Digital twin: current shifts and their future implications in the conditions of technological disruption

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Abstract: We are in the midst of a significant transformation regarding the way we produce products and deliver services thanks to the digitisation of manufacturing and new connected supply-chains and co-creation systems. This article elaborates digital twins approach to the current challenges of knowledge management when Industry 4.0 is emerging in industries and manufacturing. There are not very many studies, which have elaborated on this important question from a knowledge management perspective. This article summarised this ongoing discussion. We observe three major shifts ongoing with digital twins: first, there is a drive towards the added complexity of the environments modelled by digital twins. Secondly, the paradigm offers a general shift from analysing ex-post data to predicting the future. Third, in the future, digital twin can move from cyber-physical integration of physical and virtual entities towards cyber-physical integration of larger interconnected networks presenting a new digital twin interaction-puzzle. The identification of these shifts and their implications is a new addition to the scientific literature in the field. The article presents five scenarios of technological disruption based on Clayton M. Christensen's model. This is a novel extension of Clayton M. Christensen's original idea and model

Keywords: digital twins; simulation modelling; cyber-physical systems; CPS; Industry 4.0; technological disruption; innovator's dilemma; knowledge management

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1 Introduction

The Fourth Industrial Revolution, Industry 4.0, is changing the way business models and platforms function, and by extension, the stakes by which firms are forced to compete. Organisations today must decide how and where to invest in new technologies, and they must identify those which best meet their business needs and their future business models.

There are many digital technologies relevant to an organisational Industry 4.0 approach. Without understanding changes and opportunities brought by Industry 4.0, companies risk losing ground for their operations. This is one key scientific motivation for this article and its conceptualisation: to help organisations and firms to focus on key issues within the new systemic paradigm. In particular, this chapter relates to new modes of simulations and the rapidly developing technology of the digital twin (DT) approach.

As Industry 4.0 represents the Fourth Industrial Revolution, the emerging paradigm also represents the fourth stage in the evolution of digitalisation. As Qi et al. (2020) write, digitalisation has progressed through four evolutionary stages: digital enablement, digitalisation assistance, digital control and link and cyber-physical integration.

DT technology is the spearhead of this latest evolutionary stage of cyber-physical integration and rapidly developing virtual simulation technology (Rosen et al., 2015). It is at the forefront of the manufacturing integration of informatisation and industrialisation, pairing the datafied virtual world with the physical world of advanced manufacturing (Zheng et al., 2019). It is a digital representation mirroring real-life objects, processes, or systems (Bolton et al., 2018). The DT is composed of three basic components, which is:

1 physical entities in the physical world

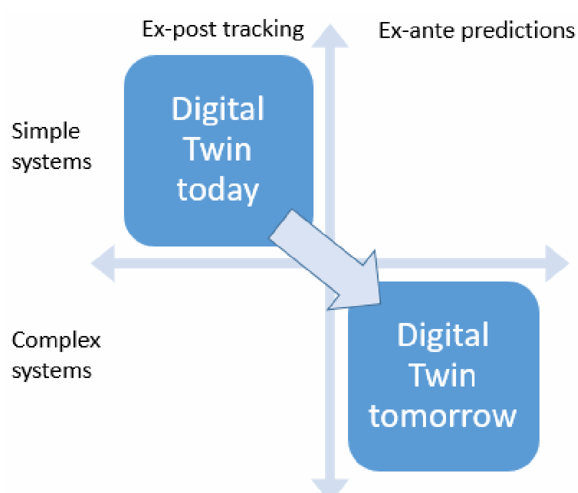
2 virtual models in the virtual world

3 the connected data between these two worlds (Qi and Tao, 2018).

While the concept of DTs is relatively new, it has attracted much attention in recent years from both academia and practitioners. For example, the Gartner hype cycle for 2019 places DT at the very peak (Panetta, 2018). Applications in real-life are also beginning to catch up. A 2018 Gartner study claimed that 48% of organisations implementing IoT were already using DT or planning to use it that same year (Quirk, 2018).

DT plays a pivotal role in the vision of smart manufacturing (Lu et al., 2020): it enables a data analytical shift from ex-post data gathering and analytics towards predicting the future. Simultaneously, the arenas in which DT is applied is widening, so that analytics companies are now, e.g., selling the idea of a 'digital twin of an organisation' (DTO).

Figure 1 The potential shift of DTs on two different dimensions (see online version for colours)



Two important simultaneous shifts in the direction of DT can thus be identified, cf. Figure 1. First, there is a shift forward from using IoT as a way of tracking various characteristics of a physical object. As we will elaborate later using various terminologies this corresponds to concepts such as digital shadow or *entity DT*. A 'real' DT enables bidirectional communication in which information from the virtual entity can flow to its physical twin and alter certain characteristics of this. For the organisation implementing the DT, this allows the virtual twin to function as a *scenario DT* (Qi et al., 2020). This represents the shift from ex-post tracking to ex-ante predictions.

The second major shifts represent the increased complexity of the systems, for which DT is applied. While formulations of the DT-concept have stressed the need for model integration with multi-physics and multiscale probabilistic simulations (Qi et al., 2020), tracking, modelling, and simulation, e.g., individual manufacturing operations is a very different beast than simulating the entire complex operational environment of an organisation.

These two proposed simultaneous shifts will, if successful, have potentially seismic impacts on many different sectors such as manufacturing, automotive industries, and healthcare, but they also require fundamentally different capabilities and a shift within the DTs-paradigm in itself. However, so far, this realisation has only been partially described in the academic literature.

The article is structured so that it first describes the technological drivers of Industry 4.0 (Section 2). In Section 3, we describe the roles of scenarios and simulations in Industry 4.0 with the focus on DT. A key part of this section is the description of where DT fundamentally differs from older technologies. Section 4 describes and discusses the proposed conceptual shift from a narrow technology to a general paradigm, and the conceptual consequences of this shift. Furthermore, we present a summary of the expected impacts of DT technologies on knowledge management functions (Section 4.6) and five possible scenarios of technological disruption in future markets (Section 4.7). The article is naturally finished with conclusions (Section 5).

