriers. Among the plethora of digital technologies, DTs look at various perspectives ranging from production processes, human actors, skills to process inputs/outputs that are relevant for strategic responses and decision making towards a digitally transformed organization – advancing several industries such as manufacturing, healthcare, automobile or retail [8]. Especially, the dynamic behaviour of current business environments – impacting approaches systematically support competitiveness such as enterprise modelling – creates a need for agility. Here, DTOs support with providing means of digitalization towards real time scenarios by building upon enterprise models that are graph-based, machine readable knowledge representations [9]. DTOs can be considered either as (a) digital technology on its own resulting in targeted DTOs like in the paint production pilot of the European project Change2Twin [11], or (b) as a part of a DT ecosystem like in the European project COGITO [12], where DTs are used to plan a construction site.

However, DTOs come with several challenges like but not limited to blurred boundaries of organizations (e.g. diverse stakeholders) and dynamic, irrational behaviour of humans and organizations (e.g. official rules, social or personal aspects) [10]. Here, hybrid intelligence enables resilient DTs by bridging human and machine intelligence. Supporting both perspectives, humans and machines, in dynamic environments, this paper proposes a hybrid model-based approach – the ‘physical experiment designer’ – facilitating digitization via targeted digitization principles (synchronously term for ‘digitization patterns’ in this paper).

The following section presents the approach and methodology of this paper by outlining the research questions, the role of modelling and the OMiLAB Innovation Environment. In section 3 related work is cited. Afterwards, the prototype of the physical experiment designer is introduced in section 4, followed by section 5 describing a paint production scenario as an evaluation sample. Finally, section 6 provides an outlook.

2 APPROACH AND METHODOLOGY

Basically, a design science approach [12] is followed using a research and experimentation environment. Specifically, a (meta) modelling approach is pursued to depict the application scenario in form of a digital model with BPMN [13] – typically used to model business processes. A prototypical approach is proposed to tackle two main research questions (RQ).

RQ1 – Which digitization principles/patterns are appropriate for DTOs?

RQ2 – Which principle/pattern is appropriate for which organizational structure?

Underlying aspects such as data integration are covered by discussing how to fill the digital model – like but not limited to a BPMN process – with process data. For this purpose, basic principles aiming at facilitating the digitization process are presented and can be instantiated with different digital technologies.

2.1 Hybrid Modelling

Modelling information systems in business has long tradition and is still relevant due to continuous dynamics [53]. A hybrid modelling approach is utilized, where meta modelling [14] and meta model merging patterns [15] are applied to integrate heterogeneous perspectives and domain models. Human interpretation such as intuition related to readability, representation or usability are addressed by hybrid models [16] as well as machine interpretation such as formally correct, complete and expressive models. Formal models – recognizable by artificial intelligence (AI) – can be referenced via semi-formal models. For example, BPMN presenting business processes in an intuitive graphical way can be extended like but not limited to deal with process variability [17], decision logic [18], simulation [19, 20] or non-functional properties like performance and reliability [21]. Discrete event simulation is not a new technique, however, predicting production alternatives supporting daily business seems to get more relevant – for instance in manufacturing [22, 23].

Meta modelling is applied to create hybrid models linked to the BPMN process models, as conceptual modelling can be seen as knowledge schemas [22]. Here, DTs enable simulation via integrating data into the process models. “A digital twin is a digital replica of an artefact, process or service that is so accurate that it can be used as basis for taking decisions. The digital replica and physical world are often connected by streams of data [11].” Using the OMiLAB Innovation Environment, the (hybrid) digital models can be accompanied with physical experiments to further elaborate on the more physical aspects towards DTs, specifically DTOs.

2.2 OMiLAB Innovation Environment

A guarded environment for dealing with industrial application cases is offered by the OMiLAB Innovation Environment [25] covering diverse perspectives. The OMiLAB layer concept (Fig. 1) consisting of business, conceptual modelling and physical layer provides means of reducing the complexity of business scenarios and guiding the digitization – respectively the digital twinning – process. Starting with modelling, several standardized as well as domain specific modelling languages are used for abstraction and simplification. Integrating simulation allows for flexibility via more dynamic interactions and processing capabilities building upon the graphical models. Physical equipment ranging from sensors over robots to related infrastructure is provided to support the creating of physical experiments.

