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Infonomics of Autonomous Digital Twins

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Abstract. High autonomy is challenging to achieve in digital twins. This is due to the lack of understanding of the socio-technical challenges and the information needs of digital twin autonomy. In this paper, we contextualize digital twin autonomy in terms of human and technical factors, identify novel socio-technical classes of digital twins with varying levels of autonomy, and define strategies that help improve autonomy across these classes. Our strategies are governed by information valuation models we developed specifically for digital twins. Our approach fosters a systematic top-down technique to improve the autonomy of digital twins.

Keywords: autonomy · digital transformation · information value.

1 Introduction

Digital twins [20] are virtual representations of physical assets. By continuously collecting data from the physical asset, digital twins maintain a live model of the physical system, allowing for advanced computer-aided services, such as monitoring, predictive analytics, and automated decision-making [29]. Digital twins are also equipped with control capabilities over the physical system, further expanding the impact of having explicit, continuously maintained models of the system that allow for enhanced reasoning capabilities as to how to control the physical system for optimal behavior. Thanks to its beneficial properties that enable higher digital maturity, digital twinning is gaining popularity in an array of domains, especially in those where the system can be managed through closed-loop control. Pertinent examples include manufacturing systems [32], smart farming systems [19], and complex manufacturing processes, such as injection molding [4].

Autonomy is the ability to make a decision about the preferred course of action to control the underlying system in an optimal fashion [38]. Autonomy allows digital twins to respond to unexpected events, which is an important trait in controlling complex systems. Experience shows that achieving full autonomy of digital twins is often a challenging problem [18] and in some cases, it might not be feasible at all [12]. The lack of trust, understandability, and explainability can severely limit how much liberty organizations are willing to give to a digital twin [6]. In lower-digitalized sectors, autonomy is additionally influenced by the sheer ability to deploy and maintain complex sensor networks, and manage voluminous data. Of course, full autonomy is not always desired. In many

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cases, human agency is required to become part of the system and the challenge is to understand how human factors align with autonomy ambitions [18]. Still, autonomy aspects should be planned early in the lifecycle of systems [6].

Providing systems with information of sufficient quality and volume is key in enabling autonomy [30]. Yet, it is currently not well-understood which classes of information contribute value to the autonomy of digital twins.

This work is the first to investigate digital twin autonomy from an information valuation perspective. We rely on *infonomics*, the discipline of asserting economic value to information [21]. Our contributions are as follows.

- We define a framework to classify levels of digital twin autonomy as the combination of the *ability* and the *liberty* to act. We identify two novel digital twin categories—*human-actuated* and *human-supervised digital twins*—to shed light on a more socio-technical view of digital twins. (Section 3)
- We define three information valuation models using well-established metrics to apply the principles of infonomics to digital twin autonomy. (Section 4)
- We define five digital twin autonomy strategies based on the information valuation models to guide organizations along their maturation journey and reach higher levels of digital twin autonomy. (Section 5)

Our work is motivated by the lessons learned from an industry project on digital twin engineering for cyber-biophysical systems [12]. We draw from this project and demonstrate the utility of our approach in Section 6.

The target audience of our work includes adopters, developers, and researchers of digital twins. Adopters can use the reference framework in Section 3 to position the status quo at their organization and subsequently, employ the strategies in Section 5. Developers can use the information valuation models in Section 4 to trace high-level autonomy ambitions to tangible concerns of data quality. Researchers can use this work to drive their research towards impactful directions.

2 Background

Digital twins are strongly coupled to their physical counterparts with the intent of controlling them for optimal behavior. For example, digital twins can be used for better control over sustainability goals [11], e.g., reduced energy consumption, reduced waste, and improved productivity. The digital twin's ability for real-time analysis, optimization, and control allows for deferring some design decisions to the operational phase and controlling the underlying asset based on data available only at operation. Most systems subject to digital twinning require real-time reasoning and control, which, in turn, necessitate elevated levels of autonomy. Rosen et al. [30] note that to achieve sufficient autonomy, digital twins require "*as much information as possible concerning the overall world state, the products to be manufactured, the geometry and affordances of the parts and tools to be used, as well as their own capabilities and configuration*". Indeed, information is a key enabler of autonomy, yet, it is currently not well-understood which classes of information contribute value to the autonomy of digital twins. This paper aims to overcome this limitation of the state of the art.