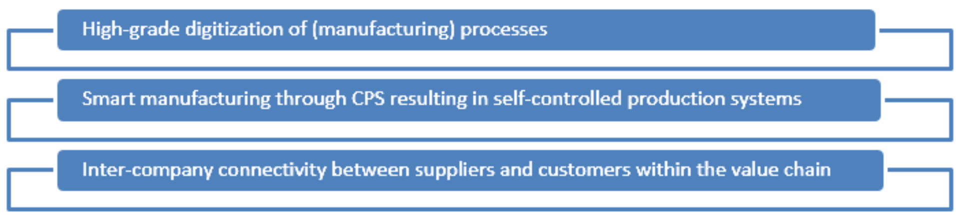
2 Technological drivers of Industry 4.0 era

Dating back to around 1760, the First Industrial Revolution (Industry 1.0) was the transition to new manufacturing processes using water and steam (Schwab, 2017). Since then, innovations have taken industrial manufacturing and modern societies forward. Some authors have noted that rather than talking about Industry 1–4 phases, we should talk of: pre-electricity age, mid-electricity age, post-electricity age, pre-computer age, mid-computer age, post-computer age, pre-digital age, mid-digital age and post-digital age (Goodwin, 2018). Similarly, we may experience also pre-DT age, mid-DT age, and post-DT age following a well-known path dependence model.

New Industry 4.0 era is expected to be founded on cyber-physical systems (CPS) with factories expected to become conscious and intelligent enough to predict and maintain the machines and control the production process. Business models of Industry 4.0 imply complete communication network(s) between various companies, factories, suppliers, logistics, resources and customers. Figure 2 illustrates one operationalisation of three dimensions of Industry 4.0, stressing elements of *digitisation*, *autonomy* and *inter-connectedness*.

For organisations, the strategic shift to real-time access to data and intelligence enabled by Industry 4.0 can fundamentally transform the way of conducting business and manage their business model. The integration of digital information from many different sources and locations (big data) drive the physical act of doing business, in an ongoing cycle. There have been big data available for many years (about over 20 years), but only a small part of it is utilised. The first phase of Big data 1.0 was in 1994–2004 (e-commerce phase), the second phase of Big data 2.0 (social media phase) was in 2005–2014 and now we live Big data 3.0 phase (IoT applications plus Big data 1.0 and Big data 2.0). In the current phase, IoT applications can generate data in the form of images, audio and video. This is a new technology environment. Throughout this cycle, real-time access to data and intelligence is driven by the continuous and cyclical flow of information and actions between the physical and digital worlds.

Figure 2 Three dimensions of Industry 4.0 (see online version for colours)



Source: Adapted from Müller et al. (2018)

3 Scenarios, simulations and DT

3.1 Simulation modelling

In Industry 4.0 era, simulation covers a primary role in every field from, finance to manufacturing, and at all levels, strategic, tactical and operational (Polenghi et al., 2018). Simulation modelling is an indispensable and powerful element of digital manufacturing (Mourtzis et al., 2014; Rodic, 2017; Alcacer and Cruz-Machado, 2019). Simulation allows experiments for validation of products, processes, or systems design and configuration, and it is defined as an operation imitation, over time, of a system or a real-world process.

3.2 The DTs approach

An important driver for the development of DTs was the incentive to create an alternative to expensive space industry investments in physical duplicates for testing (Tao and Zhang, 2017; Tao et al., 2018). Instead of creating two physical copies of the same space shuttles, a physical system could be twinned with a virtual copy – i.e., its DT. While initial investment costs may be lower in other industries than for NASA space shuttles, many manufacturing industries have an interest in providing a 'safe environment' for piloting and testing new products, new manufacturing methods, etc.

DTs allow the organisation to "to be able to design, test, manufacture, and use the virtual version of the systems (…) before the physical system is actually produced" (Grieves and Vickers, 2017).

While academic research has spread rapidly during the latest decade, a general definition of the features and scopes of DT has not yet been reached (Cimino et al., 2019). Recently, however, a shared understanding seems to rise that to meet the criteria of a 'real' DT, data must flow bi-directionally, i.e., both in the physical-to-digital and virtual-to-physical directions (Kritzinger et al., 2018; Cimino et al., 2019; Talkhestani et al., 2019).

Here, authors distinguish between:

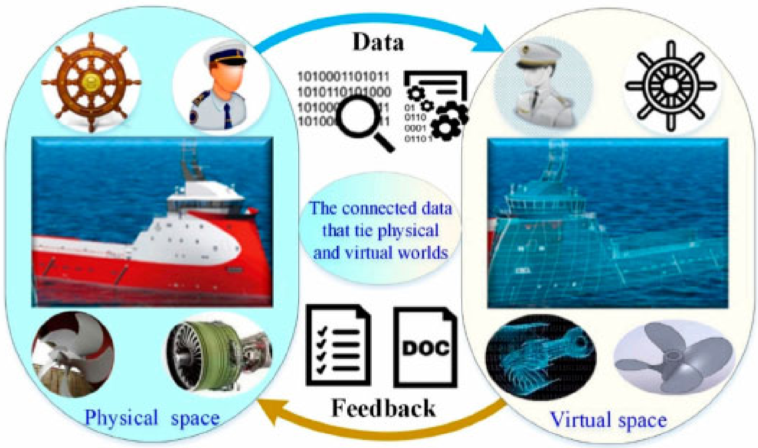
1 a digital model, which models the physical object without direct interaction between the physical and virtual objects

2 a digital shadow where only the physical entity sends data and updates the virtual one

3 a DT, where the physical entity also can act upon data from the virtual entity.

A simplified version of a DT with bidirectional feedback is shown in Figure 3.