The modelling components are leveraged by the meta modelling platform ADOxx [35] – free for academic purposes – facilitating the creation of domain-specific modelling languages, coming with a microservice framework [36] and bringing together more than 5.000 developers in an open community. Community support is also provided by the OMiLAB NPO [37] powering the OMiLAB laboratory environments.

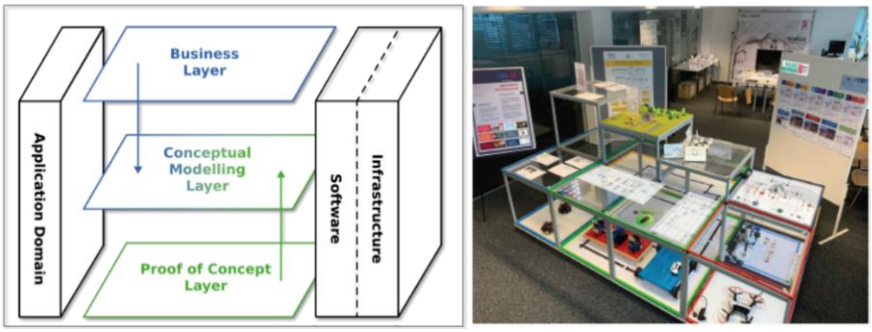


Figure 1: OMiLAB Layer Concept (left) and Realization of the Industrial OMiLAB Innovation Corner at BOC Vienna (right) [25]

3 RELATED WORK

Recently, diverse challenges emerge from integrating virtual (network, software, communication protocols, etc.), social (human roles, organizational structures, etc.) and physical (sensors, robots, buildings, etc.) components [34], such as intertwining components, models varying in concepts, formality and abstraction, or uncertainty and disruptions due to dynamic contexts. Increasing complexity – e.g. related to scale, connectivity and uncertainty – raises a need for considering multiple disciplines and heterogeneous perspectives.

3.1 Digital Twins of Organizations

While traditionally DTs were considered as a digital representation of an asset such as a manufacturing machine, in these days digital copies of nearly everything – promising for most industries – can be created [29]. Three evolutionary stages for DTs – digital model, digital shadow and DT – can be differentiated [30]. While digital models are usually characterized by manual dataflows interacting with the real-world object, they allow for processing enabling digitization, visualization, simulation, emulation, extraction, orchestration, prediction or advanced individual usage scenarios [31]. A digital shadow can be considered as a hybrid version of digital model and twin, while a DT is characterized by automated data flows.

Several classifications such as DT of products, production and performance [32] as well as various specifications such as targeted DT [43] facilitating both, technology and business considerations [33] can be found in literature. A DTO enables an organization to adapt – ranging from the identification of business processes to informed decisions making – according to Gartner [5] and increases agility via digitization [9]. Five principles are followed during the dynamic evolution of a DTO [6]: starting with what is available, data is set free, digitization is increased, new digital opportunities are considered, and models are progressed. In contrast to classical DTs often focusing on machine or sensor data, DTOs aim at more holistic digital models considering data flows ranging from organizational assets over people to their interactions. While the complexity of such comprising models – including social, ethical, policy, technical, etc. issues – must somehow be handled, at the same time advanced simulation and decision making for increased efficiency, competitiveness and agility are facilitated.

3.2 Digitization Principles and related Concepts

The digitalization of processes in enterprises is challenged by the systematic identification of digitalization potentials – a pattern-based approach seems promising compared to time consuming expert analysis [52]. The bigger picture counts for digital transformation affecting whole organizations [40]. Digital technologies are rapidly developing, creating a need for synergizing technological and managerial expertise. Proactive management and organizational agility are critical when thinking of the high technological dependence (e.g. for remaining competitive), as companies experience a lack of understanding when it comes to digital transformation and its implementation. [38] presents four design principles, in which digitally mature companies are clearly advanced compared to those in digital development – *design thinking* to develop different perspectives for more flexibility, *prototyping* following an engineering philosophy to accelerate the adaption process, *development sprints* for emergent processes managed iteratively and in short sequence and *open stakeholder integration* handling expectations. Those principles were developed in accordance with the strategic management principles from [39]: (1) renewal through development of new competencies, (2) application scenarios define complexity handling, (3) strategic options are a development process and not predefined, and (4) strategic processes through integration instead of hierarchy. For instance, management approaches such as lean principles (e.g. management by walking around or value stream mapping) can be target oriented at digitizing checklists and workorders [48].