ISO 23247 is a standard that provides general principles for developing digital twins in manufacturing.[3] Its second part, the ISO 23247-2:2021 defines a reference architecture with three functional and one extra-functional entity. Later in this work, specifically in Section 4, we relate digital twin information value models to the three functional entities.The *User Entity* provides user interfaces to interact with the digital twin. Here, the user may be a human or another application, e.g., simulators, analysis tools, or other digital twins. The *Core Entity* is comprised of sub-entities and functional entities that implement functionality for digitally representing and assessing components of the physical twin. Finally, the *Data Collection and Device Control Entity* contains functional entities for collecting data from the physical twin and for controlling and actuating it.

The reader is referred to Shao [32] for more details and use cases.

Infonomics is the discipline of asserting economic value to information, first defined by Laney [21]. Assessing the economic value of information helps organizations treat information as a financial asset. In our work, we rely on the **data quality metrics** of infonomics (see Table 1). Below, we give a brief excerpt of these metrics. The reader is referred to Laney [21, pp. 246–249] for details.

The first group of Laney's data quality metrics are *objective* metrics. *Validity* measures how well available data accurately represents reality. *Completeness* is the percentage of data recorded out of the total available data. *Integrity* measures the correctness of linkages between records. *Consistency* tells how much data formats vary. *Uniqueness* is the ratio of alternate forms of data that exist. *Precision* is the degree of exactitude of a value. (While a value may be completely accurate, its applicability may be suboptimal because of its lack of precision.) *Timeliness* is the likelihood that data is faithful to reality at any given time.

The second group defines *subjective* metrics. *Existence* measures if key ideas are represented in information assets. *Scarcity* is the likelihood that other organizations do not have the same data. *Relevance* is the number of business processes that could benefit from the data. *Usability* is the degree to which data is helpful in business functions. *Interpretability* is the degree to which data can be understood. *Believability* is the degree to which stakeholders trust data. *Objectivity* is the degree to which the data source is believed to be free of biases.

3 A Classification Framework of Digital Twin Autonomy

We now define a classification framework to relate different levels of digital twin autonomy. We argue that autonomy is not unidimensional, but rather, an artifact of orthogonal technical and human aspects. As shown in Figure 1, in this frame of thinking, technical aspects determine the digital twin's *ability* to act. This includes, e.g., proper equipment, actuators, algorithms, and communication networks to be in place to control the physical twin. Human aspects determine the digital twin's *liberty* to act. This includes, e.g., the trust stakeholders have

[3] `https://www.iso.org/standard/75066.html`

in the digital twin, which can be fostered, e.g., through explainability [9] and experimentability [5]. These dimensions give rise to classes of digital twins with different autonomy characteristics.

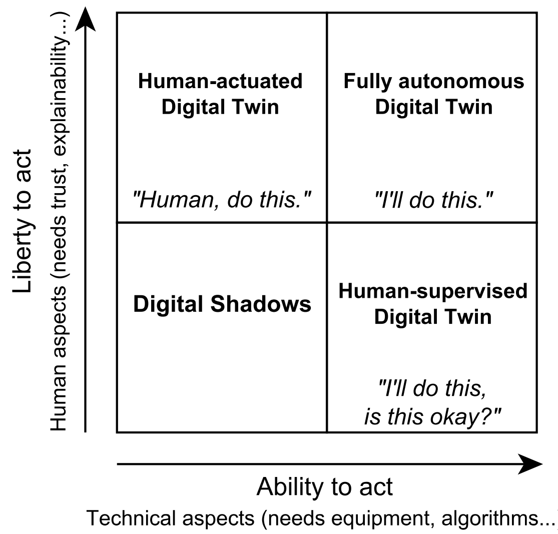

Fig. 1. Classification framework of digital twin autonomy.

3.1 Levels of Digital Twin autonomy

Digital Shadow: no ability and no liberty. Digital shadows, as defined by Kritzinger et al. [20], are virtual replicas of physical systems that capture the prevalent state of the system but have no means to control the physical system. That is, a change in the state of the physical system will be reflected in the digital replica, but not the other way around. The limitation in control is clear in most works focusing on digital shadows, although the reasons are less obvious. In our classification framework, the reason for this limitation is twofold. First, digital shadows have no ability to act. That is, means of control, such as actuators and software might not be available. Second, digital shadows have no liberty to act either. This limitation might be by design when stakeholders do not require more elaborate functionality to support their goals. Often, digital shadows are seen as precursors of digital twins [3], with reduced functionality that is to be developed later as the system and the digital maturity of the organization evolves. Despite the limited autonomy, digital shadows are considered key enablers of important digitalization trends, such as Industry 4.0 [7].