Figure 3 General DT mode for a product (see online version for colours)



Source: Tao et al. (2018)

One of the most elaborated definitions of DTs is provided by Talkhestani et al. (2019). They state that a DT is a digital representation of a physical asset with several necessary features:

- A DT has to be a digital representation of a physical asset, including as realistic as possible models and all available data on the physical asset.
- The data has to contain all process data, acquired during operation as well as organisational and technical information created during the development of the asset.
- A DT has to be always synchronised with the physical asset.
- It has to be possible to simulate the DT of the behaviour of the physical asset.

With this definition, the DTs approach is based on complex cyclical flows.

3.3 *What is new by DT?*

According to Panetta (2018), the idea of a DT is not 'new', but "today's digital twins are different in four ways: (1) the robustness of the models, with a focus on how they support specific business outcomes, (2) the link to the real world, potentially in real-time for monitoring and control, (3) the application of advanced big data analytics and AI to drive new business opportunities, (4) the ability to interact with them and evaluate 'what if' scenarios."

DT is different from traditional simulation models such as computer-aided design/computer-aided engineering (CAD/CAE) in that they relate to a *specific instance*, that is a particular physical object or entity (Madni et al., 2019). A DT is not just any model; it is a model of something that exists or could exist, in the real world. Furthermore, the bidirectional communication feeding continuous information from the virtual to the physical world is a novel feature separating DTs from other virtual simulation systems.

For the specific instance, DTs can ‘tell’ the story (events, experiences, history, wear and tear) of its physical twin over the physical twin’s life cycle (Madni et al., 2019). Using the example of a braking system, it allows the experimenter to not only simulate how the generic braking system would operate in certain conditions but to simulate how a braking system with the exact specific operational characteristics (how many miles it has driven, what is the repair history, etc.) will behave. Driven by IoT, this makes DTs a core technology in the field of predictive maintenance.

Being a virtual representation, a DT is easier to manipulate and study in a controlled environment than its physical counterpart in the operational environment (Madni et al., 2019). DTs are therefore able to offer several new benefits:

- validate system model with real-world data
- provide decision support and alerts to users
- predict changes in physical systems over time
- discover new application opportunities and revenue streams.

An important part of the current value capture from DTs comes from these elements crucial in maintenance and operation management: The ability to optimise the scheduling of operations and maintenance of the physical twin. The more disruptive both breakdowns and maintenance operations are to continued operations; the more value might be captured by optimised scheduling.

This is also the case for situations related to human health, in which optimal information delivered at the right time can be, literally, life-saving.

4 From the shopfloor to a general paradigm

4.1 Taking DT beyond the shopfloor

The idea of DT has proliferated in recent years to several contexts beyond manufacturing and the shopfloor. As an example, Gartner has coined the term ‘DTO’ which “enables the dynamic virtual representation of an organization in its full operational context.” This was named by Gartner as one of the Top 10 Strategic Technology Trends for 2019 (Cearney, 2018).

This is only one of several recent trends that suggest that the idea of DTs can be moving from describing a relatively narrow technology to a general paradigm of cyber-physical integration. In the case of DT being a general paradigm, challenges and possibilities must be approached in a broader way than the technical research which has dominated the field until now.

4.2 New arenas for DT

Near-term, DT appears most likely to gain ground within sectors such as manufacturing and maintenance activities (Madni et al., 2019).

Tao et al. (2018) argue that DT offers a multitude of new opportunities during the design phases. For the conceptual design, designers can integrate the physical properties of the product as well as the historical data of users. When designing a new bike, knowledge of intended customer's bike habits and physical traits can be important qualifiers. In the detailed design phase, dynamic feedback from the shopfloor or customers can in incorporated. And in a virtual verification stage, tests can be made of the final product against key parameters, allowing for rapid design changes before mass manufacturing.

Tao et al. (2018) also show how DTs can be used in product manufacturing as well as for maintenance, repair, and operation (MRO). The vision of including all current and future lifecycle phases (Boschert and Rosen, 2016) is slowly being realised in the manufacturing industry.

DT is also becoming an important tool for town planning and urban development as a continuation of building information modelling (BIM), which is becoming standard in the construction industry (Borrman et al., 2018). For larger areas, smart city digital twins (SCDT) illuminate cities' human-infrastructure-technology interactions (Mohammadi and Taylor, 2017), and enables informed urban development choices and rapid responses to emergencies (Weekes, 2019). Large visual 3D models are being deployed in smart cities around the world, but the level of ambition and technical ability is constantly rising. In 2019, the new Indian state capital Amaravanti is thought to be the first-ever city born with a DT.

4.3 Complexity

In manufacturing DT offers an opportunity to simulate and optimise production systems, including logistical aspects, and enables detailed visualisation of processes from single components to the entire assembly process (Kritzinger et al., 2018). The new era for the DT approach in knowledge management is applications beyond manufacturing contexts. The immediate challenge will be for organisations to manage the 'physical to digital'-step and capture different types of data into a digital record.

We can use an office building as an example. Today people are employed at the premises to transport physical objects around the complex, for example, mail, stationery, or IT equipment, soon all this might be transported faster and more cost-efficient by autonomous drones or robots, also reducing the need for decentralised storage and office space. However, for this to work effectively, digital records of the premises – effectively capturing four dimensions, including both the air and time – needs to be established to capture what humans today can capture immediately with their bare eyes. Those organisations succeeding in adapting DTs will be those skilled at semantic data management (Abramovici et al., 2016).

As DTs move from tracking, modelling, and simulating more or less confined environments towards tracking, modelling, and simulating larger systems, complexity rapidly increases.

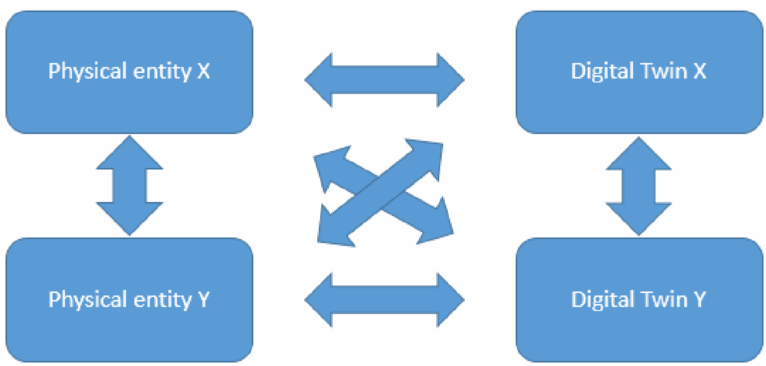
Understanding the features, elements, and constraints of complex systems will be paramount. Models are a kind of hypothetical generalisations of complex matters, and the more complex the matter is, the more the model is likely to be a simplification.