In contrast, [49] aims at mapping and associating business procedure elements to digital services, not covering physical aspects such as sensors. A set of services is provided that can be directly incorporated into models via a web application. Not only (micro-)services but also engineering software can be integrated following a process driven approach [50]. Industry 4.0 – specifically cyber physical systems consisting of various components (e.g. sensors, actuators, etc.) – creates a need for managing complex resources in a flexible, scalable way considering performance and reliability analysis, for instance enabled by a BPMN extension [51]. [54] approaches discovering process models and creating high level BPMN models based on real-life event logs reflecting process behaviour. However, underlying process aspects such as resources (e.g. times or costs), responsibilities and states need sophisticated digitization for being reflected in digital shadows and interact with DTs, while basics such as textual process task descriptions can be collected in digital models without advanced digitization needs.

Considering implications from literature, this paper aims at proposing an open, integrative and design-oriented approach for assisting digitization journeys towards DTOs.

4 PROTOTYPE – „PHYSICAL EXPERIMENT DESIGNER"

Physical experiments are established following three development phases. First, the ***use case requirements collection*** covers use case relevant aspects such as application scenario details, domain characteristics, expectations and goals. Among the plethora of existing methods, any suitable technique for requirements engineering (e.g. successfully utilized in software engineering) can be applied like but not limited to observations, interviews, workshops or user stories [26]. Second, the ***model design*** phase supports the design of digital models building upon the identified requirements. Starting with, creative approaches such as design thinking [27, 28] can facilitate conceptualizing relevant knowledge in form of models. Ideally, this phase can be concluded with the design of BPMN processes and related KPI models. However, depending on the application case, several model design iterations including different modelling approaches ranging from standardized to domain specific modelling methods – consisting of a technique divided in a (graphical) language and a procedure, and mechanisms & algorithms [14] – may be necessary. Third, ***digitization assistance*** is provided in form of digitization patterns supported and implemented by hardware, software, models and so on. The idea is to create, design and engineer physical experiments in order to bridge use cases with digitization patterns facilitating the development of DTOs. Fig. 2 shows an overview of the physical experiment designer. Use case requirements and key questions are used to extract the digitization needs. By applying simplification and abstraction, the models are designed focusing on the digitization relevant aspects. If the use case envisions a digital shadow or twin, the digital model is extended by selecting appropriate digitization patterns for sensing and actuating/triggering. Among several concepts – discussed in a targeted meta model (see Fig. 3) presenting also their relationships – the suitable ones must be selected considering the target digitization degree and with respect to the application case and its requirements.

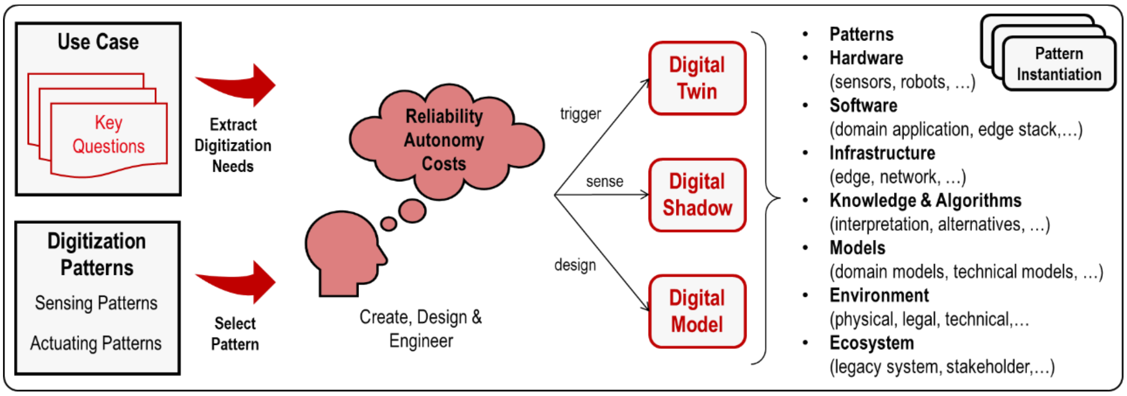


Figure 2: Creating, Designing and Engineering Physical Experiments for bridging Use Case and Experiment Requirements with Digitization Patterns towards Digital Twins

Building upon the models from the model design phase, the question on how to fill the digital models with data emerges (RQ1). Supporting this step, predefined digitization principles are proposed to facilitate the digital transformation process. These digitization patterns can be classified in two groups: sensing and actuating patterns (see Table 1). Sensors and actuators can be seen as key concepts for enabling interoperability in dynamic environments such as Industry 4.0 [55]. The remaining question is, which characteristics of the digital model should be physically digitized by which pattern – considering if high reliability or dynamic decision making is required for the use case. Sensing patterns can be characterized by the reliability degree (e.g. compare review on sensor reliability [56]), while actuating patterns are characterized by the point of decision (e.g. compare decision making with wireless sensor and actuator networks based on local/global information [57]).