Fully Autonomous Digital Twin: ability and liberty. At the other end of the autonomy spectrum, fully autonomous digital twins both possess the ability to control the twinned physical system (physical twin) and enjoy substantial liberty to do so. The ability to control the physical twin is due to the proper technical enablers in place both on the digital side (e.g., real-time simulators [14]) and on the physical side (e.g., actuation infrastructure for control). Fully autonomous digital twins had a transformational impact in many domains including production control [30], maintenance [10], and layout planning [34].

Human-supervised Digital Twin: ability but no liberty. A distinct autonomy class of digital twins emerges when the technical underpinnings of the digital twins would enable it to act, however, the digital twin lacks the liberty to do so. This is one of the autonomy classes of digital twins exhibiting substantial interplay between human and machine, rendering it a true socio-technical system [15]. Removing the human from the loop to achieve full autonomy might not be possible for a number of human aspects. For example, an organization might decide, that human intelligence is vital in a given setting because business goals might be cumbersome to elicit and encode in the digital twin. Another example might be the lack of trust in the digital twin which is a typical scenario in lower-digitalized domains where stakeholders are less tech-savvy.

Levels of human supervision vary across domains, with reference frameworks being tied to specific sectors. In autonomous driving, for example, the SAE J3016 standard defines six levels of autonomy from no autonomy (Level 0)—e.g., providing warnings and momentary assistance, such as automatic emergency braking—to full autonomy (Level 5)—driving the vehicle without a driver [16]. Human supervision, oversight, or other forms of participation are particularly important when humans or societies are part of the twinned physical system. Caldarelli et al. [8] warn that digital twins designed or operated without proper explanation or human oversight might negatively affect citizenry, but designed human participation fosters adaptive and sustainable solutions.

Human-actuated Digital Twin: liberty but no ability. Human-actuated digital twins emerge when stakeholders around the digital twin intend to allow high liberty however, the digital twin is not equipped with the ability to control the physical twin. In human-actuated digital twins, the digital twin makes decisions and the human staff executes them. Clearly, real-time actuation is not possible in these cases due to the delay and imprecision associated with this control mode. However, human-actuated digital twins can still be sufficient solutions. The first notion of human-actuated digital twins appears in previous work [12] in the context of smart agronomy, where the underlying system changes at a substantially slower rate than traditional engineered systems. Thus, slow actuation might be sufficient. Additionally, placing the human in the loop allows for recognizing potentially undesirable control decisions, often without the need to involve an expert. Another pertinent example is due to Wang et al. [36] who propose the notion of human digital twins. Human digital twins include "*physical representations and virtual models of humans to accurately track and reflect* *the human motion, perception, and manipulation activities and capabilities and to address the challenges in the human-centric manufacturing*".

3.2 What to do with levels of autonomy?

The desired level of autonomy of a digital twin depends on the problem at hand and is heavily influenced by the digital maturity of the adopting organization.

Achieving full autonomy might not be the goal of every organization. Increasingly often, experts are calling for tighter integration of digital twins with human agencies, arguing that high levels of digital twin autonomy should be achieved without sacrificing human agency [18]. Indeed, digital twins are not meant to be solely technical implementations. In our work, we maintain the view that digital twins are typically socio-technical systems with the human in the loop.

In their interviews with experts, Muctadir et al. [25] encounter multiple opinions about humans playing an important role in a digital twin and therefore, they should be considered as components of digital twins. In this work, we maintain the view that there are classes of digital twins that should be viewed as socio-technical systems with substantial human effort in the loop and that autonomy and human involvement span a spectrum that organizations should consider when choosing their digital twinning journeys. Embracing the human in the loop aligns well with the core ideas of the new wave of industry practices, such as Industry 5.0[4], which attempt to bring the human back in the loop.

Independently from the targeted level, autonomy must be addressed in a systematic way. To this end, organizations need guidelines to improving the autonomy of their digital twins. To support such maturation journeys, Section 4 defines high-level information valuation models that improve digital twin autonomy while Section 5 defines five elementary digital twin autonomy strategies.