If the idea of DTs builds on the notion that it *fully* captures the physical world (cf. Lu et al., 2020), then this simplification represents a break with the trend. To overcome this potential gap of understanding, multidisciplinary research on the functions of complex systems will be necessary.

4.4 Co-simulations and the new DT-puzzle

Another element of added complexity likely to occur with the technical developments and the maturation of DT technology is the need for co-simulations between several DTs (Talkhestani et al., 2019).

Figure 4 New DT-puzzle (see online version for colours)



We speculate that it will not be enough to speak of bidirectional communications between virtual entity X and physical entity X, but of a much more complicated interaction and flow of data in which virtual entities must communicate with each other (from virtual entity X to virtual entity Y), but also those physical entities must communicate with *other physical entities*' DTs. This complex puzzle is illustrated in a simplified version in Figure 4 – in reality, these entities will not be constrained to be networked with just a few entities, but instead, they can appear in a network of million entities.

4.5 New challenges for DT

In summary, we have identified three major shifts in DT technology, each with particular implications for new research themes.

First, it moves the target of IoT-analytics from ex-post analytics to ex-ante predictions.

Secondly, even as technology is still within its formative phase, there is a move towards added complexity. Unless this ends up considered as a major oversell from eager consultants and market actors, there is a need to capture the added complexity fruitfully in new models.

Thirdly, as academics and businesses begin to successfully utilise DT to achieve cyber-physical integration of a physical entity and its virtual twin, we must begin to prepare for the next phases which include interaction and integration among interconnected DTs.

Research on the implications of these three elements has been very sporadic so far, but with the proliferation of research on DT suitable attention will hopefully be given to these questions soon.

4.6 DT technology and knowledge management

The dynamics of knowledge processes represent a major research topic in knowledge management studies (Zlahtic et al., 2017). Traditionally, Nonaka and Takeuchi's (1995) theoretical framework of socialisation-externalisation-combination-internalisation (SECI) has provided a fundamental and well-known basic model to analyse knowledge creation practices. The SECI model can be applied to understand DT technology and applications. In general, we can claim that the DT approach can have impacts directly and indirectly on the process of SECI (see Nonaka and Takeuchi, 1995). On the basis of previous sections in this article, we can note the following implications of the DT approach:

1 Industry 4.0 approach will be implemented with the DT technologies and this will have impacts on knowledge management processes of the Industry 4.0 era.

2 Simulation modelling and the concept of CPS are linked to the DT approach (Section 3.1–Section 3.3), which means that there will be at least indirect impacts on the knowledge management processes in organisations.

3 The DT approach was originally linked to product-lifecycle-management-model (Tao and Zhang 2017), which means that the DT approach will have both direct and indirect impacts of the knowledge management processes in industrial productions and organisations.

4 The DT approach have now been adopted in:

   a product and service development (DTs of products and services)

   b organisational analyses (organisational DT)

   c city planning (infrastructural DT)

   d the healthcare and digital learning sectors (personal DT)

   which means that various direct and indirect impacts of knowledge management will be observed in the future.

5 The DT approach will be helpful and challenging driver in the management of complex systems (Section 4.3), which means paramount impacts on current knowledge management systems.

Key reflection based on this article is that the DT approach can be both helpful but also very challenging for the key functions of knowledge management. The interpretation of the different tools and methods as enablers for knowledge creation is a key issue in knowledge-oriented studies on lean product development (LPD) (Solaimani et al., 2019), which is also key elementary character of Industry 4.0 approach. A general observation in the knowledge management field has been that there is a phenomenon of increasing knowledge complexity (Nonaka, 1994). From this knowledge complexity perspective, the DT approach can be a promising approach for the practitioners of organisational knowledge management.

We can expect that standardisation and systematisation of routine activities continue in many professions. We will also find new and better ways to share expertise in society and industries. The concept of professionalism will change radically and we will see the post-professional society, where expertise is available online [Susskind and Susskind, (2015), pp.303–308]. The DT approach will probably be an elementary part of this transformation process.

To sum up, ongoing technical and social transformations imply many challenges for the knowledge management research and new pragmatic applications of knowledge management systems. Probably, Knowledge management 4.0 research program will be needed to investigate new needs and challenges.

4.7 Disruption scenarios of DT technology

In Section 4.6, we present five scenarios of technological disruption caused by DT solutions. These alternative scenarios are novel extensions of Christensen's (2002) innovation theory. Christensen's (2002) research work has been very important for innovation and management studies, and his theory of disruptive innovation has been termed as the most influential business idea of recent years (*The Economist*, 2017). From this scientific perspective, it is very relevant to discuss how disruptive innovation framework works in the context of DT framework (see Christensen et al., 2004, 2019). Our analyses will provide a scenario extension to Cristensen's theory of disruptive innovations. These scenarios summarise recent discussion (Ander, 2002; Westerman et al., 2014; McAfee and Brynjolfssen, 2017) about technological transformation and digital era transformations. All these scenarios are possible to observe in different branches of modern industries.

The first scenario is the so-called status quo scenario where nothing very special happens although disruptive agents try to disrupt dominating industries, which is a business-as-usual situation in many markets. This Scenario '0' is visualised in Figure 5.

Figure 5 is a basic framework of business disruption. In the following sections, we present four scenarios of business disruption. All scenarios are based on ceteris paribus – assumptions. Ceteris paribus means "with other conditions remaining the same; other things being equal." The logic of a disruption process is linked to these alternative ceteris paribus assumptions, where either dominant or disruptive actor has progressive or regressive development processes in its business administration.