Table 1: Creating, Designing and Engineering Physical Experiments for bridging Use Case and Experiment Requirements with Digitization Patterns towards Digital Twins

	Pattern	Characteristic	Sample Usage
Sensing	Ignore	n/a	n/a
	Estimate	low reliability	camera for image recognition
	Count & Calculate	medium reliability	RFID for inventory counting
	Measure	high reliability	scale sensor for weight measurement
	Measure & Check	very high reliability	scale sensor compared with usage and historical data
Actuating	Guided Action	no decisions needed	robotic vehicle with a line follower for following a guided path
	Random Action	random conduction of automated behaviour	robotic vehicle selecting movements randomly for vacuum cleaning
	Fixed Binding	fixed decisions before triggering automated behaviour	LED sensor for traffic light
	Pre-Binding	selected decisions directly at the beginning of triggering automated behaviour	face recognition for door opening
	Late Binding	decisions directly before each automated behaviour action	AI for self-driving vehicles

For example, when thinking of BPMN models, execution times can be digitized by measuring process steps via timestamps, while the *count & calculate* pattern may be used to deal with resources (such as raw materials) in a production process. When selecting the suitable pattern, the organizational patterns and their characteristics – partially evaluated through requirements collection – must be taken into account (RQ2). For instance, when having a non-critical paint production process, sensing patterns with lower reliability may be enough, while critical medication transportation processes may require very high reliability (e.g. ensure perfect temperature for cooled medication). So far, basic reliability levels are defined by the sensing patterns. However, also the selection of specific sensors for implementing the pattern can influence the cost-efficiency ratio and may come with minor reliability improvements.

The digitization designer prototype aims at heterogeneous stakeholders dealing with digitization, digital transformation and digital twinning use cases. The open and design-oriented requirements collection and modelling phases aim at integrating stakeholders with technical background as well as those focused on business aspects. Basic knowledge of the application scenario, the use case company and the industry are assumed, but not necessarily required when going through the phases of the digitization designer. When it comes to implementing the physical experiment in the real use case environment, technology expertise is presumed. Basically, the physical experiment builds upon the following three main building blocks.

4.1 Modelling Methods

A plethora of different modelling approaches – specifically applied in the model design phase – ranging from BPMN describing a sequence of actions to DMN [18] allowing for data interpretation based on specified conclusions exists. Therefore, the selection of a modelling method sufficiently expressing organizational assets, interaction and data flows as well as handling complexity related to DT of organizations must be chosen for the development of the digital model.

Meta modelling is applied to reference and merge concepts ranging from physical digitization assets over use case considerations to digital models. Fig. 3 depicts the proposed meta model (created with [41]) covering the most relevant concepts for digitization and specifically for the physical experiment designer. Depending on the selection of physical elements, either a digital model, a digital shadow using sensors or a DT using actuators is developed.