4 Information Valuation Models for Digital Twins

We now define three information valuation models for digital twins based on the data quality metrics of Laney [21] discussed in Section 2. We opt for defining new valuation models because the information valuation models of Laney's infonomics are either too general or too finance-focused to drive autonomy decisions about digital twins. However, as pointed out by Bendechache et al. [2] in their recent systematic survey of data valuation, Laney's metrics are still adequate and provide the most comprehensive, multi-dimensional view of data quality. Thus, we rely on published metrics, but use them in our new information valuation models. For completeness, we also consider the model quality metrics of Mohagheghi et al. [24], aligned with Laney's metrics. Our models are related to the three key entities outlined in the ISO 23247-2:2021 reference architecture and explained in Section 2: reasoning, control, and the user entity.

[4] `https://research-and-innovation.ec.europa.eu/research-area/industrial-research-and-innovation/industry-50_en`

Table 1. Metrics of data and model quality, and their influence on the three information valuation metrics for digital twin autonomy.

	Data quality metrics (Laney [21])	**Model quality metrics** (Mohagheghi [24])	**DT valuation model**		
			RVI	**AVI**	**UVI**
Objective	Validity		•		
	Completeness	C2-Completeness	•		
	Integrity	C3-Consistency	•		
	Consistency	C3-Consistency	•		
	Uniqueness		•		
	Precision			•	
	Timeliness			•	
Subjective	Existence	C1-Correctness			•
	Scarcity		•		
	Relevance				•
	Usability				•
	Interpretability	C4-Comprehensibility			•
	Believability				•
	Objectivity		•		
		C5-Confinement			•
		C6-Changeability	•		

A shortcoming of Laney's information models is that about half of them rely on subjective judgment and therefore, their actionability is questionable. This limitation renders them unsuitable for scalable, automated decision-making [2]. Therefore, we refrain from exactly defined formulas and instead, we define which metrics influence our models. This information is still sufficient to understanding how the improvement of metrics can drive digital twin autonomy.

For completeness, we also draw from the modeling domain and correlate the model quality metrics of Mohagheghi et al. [24] with Laney's metrics.

Table 1 shows the mapping of our three information valuation models onto the metrics of data quality [21] and model quality [24].

Reasoning Value of Information (RVI). RVI measures the value of the information at hand for automated reasoning, e.g., to analyze the physical twin and derive the appropriate control strategy. This class of information is crucial in developing complex reasoning that is primarily achieved through real-time analytics and simulation. Thus, the RVI is related to the *Core Entity* of ISO 23247, particularly to the *Digital Modeling*, *Simulation*, and *Analytic Service* Functional Entities (FEs). As shown in Table 1, RVI is primarily influenced by *objective* metrics, such as validity and consistency. This is intuitive, as the quality of the reasoning is contingent on the quality of the input data. Reasoning with invalid data leads to incorrect results, compromising automated decision-making.

This information model is best implemented by suppliers of digital twins who understand how much of the capabilities of reasoning-related FEs can a digital twin utilize under the prevalent RVI profile. To increase the RVI, suppliers can improve objective metrics, e.g., completeness, by increasing the ratio of recorded and total data; or integrity, by establishing links between data records.

Control Automation Value of Information (AVI). AVI measures how much value the information at hand provides for automating the control of the digital twin over the physical twin. This class of information is crucial in developing automated control capabilities that are typically achieved through precise actuation. Thus, the AVI is related to the Data Collection and Device Control Entity of ISO 23247, particularly to the Device Control Sub-Entity. As shown in Table 1, AVI is primarily influenced by two of Laney's *objective* metrics: precision and timeliness. Controlling a physical twin in an automated manner is only feasible if sensor data is available in adequate precision and timeliness as otherwise, the controlling actions steer the physical twin in inadequate or even misleading directions, potentially causing distortions like the bullwhip effect [22].

This information model is best implemented by experts with a proper understanding of the physical twin's actuation infrastructure, and preferably, with the ability to implement improvements in its instrumentation (data collection facilities and actuation). To increase the AVI, experts can improve the two influencing metrics—precision, e.g., by increasing the precision of sensor data; and timeliness, e.g., by automating data collection at every point of the system to shorten update periods of the digital twin.