A typical reason for these changes can be linked to poor or superior knowledge management competencies in firms or in business organisations, which can be linked to poor knowledge management systems or poor knowledge leadership competencies (see Zouari and Dakhli, 2018; Durst et al., 2019; Ode and Ayavoo, 2019; Antunes and Pinheiro, 2020; Hock-Doepgen et al., 2020). Especially in the cases of DT applications, failures can be linked to supply chain management and to the orchestration of technological digitalisation (see Schniederjans et al., 2020). In the general field of knowledge management, there are four main hypotheses which are often expected to hold, if knowledge management in an organisation works:

1 KM practices have a direct and positive influence on firm innovation

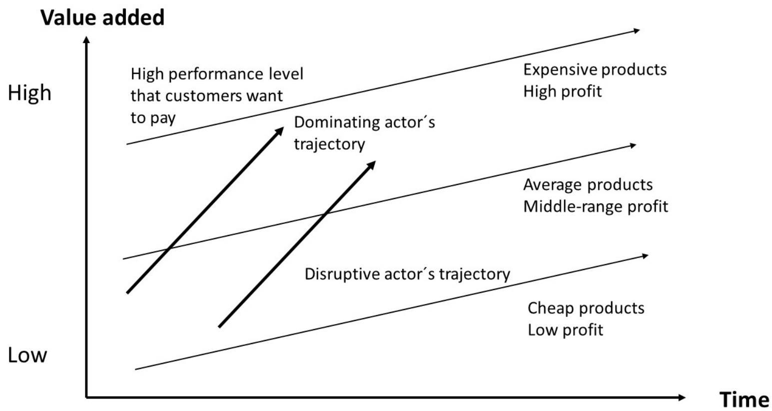
2 knowledge generation will have a positive influence on firm innovation

3 knowledge diffusion will have a positive influence on firm innovation

4 knowledge storage will have a positive influence on firm innovation.

We can summarise that modern knowledge management plays a central role as a potential source of business disruption. Let us move to special DT scenario analyses.

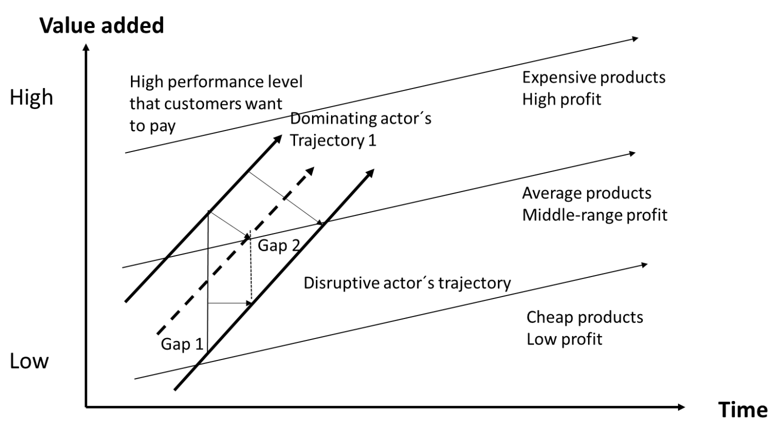
Figure 5 Scenario '0'



Note: Status quo – business as usual disruption scenario.

In the case of Scenario A, the reason for the disruption is that the dominating actor is not able to develop or renew its DT technology and it loses its strong position. The gap between a dominating actor's trajectory and a disruptive actor's trajectory becomes narrower (see Figure 6).

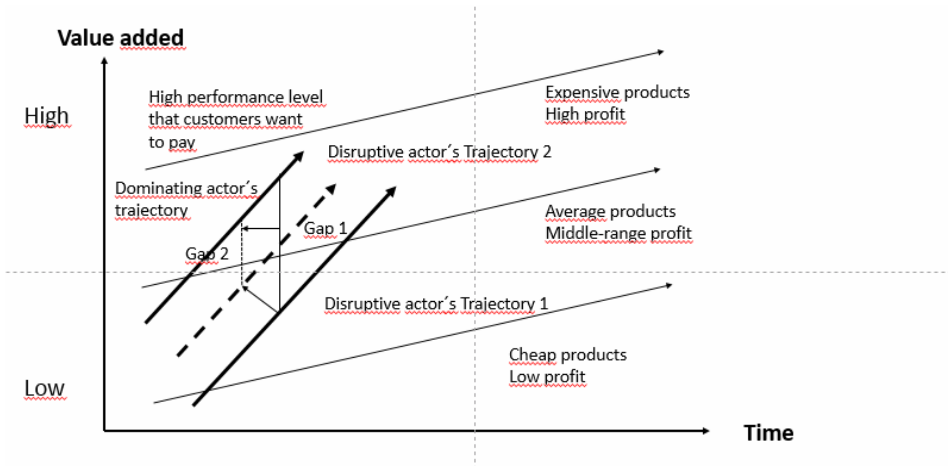
Figure 6 Scenario A



Notes: Scenario A: dominating actor's trajectory 1 goes down, from a trajectory 1 to a trajectory 2. The gap between a dominating actor's trajectory and a disruptive actor's trajectory becomes narrower.

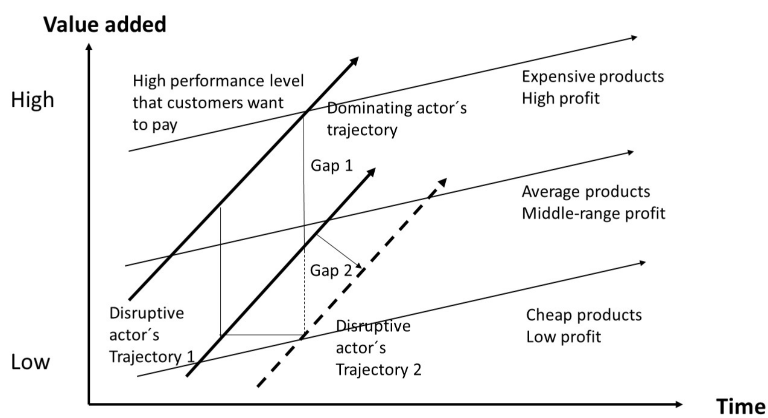
In Scenario B, the reason for disruption is that a disruptive actor is adopting DT technology, but the dominating actor is not doing progress and the gap between the dominating and the disruptive actors becomes narrower. This change leads to a situation where the disruptor's trajectory will be closer to the dominating actor's trajectory in the end compared to the original situation. The dominant actor will be challenged (see Figure 7).