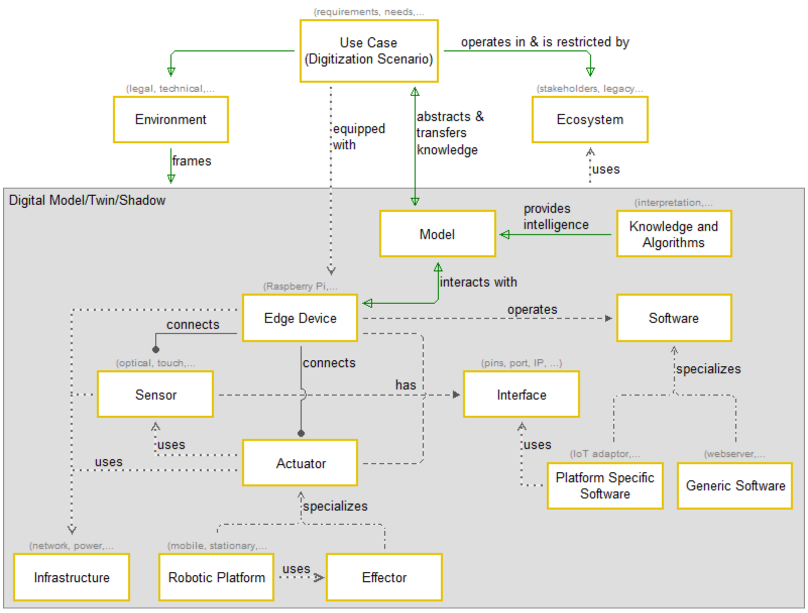


Figure 3: Meta Model for the Physical Experiment Designer

So far, the meta model builds upon physical experiments such as the paint production experiment described in [58] and [59]. In contrast to this bottom-up approach, the idea is to switch the perspective and start with the meta model to facilitate the experiment establishment in future. Additional functionality extending the meta model should enable making notes in the models, interpreting simulations and searching for suitable digitization solutions.

4.2 Domain Specific Services

Service orientation is a means of supporting flexibility and changeability when dealing with production processes [42]. Two major types of services are differentiated in the meta model – services that enable the creation of the DT and services that facilitate the operation of the DT. The provision of software (e.g. for edge devices, sensors, etc.) required for the development of DT can be considered as enabler, while services like but not limited to time series databases [45], (meta) model database for provided by ADOxx, visualization with dashboards building upon microservices [36], discrete event simulation of graph-based models [46] or prediction [44] leverage the operation of DTs. Numerous services – e.g. implemented as microservices and provided in the meta model in form of knowledge and algorithms – facilitate the DT building and operation. For instance, the digital model can be leveraged with services capturing sensor data, dashboards can be used to visually present models as well as simulation results and querying can be applied on top of the models to ensure compliance with defined KPIs.

4.3 Physical Experimentations

The OMiLAB Innovation Environment offers physical experimentation equipment, in order to capture physical aspects of digitization such as integrating sensors and actuators or underlying considerations such as connectivity or power supply. For instance, equipment like but not limited to edge devices (e.g. Raspberry Pi or Arduino microcontrollers), domain substitutes (e.g. paper figures representing raw materials), sensors (e.g. RFID readers or cameras), or actuators (e.g. robotic arms or vehicles) is provided.

Depending on the purpose of the physical experiment in the laboratory setting, the physical experimentation equipment may differ from the actual use case digitization equipment, for example in terms of reliability, costs or equipment producers. For instance, as in contrast to the physical experiment, more sophisticated considerations related to the ecosystem and the environment are required in a real-world setting (e.g. dusty production halls or legal policies).

5 H2020 EU-PROJECT CHANGE2TWIN: PAINT PRODUCTION USE CASE

Starting with the ***use case requirements collection***, key questions for (a) the use case and (b) the experiment emerged based on textual use case descriptions and in discussion sessions. The former covers questions related to the establishment of a real time inventory, the traceability and the documentation of the production process. Based on the requirements of the paint production company (e.g. currently using analogue machines), among others, the digitization of the raw material warehouse and the digitization of the production process could be derived as use case challenges. In contrast, the experiment aims at reviewing the technology (e.g. RFID sensors, etc.) that supports dealing with the digitization challenges in a lab setting.

BPMN is applied for the production process ***model design***. Modelling workshops were conducted in which the company's leading computer engineer and an external software engineering consultant contributed relevant domain knowledge. The resulting digital model of the production process was used to depict and review the digitization challenges. In this use case, BPMN was chosen due to the familiarity of the stakeholders. However, a targeted domain specific modelling language could be reasonable for optimally supporting the industrial case, for instance by allowing to model raw material flows from warehouses to production lines.

Digitization assistance is applied in form of implementing patterns such as *ignore* and *count & calculate* by introducing sensors. The experiment presented in Fig. 4 shows an association in form of a tea production experiment depicting similar characteristics compared to the paint production use case. The raw material warehouse in the top part of the figure consists of two types of materials. Basic materials in silos are ignored as they can be considered to be always available and specialized materials that need some inventory management can be counted & calculated to digitize the inventory monitoring. Basically, the physical experiment applies means of abstraction, simplification and association to focus on the digitization and DTO relevant aspects and ease the understanding and awareness among diverse stakeholders. In this use case, the physical experiment is used to evaluate the technology before implementing it in the real factory setting. Required software (e.g. BPMN modelling tool, microservices, etc.), hardware (e.g. microcontrollers, RFID readers, camera, etc.) and infrastructure assets (e.g. database, network, etc.) for the experiment are provided in the OMiLAB Innovation Environment. Table 2 presents selected components relevant for the digitization process, where the components may differ between the use case and the associated physical experiment, as the key questions for the use case cover for instance the digitization of the warehouse considering a dusty environment, while the experiment focuses on evaluating the technology in a laboratory setting.