User Value of Information (UVI). UVI measures how much value the information at hand provides for human users to comprehend the workings of the digital twin. This class of information fosters trust in the digital twin's working and allows the human to potentially become an active participant who works *with* the digital twin. Thus, the UVI is related to the User Entity of ISO 23247. As shown in Table 1, the UVI is primarily influenced by Laney's *subjective*—i.e., human-centered—metrics like usability, interpretability, and believability.

This information model is best implemented by working with the stakeholders of the digital twin—including expert users and decision-makers—to gauge their ability to comprehend the goals of the digital twin. Controlled experiments and focus groups are proper ways to measure the perceived value of the digital twin by the users. Improving the UVI might be achieved, e.g., through increasing interpretability by putting intuitive reporting interfaces in place; or through increasing believability by allowing experimentation with the digital twin.

5 Autonomy Strategies for Digital Twins

To highlight the utility of the information valuation models to drive the improvement of digital twin autonomy, we now define five digital twin autonomy strategies that leverage the information valuation metrics defined in Section 4 and span maturation trajectories towards more autonomous digital twins.

The five strategies are summarized in Table 2. Different combinations of RVI, AVI, and UVI give rise to desirable strategies that improve the autonomy of a digital twin in one or both of the dimensions shown in Figure 1. Strategies (1) and (2) focus on the technical aspect of improving the digital twin's *ability to act*. Strategies (3) and (4) focus on the human aspect of improving the digital

Table 2. Autonomy strategies for digital twins

Inf. value			**Strategy**	**Improvement**	
RVI	**AVI**	**UVI**		**Inf. value**	**Dimension**
Low		High	Externalize KPIs	RVI$\uparrow$	Ability
High	Low	High	Improve actuation	AVI$\uparrow$	Ability
High		Low	Improve explainability	UVI$\uparrow$	Liberty
	High	Low	Enable experimentation	UVI$\uparrow$	Liberty
High	High	High	Human-computer collaboration	$*\uparrow$	Ability&Liberty

twin's *liberty to act*. Finally, strategy (5) shows a combined strategy that acts in both dimensions of ability and liberty.

Externalize KPIs. Low RVI limits the ability of the digital twin to act. High UVI indicates that users still find the available information useful. Information with low RVI and high UVI indicates that users might have tacit knowledge that was not properly externalized. Externalizing tacit knowledge into explicit KPIs will drive the reasoning of the digital twin and increase its RVI.

Externalization of KPIs can be generally achieved by requirements elicitation, prototyping, and following the SECI knowledge creation model [27].

Improve actuation. When RVI and UVI are high (e.g., followed by externalizing KPIs, as explained in the previous point), AVI can still be low. This means despite both the human and the digital twin find it useful, the information at hand is still insufficient to drive actuation at the right levels, limiting the digital twin's ability to act. Improving actuation capabilities increases the AVI of information and by that, fosters higher levels of autonomy.

Improving actuation might include instrumenting the physical twin with a better-performing actuator ensemble, relying on robotized means of actuation, and improving the precision and timeliness of actuation instructions.

Improve explainability. When the UVI is low, the *liberty* of the digital twin to act is inevitably limited. A pertinent example of human factors that limit liberty is the lack of explainability of the digital twin's reasoning and actions. When the UVI is low but the RVI is otherwise high, i.e., the digital twin possesses the ability to reason at high levels, improving the explainability of reasoning is a beneficial strategy. By improving explainability, humans can gradually gain more trust in the reasoning capabilities and qualities of the digital twin.

Better explainability can be achieved, e.g., by visualizing the digital twin's reasoning, or by generating examples and counterexamples of simulation results.

Enable experimentation. Low UVI can coincide with high AVI. This means the information at hand allows the digital twin to control the physical twin appropriately. However, low UVI indicates potential trust issues in the digital twin's capabilities. Enabling experimentation with the digital twin is a beneficial strategy in these cases. Through a series of experimentation scenarios, the human can gain trust in the digital twin's ability to control the physical asset properly.

The emerging field of experimentable digital twins [31] is focusing on enabler techniques in which humans can interactively simulate in the virtual space, or in the virtual-physical space [26].

Human-computer collaboration. There are cases when each of RVI, AVI, and UVI are high and the digital twin might have reached the Fully Autonomous level (Figure 1). This fortunate situation allows for facilitating advanced mechanisms to further improve both the ability and liberty of digital twins. Human-computer collaboration is one of these mechanisms that requires strong foundations in each information valuation model.