Figure 7 Scenario B



Notes: Scenario B: disruptive actor's trajectory 1 goes up, from a trajectory 1 to a trajectory 2. The gap between a dominating actor's trajectory and a disruptive actor's trajectory becomes narrower.

Figure 8 Scenario C

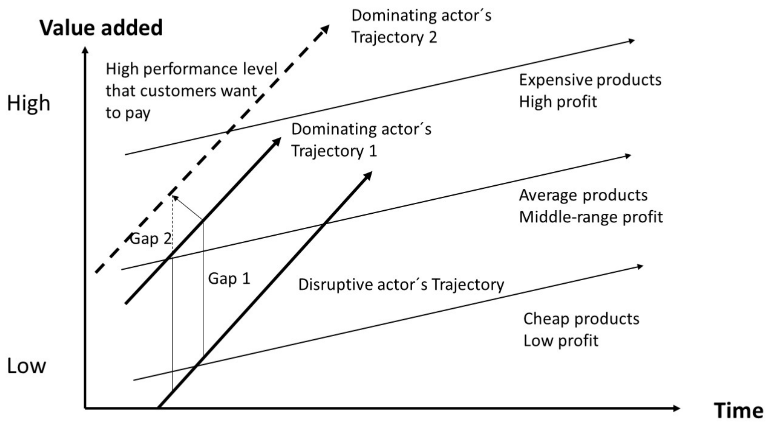


Notes: Scenario C: disruptive actor's trajectory 1 goes down, from a trajectory 1 to a trajectory 2. The gap between a dominating actor's trajectory and a disruptive actor's trajectory becomes broader.

In Scenario C, the reason for disruption is that a disruptive actor's trajectory 1 goes down, from a trajectory 1 to a trajectory 2. This change leads to a situation where the gap between a dominating actor's trajectory and a disruptive actor's trajectory becomes broader (Figure 8).

In the case of Scenario D, a dominating actor's scenario trajectory 1 goes up, from a trajectory 1 to a trajectory 2. The gap between a dominating actor's trajectory and a disruptive actor's trajectory becomes broader. In the final situation, the dominating actor has a stronger position in the market (Figure 9).

Figure 9 Scenario D



Notes: Scenario D: dominating actor's trajectory 1 goes up, from a trajectory 1 to a trajectory 2. The gap between a dominating actor's trajectory and a disruptive actor's trajectory becomes broader.

In Figures 6–9, we illustrate these four disruptive scenarios A–D.

The gap between the dominating actor and the disruptive actor becomes narrower due to new possibilities enabled by DT technology. Disruptive actors can utilise DTs to enact cost-saving measures in production and MRO-phases, and with lower costs, the entirety of the given industry is shifted towards selling cheaper products with a lower profit margin. This scenario reflects the disruptive innovation situation, where incumbents' offerings overshoot performance requirements of less-demanding customers, and opens the door for disruptors to gain market shares by providing a 'good enough' product (cf. Christensen et al., 2015).

The gap between the dominating actor and the disruptive actor becomes narrower, as the disruptive actor successfully changes its trajectory. Here, the disruptive actor utilises DTs to create higher value-added products, for example through a servitisation logic or by using DTs to unlock new potential revenue streams within existing production setups.

In this case, the observed change means lighter market competition caused by DTs technologies. A disruptor has a more challenging position in this case than in the original situation, for example, because the strong dominant and incumbent firms can be DT first-movers or able to create an economy of scale in the development and deployment of DTs within their industry. In a possible illustration of this scenario, General Electric claims that DTs help avoid one billion dollars of annual losses already today (Saracco, 2019). This helps the dominating firm to ensure its position.

In this scenario, a disruptor has a more challenging position in this case than in the original situation, because the gap is broader after a progressive change of dominant actor. Here, the dominating actor utilises DTs to increase the value-added from its products. As the dominant actor creates an even strong value proposition, the likelihood of success for the disruptive actor declines. An illustrative example of an industry where dominant actors' are pushing for this scenario is the pharmaceutical industry, where a current hypothesis is that DTs of patients could enable personalised medicine (cf. Björnsson et al., 2020; Goecks et al., 2020). Personalised medicine provides higher value for the customers (patients), and potentially raises both sales prices and profit margins for the large corporations producing it.

These scenario analyses inform us about potential changes in many industrial markets. Both dominating and disruptive actors can adopt DT technologies and use new DTs technologies progressively. DTs can be deployed both as a method of lowering costs to sell cheaper products, or it can be deployed as a driver for selling higher priced products with more value added. Which of these methods which will dominate, and whether the strongest DT-adoptor will be dominating or disruptive actors will determine the future role of DTs in many industries. We believe it is likely that all of the four scenarios A–D will come to happen across different industrial sectors and different sectors of the economy. The four scenarios are extensions of Christensen's innovation management theory.

5 Conclusions

In the era of Industry 4.0, CPS and DTs have the potential to become dominant technologies across many domains. Research on DTs has accelerated over the latest few years, and technological development is happening at a rapid speed.

Beyond mere technological elements, two major shifts with major implications are present at the forefront of current DT-development. First, the operational physical environment, which DTs attempt to capture, is becoming more complex. Secondly, DT pushes the entire field of IoT data analytics from ex-post data tracking to ex-ante predictions of the future. As these two developments merge and spread, we can talk of a new DT-paradigm. The implications of these developments have hitherto not been studied, but this article is an attempt to highlighting the importance of the shifts to kickstart a relevant research paradigm. This research paradigm must also prepare for the next phase of DT technologies in which integration happens not only between a physical entity and its own virtual twin, but also between, e.g., a physical entity and the virtual twin of another physical entity. This shift and its implications have not to our knowledge been studied in detail previously.