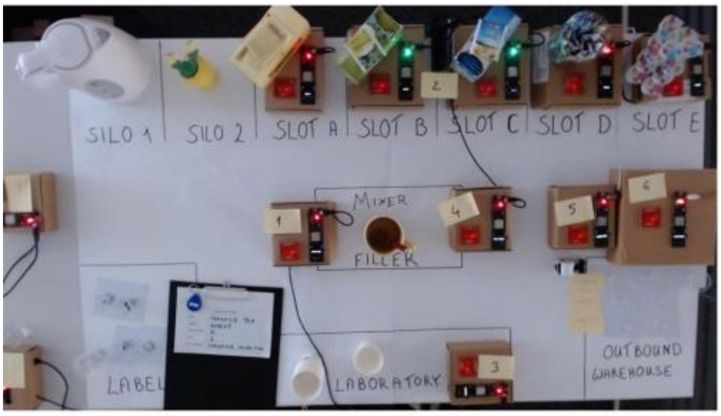
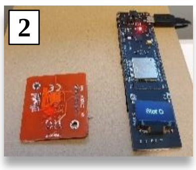


Figure 4: Physical Experiment – OMiLAB Innovation Corner [innovation-laboratory.org/experiments/paint-production/overview/]

Table 2: Comparison of selected Components relevant for Digitization

	Use Case (1)	Experiment (2)	
Edge Devices	Raspberry Pi 4, ESP32	Raspberry Pi 3B, ESP32	
Sensors	MFRC522 Module	NFC Module, RC522 RFID Sensor, C920 Logitech Webcam	
Infrastructure	Company Network, SQL Server DB, Edge Device Box	OMiLAB Network, KairosDB, Paper Box	
Software	Node JS, WebApp, REST	IoT Adaptor, Dashboard, REST	
Environment	Raw Material Warehouse, Paint Production Line	OMiLAB Innovation Environment, Laboratory Setting	
Ecosystem	SAP System, Production Workers, Managers	Microservice Framework	

6 OUTLOOK

The physical experiment designer raises the question of how to guide human-decision making towards a smart physical experiment. AI has not only the potential to contribute up to $15.7 trillion to the global economy by 2030 [47], but also to enrich hybrid decision making. Hence, AI may provide support in all three phases of the physical experiment designer. For instance, AI may facilitate the information retrieval when thinking of the requirements collection (e.g. with prediction or pattern recognition), support the model processing during the model design phase (e.g. with simulation, optimization or trust indication), as well as leverage the physical experiment with targeted AI services for interaction (e.g. with chatbots or speech recognition). So far, the presented paint production use case aims at technology evaluation and review by establishing the physical experiment. AI may be used to leverage the scenario for instance by introducing image recognition for monitoring the raw material status facilitated by (a) a *modelling method* supporting KPI models and indicating trust levels, (b) *domain specific services* such as neuronal networks processing the images and presenting the results on a dashboard, and (c) *physical experiment* equipment such as a Raspberry Pi and a camera implementing the *estimate* pattern by continuously taking material pictures. However, other use cases such as the railway construction in COGITO rather focus on discussing tracking the equipment on a dynamic construction site or optimizing the work line balance. Hence, the physical experiment may rather focus on checking the applicability and plausibility of the digitization concepts used for dynamic monitoring instead of evaluating the technology.

Ideally, the digitization journey towards a DT should not start with experiment building but count on the presented meta model that allows integrating business and technology aspects via hybrid modelling and meta model merging. Hence, the perspective will be switched to model use cases, interpret simulations and identify solutions via the physical experiment design. In contrast, the above proposed AI integration focuses on use case content related aspects, whereas in future AI functionalities will be integrated into the meta model in order to leverage the physical experiment designer with advanced decision support capabilities during the experiment creation. For instance, the pattern selection can be facilitated via a list of predefined pattern alternatives automatically extracted from the identified use case requirements.

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