Human-computer collaboration is considered the next generation of digital twin techniques as of today, including concepts such as human digital twins [36], human-centric digital twins [1], and citizen twins [28].

6 Illustrative case

To illustrate the utility of our approach, we reconstruct the engineering process of one of our previous industry cases [12] and demonstrate how stakeholders can utilize the framework and autonomy strategies presented in this paper.

Setup. The case presents a smart farming company that operates production facilities (e.g., greenhouses). The company's goal is to automate decision-making in their production facilities. Decision-making includes controlling environmental conditions in the most efficient ways so that crop growth is appropriately stimulated. Their real-time decision-making and control capabilities position digital twins as the primary candidates to support the company's goals.

In lower-digitalized sectors, such as agriculture, employing digital solutions is substantially hindered by the lack of organizational capabilities and stakeholder trust. Therefore, change must happen in well-scoped incremental steps as the organization proceeds through its path of digital maturation.

The digital twinning journey in this case is sequenced into three phases: proof-of-concept (Section 6.1), prototype (Section 6.2), and deployment (Section 6.3).

6.1 Simulator proof-of-concept

Targeted class of autonomy. Digital shadow.
Aim. The company aims to kick off their digital twinning journey with a safe and cost-efficient prototype. There is no expectation in this phase to control the physical twin. Rather, the simulation facilities of the digital side must be developed and their capabilities must be demonstrated. The goal of the deliverable is to support the reasoning and decision-making of subject matter experts. In

essence, the digital shadow is a simulator that takes real-time data and presents predictions to subject matter experts.
Goal. Improve RVI. This is a requirement for building faithful simulators.
Strategy. Externalize KPIs. This strategy (Table 2) improves the RVI. By that, it aids the development of more comprehensive and detailed simulation facilities. As a result, the ability of the digital twin will improve, but still not sufficiently to act autonomously or by the human in the loop.
Implementation. By Table 1, RVI is improved by eliciting domain knowledge from agronomists and engineers to increase (1) the completeness of externalized KPIs and (2) resolve any inconsistencies among them (e.g., by goal modeling [37]).

6.2 Prototype

Targeted class of autonomy. Digital shadow → human-supervised digital twin.
Aim. In this phase, the company aims to improve the digital shadow by developing mechanisms that would control the conditions in the production room.
Goal. Improve the AVI. Thanks to the previous stage, the RVI is sufficiently high, but the AVI is still low and needs to increase.
Strategy. Improve actuation. By that, the AVI will increase, allowing for finding partial autonomy scenarios in which the digital twin could make decisions. However, due to a lack of trust, the company decides for limited control by the digital twin. There is a human in charge who approves the decisions of the digital twin.
Implementation. Following Table 1, AVI is improved by (1) acquiring actuators that improve precision (e.g., irrigation equipment with refined positioning capabilities); (2) improving the timeliness of actuation (e.g., by tuning the temperature controllers to reach the desired room temperature faster).

6.3 Gradual improvement and deployment

Targeted class. Human-supervised digital twin → human-actuated digital twin.
Aim. In the final phase, the company aims to remove the single decision-maker from the loop and push decision-making closer to staff members. Such a human-machine ensemble allows for complex control operations, e.g., manipulation of plants, without having to acquire precision robotics or hire specialized skills.
Goal. Improve liberty. The main challenge in this phase is that the stakeholders might not have enough trust in the digital twin to remove the subject matter expert from the decision-making process.
Strategy. Enable experimentation. By Table 2, liberty can be improved either by enabling experimentation or by improving explainability. In our case, the company opted for the former. Experimentation improves the UVI by allowing subject matter experts to gain an understanding of the digital and physical twin.
Implementation. Following Table 1, we improve UVI through increasing interpretability and believability. This is achieved by developing (1) interactive user interfaces that allow for advanced visualization, and (2) features for short-length what-if analysis that can be verified in the physical experimental setting.

6.4 Reflection

The above case demonstrated how our framework and autonomy strategies span a clear, systematic chain of arguments from high-level aims to specific implementation details. The framework was not available at the time of the project we draw from [12], but it would have aided our efforts greatly.