Novel applications of the DT approach can also have an impact on knowledge management. We note how this can be reflected in the classical SECI-model of Nonaka and Takeuchi (1995). Knowledge management systems of Industry 4.0 era will be different compared to previous historical Industry 1.0, 2.0, 3.0 eras. Ongoing technical and social transformations imply many new challenges for knowledge management research and new pragmatic applications of knowledge management systems. Probably, Knowledge management 4.0 research program will be needed to investigate new needs and challenges.

In this study, we presented also Christensen's (2002) original idea and model. We made an extension to this model presenting four disruption scenarios. All these scenarios are possible to happen in different branches of modern industries.

References

Abramovici, M., Göbel, J.C. and Dang, H.B. (2016) 'Semantic data management for the development and continuous reconfiguration of smart products and systems', *CIRP Annals*, Vol. 65, No. 1, pp.185–188.

Alcacer, V. and Cruz-Machado, V. (2019) 'Scanning the Industry 4.0: a literature review on technologies for manufacturing systems', *Engineering Science and Technology, an International Journal*, Vol. 22, No. 3, pp.899–919.

Ander, R. (2002) 'When are technologies disruptive? A demand-based view of the emergence of competition', *Strategic Management Journal*, Vol. 23, No. 8, pp.667–688.

Antunes, H.d.J.H.G. and Pinheiro, P.G. (2020) 'Linking knowledge management, organizational learning and memory', *Journal of Innovation & Knowledge*, Vol. 5, No. 2, pp.140–149.

Björnsson, B., Borreback, C., Elander, N., Gasslander, T., Gawel, D.R., Gustafsson, M., Jörnsten, R., Lee, E.J., Li, X., Lilja, S., Martinez-Enguita, D., Matussek, A., Sandström, P., Schäfer, S., Stenmarker, M., Sun, X.F., Sysoev, O., Zhang, H. and Benson, M. (2020) 'Digital twins to personalise medicine', *Genome Medicine*, Vol. 12, No. 4, DOI: https://doi.org/10.1186/s13073-019-0701-3.

Bolton, R.N., McColl-Kennedy, J.R., Cheung, L., Gallan, A., Orsingher, C., Witell, L. and Zaki, M. (2018) 'Customer experience challenges: bringing together digital, physical and social realms', *Journal of Service Management*, Vol. 29, No. 5, pp.776–808.

Borrman, A., König, M., Koch, C. and Beetz, J. (2018) *Building Information Modeling*, in Borrman, A., König, M., Koch, C. and Beetz, J. (Eds.), Chapter 1, Springer, Cham.

Boschert, S. and Rosen, R. (2016) *Megatronic Futures: Challenges and Solutions for Megatronic Systems and their Designers*, in Hehenberger, P. and Bradley, D. (Eds.), Chapter 5, Springer, Cham.

Cearney, D. (2018) *The Top 10 Strategic Technology Trends for 2019*, 29 November [online] https://www.slideshare.net/ratinecas/the-top-10-strategic-technology-trends-for-2019 (accessed 10 March 2019).

Christensen, C.M. (2002) *Innovator's Dilemma: When New Technologies Cause Great Firms to Fail*, Harvard Business Review Press, Boston, MA.

Christensen, C.M., Anthony, S.D. and Roth, E.A. (2004) *Seeing What's Next: Using the Theories of Innovation to Predict Industry Change*, Harvard Business School Press, Boston, MA.

Christensen, C.M., Ojomo, E. and Dillon, K. (2019) *The Prosperity Paradox: How Innovation Can Lift Nations Out of Poverty*, Harper Business, New York, NY.

Christensen, C.M., Raynor, M. and McDonald, R. (2015) 'What is disruptive innovation?', *Harvard Business Review*, Vol. 59, No. 12, pp.44–53.

Cimino, C., Negri, E. and Fumagelli, L. (2019) 'Review of digital twin applications in manufacturing', *Computers in Industry*, Vol. 113, No. 103310, pp.1–15.

Durst, S., Hinteregger, C. and Zieba, M. (2019) 'The linkage between knowledge risk management and organizational performance', *Journal of Business Research*, December, Vol. 105, pp.1–10.

Goecks, J., Jalili, V., Heiser, L.M. and Gray, J.W. (2020) 'How machine learning will transform biomedicine', *Cell*, Vol. 181, No. 1, pp.92–101.

Goodwin, T. (2018) *Digital Darwinism. Survival of the Fittest in the Age of Business Disruption*, Kogan Page Limited. London, UK.

Grieves, M. and Vickers, J. (2017) *Transdisciplinary Perspectives on Complex Systems: New Findings and Approaches*, in Kahlen, F-J., Flumerfelt, S. and Alves, A. (Eds.), Chapter 4, Springer International Publishing, Cham, Switzerland.

Hock-Doepgen, M., Clauss, T., Kraus, S. and Cheng, C-F. (2020) 'Knowledge management capabilities and organizational risk-taking for business model innovation in SMEs', *Journal of Business Research*, in press [online] https://doi.org/10.1016/j.jbusres.2019.12.001.

Kritzinger, W., Karner, M., Traar, G., Henjes, J. and Sihn, W. (2018) 'Digital twin in manufacturing: a categorical literature review and classification', *IFAC-PapersOnLine*, Vol. 51, No. 11, pp.1016–1022.

Lu, Y., Liu, C., Wang, K.I-K., Huang, H. and Xu, X. (2020) 'Digital twin-driven smart manufacturing: connotation, reference model, applications and research issues', *Robotics and Computer-Integrated Manufacturing*, Vol. 61, No. 101837, pp.1–14.

Lyons, D. (2016) *Disrupted: Misadventure in the Start-up Bubble*, Hachette Books, New York, USA.

Madni, A.M., Madni, C.C. and Lucero, S.D. (2019) 'Leveraging digital twin technology in model-based systems engineering', *Systems*, Vol. 7, No. 1, pp.1–13.

McAfee, A. and Brynjolfssen, E. (2017) *Machine, Platform, and Crowd – Harnessing Our Digital Futures*, W.W. Norton and Company, New York and London.

Mohammadi, N. and Taylor, J.E. (2017) 'Smart city digital twins', *2017 IEEE Symposium Series on Computational Intelligence (SSCI)*.

Mourtzis, D., Doukas, M. and Bernidaki, D. (2014) 'Simulation in manufacturing: review and challenges', *Procedia CIRP*, Vol. 25, pp.213–229.

Müller, J.M., Buliga, O. and Voight, K-I. (2018) 'Fortune favors the prepared: how SMEs approach business model innovations in Industry 4.0', *Technological Forecasting and Social Change*, Vol. 132, No. 7, pp.2–17, Elsevier.

Nonaka, L. (1994) 'A dynamic theory of organizational knowledge management', *Organization Science*, Vol. 5, No. 1, pp.14–37.

Nonaka, L. and Takeuchi, H. (1995) *The Knowledge-Creating Company. How Japanese Companies Create the Dynamics of Innovation*, Oxford University Press, Oxford.

Ode, E. and Ayavoo, R. (2019) 'The mediating role of knowledge application in the relationship between knowledge management practices and firm innovation', *Journal of Innovation & Knowledge*, 9pp, in press.

Panetta, K. (2018) *Gartner Top 10 Strategic Technology Trends for 2019*, 15 October, Gartner [online] https://www.gartner.com/smarterwithgartner/gartner-top-10-strategic-technology-trends-for-2019/ (accessed 11 August 2020).

Polenghi, A., Fumagelli, L. and Roda, I. (2018) 'Role of simulation in industrial engineering: focus on manufacturing systems', *IFAC PapersOnLine*, Vol. 51, No. 11, pp.496–501.

Qi, Q. and Tao, F. (2018) 'Digital twin and big data towards smart manufacturing and Industry 4.0: 360 degree comparison', *IEEE Access*, Vol. 6, pp.3585–3593.

Qi, Q., Tao, F., Hu, T., Anwer, N., Liu, A., Wei, Y., Wang, L. and Nee, A.Y.C. (2020) 'Enabling technologies and tools for digital twin', *Journal of Manufacturing Systems*, in press.

Quirk, E. (2018) 'Gartner survey reveals increased IoT implementations and use of digital twins in 2018', *Solutions Review*, 19 March [online] https://solutionsreview.com/business-process-management/gartner-survey-reveals-increased-iot-implementations-and-use-of-digital-twins-in-2018/ (accessed 11 August 2020).

Rodic, B. (2017) 'Industry 4.0 and the new simulation modelling paradigm', *Organizacija*, Vol. 50, No. 3, pp.193–207.

Rosen, R., von Wichert, G., Lo, G. and Bettenhausen, K.D. (2015) 'About the importance of autonomy and digital twins for the future of manufacturing', *IFAC-PapersOnLine*, Vol. 48, No. 3, pp.567–572.

Saracco, R. (2019) 'Digital twins: bridging physical space and cyberspace', *Computer*, Vol. 52, No. 12, pp.58–64.

Schniederjans, D.G., Curado, C. and Khalajhedayati, M. (2020) 'Supply chain digitalisation trends: an integration of knowledge management', *International Journal of Production Economics*, Vol. 220, No. 107439, pp.1–11.

Schwab, K. (2017) *The Fourth Industrial Revolution*, World Economic Forum, New York, USA.

Solaimani, S., Talab, A.H. and van der Rhee, B. (2019) 'An integrative view on lean innovation management', *Journal of Business Research*, Vol. 105, No. 12, pp.109–120.

Susskind, R. and Susskind, D. (2015) *The Future of the Professions. How Technology Will Transform the Work of Human Experts*, Oxford University Press, Oxford.

Talkhestani, B.A., Jung, T., Lindemann, B., Sahlab, N., Jazdi, N., Schloegl, W. and Weyrich, M. (2019) 'An architecture of an intelligent digital twin in a cyber-physical production system', *Automatisierungstechnik*, Vol. 67, No. 9, pp.762–782.

Tao, F. and Zhang, M. (2017) 'Digital twin shop-floor: a new shop-floor paradigm towards smart manufacturing', *IEEE Access*, Vol. 5, No. 17515825, pp.20418–20427.

Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H. and Sui, F. (2018) 'Digital twin-driven product design, manufacturing, and service with big data', *International Journal of Advanced Manufacturing Technology*, Vol. 94, Nos. 9–12, pp.3563–3576.

The Economist (2017) 'Jeremy Corbyn, entrepreneur', *The Economist*, 15 June.

Weekes, S. (2019) 'The rise of digital twins in smart cities', *Smart Cities World* [online] https://www.smartcitiesworld.net/special-reports/special-reports/the-rise-of-digital-twins-in-smart-cities (accessed 11 August 2020).

Westerman, G., Bonner, D. and McAfee, A. (2014) *Leading Digital. Turning Technology into Business Transformation*, Harvard Business Review Press, Boston, MA.

Zheng, Y., Yang, S. and Cheng, H. (2019) 'An application framework of digital twin and its case study', *Journal of Ambient Intelligence and Humanized Computing*, Vol. 10, No. 3, pp.1141–1153.

Zlahtic, B., Kokol, P., Zorman, M., Podgorelec, V. and Zlahtic, G. (2017) 'Knowledge management in organisations: mapping the research literature', *International Journal of Web Engineering and Technology*, Vol. 12, No. 1, pp.4–20.

Zouari, M.B.C. and Dakhli, S.B.D. (2018) 'A multi-faceted analysis of knowledge management systems', *Procedia Computer Science*, Vol. 138, pp.646–654.