First, the framework helps identify quick wins. Scoping subsequent steps in a digital twin project is less complex and much safer if the current level of autonomy is well-understood and the required steps of evolution are tied to specific data quality metrics. These links foster better requirements that will deliver the desired evolutionary step. Second, the framework allows for articulating various kinds of high-level goals. In Section 6.1 and Section 6.2, the goals were related to specific information models. However, in Section 6.3, the goal was related to a dimension in the reference framework (Figure 1). In each situation, the end-to-end correspondence to data quality metrics ensures sound technical outcomes. Third, although outside of the scope of this paper, the framework allows for composing and analyzing sequences of decisions. In Section 6.3, the *Enable experimentation* strategy was a viable option because, in previous phases, the RVI and AVI were sufficiently improved. Augmenting our framework with temporal semantics to allow for analyzing sequences of strategic decisions, potentially governed by digital twin evolution frameworks [13] are left for future work.

Threats to validity. The main threat to the validity of our approach is that it has been validated only in one industry case. We attempted to mitigate this threat by sampling further digital twinning reports, but the scientific literature on the twinning itself does not offer sufficient details into the strategic decision-making of projects. Therefore, we resorted to validating our approach on a real, large-scale industry case in which we had access to every decision and were part of the strategic process. As a consequence of using one case, overfitting might occur. We attempted to mitigate this risk by maintaining a general discussion and drawing only conclusions that we felt confident to generalize.

7 Related work

Tekinerdogan and Verdouw [33] define the digital autonomy architectural pattern for digital twins. Autonomy, in their terms, does not require manual human intervention as the digital twin reacts to changing conditions. They associate autonomy with the ability to learn from previously encountered situations and adapt control actions accordingly. Our framework focuses more on the human elements of digital twin autonomy. Hribernik et al. [18] focus on the *ability* dimension of autonomy and emphasize the crucial role of adaptation as autonomous systems must also act proactively with respect to their own purposes. Bradshaw et al. [6] discuss seven myths of autonomy. One of their key findings is that despite common belief, there is no such thing as a fully autonomous system. Humans usually cannot be fully removed from the system, nor is it always desirable to do so. Our work shares these views and exactly for these reasons, we advocate approaching digital twin autonomy from a socio-technical point of view and investigate the borders between digital twin and human autonomy, as recommended by Hribernik et al. [18]. Henry Hexmoor and Tuli [17] define autonomy as an artifact of the human's individual trust in the system and the system's ability to execute its mission. In their framework, individual trust is further decomposed into factors such as benevolence and capability of subsystems, and investigate human-analogous traits of autonomous systems such as sociability, frustration, and disposition. These metrics might be useful in further refining and quantifying human-machine dynamics in our framework.

We based our work on the infonomics theory of Laney [21], but there are a number of other valuation models available. Lu and Zhu [23] propose evaluation methods for the Enterprise Value of Information (EVI), based on qualitative metrics (such as information authenticity and degree of coverage) and quantitative metrics (such as information flux and information cost). Viscusi and Batini [35] relate information value to metrics such as information quality, information structure, information infrastructure; and utility which is mostly determined by information diffusion. Neither of these information valuation models is specific to digital twins and seems to be focusing on qualitative metrics that, similarly to Laney's metrics, lack actionability. A comprehensive and recent review of data valuation models is due to Bendechache et al. [2].

8 Conclusion

In this paper, we have presented how different classes of information contribute to the autonomy of digital twins. We defined three novel information valuation models based on the established theory of infonomics [21] to understand the influence of information on autonomy. We have outlined five strategies to improve autonomy by increasing the value of information in the different valuation models. While likely not an exhaustive list of all possible digital twin information valuation models, the comprehensive nature of the ISO 23247 reference framework the models are linked to suggests an appropriate coverage of the main concepts and relationships among them. To situate digital twin autonomy efforts in a comprehensive framework, we proposed one in terms of two orthogonal dimensions: a more technology-focused dimension, *ability*; and a more human-focused dimension, *liberty*. We contextualized two traditional and identified two novel socio-technical classes of digital twins. Our information valuation models, digital twin autonomy strategies, and our framework foster a systematic top-down approach to improving the autonomy characteristics of digital twins.

In line with Bradshaw et al. [6], we argue that autonomy must be considered early in the engineering process of the digital twin. Our approach helps to reason about autonomy already at an early phase. At the same time, we emphasize that human agency should be considered as a first principle in digital twinning.

Future work will focus on augmenting our framework with temporal semantics to allow for reasoning about compositions of autonomy strategies, as well as applying the framework to more digital twin projects for validation purposes.

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