SERVICE VALUE CREATION USING A DIGITAL TWIN

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ABSTRACT

Purpose: The purpose of this exploratory paper is to discuss the concept of the digital twin from the perspective of service value creation, and to describe how it can be structured and designed in different dimensions.

Design/Methodology/Approach: The study is based on a review of literature on the structure of the digital twin and its service value contribution and is built on the concept of data-driven service design. Additionally, a series of in-depth interviews and a quantitative survey were conducted with manufacturing firms, in order to validate the findings from the literature.

Findings: The digital twin is generated from a service perspective to conceptualize services that create value for a range of actors within the ecosystem. Given the concepts of service-dominant logic and service design, approaches are described for designing and delivering value to customers based on the digital twin. The technological concept of the digital twin is made up of the different layers of the twin and their contribution to value creation. The twin is structured in a number of layers representing the component, the assembly, the machine, the shop floor / production line, the factory, and the business system. Each of these layers is characterized by specific modeling tools and data requirements and has a particular value contribution to services. This value contribution can be assigned to different phases of the product life-cycle and to the actor who benefits from the services. Following service-oriented approaches, value is created by linking the digital twin, as a source of data, to the relevant actors in the ecosystem at the appropriate time and translating the data into relevant information to support decision making.

Research limitations/implications: The concept developed in this paper assists academics and practitioners to design a digital twin as a means of service value generation. However, further research is required to verify the applicability and implementation in different contexts.

Practical implications: The concept for the digital twin presented in this paper provides a framework which can be used for designing and delivering service value by manufacturing firms.

Originality/Value: The innovation of this paper is the approach to the digital twin from the perspective of service value creation, which leads to its structuring in different layers that are relevant for business.

Paper type: Conceptual paper.

KEYWORDS: digital twin, smart services, service science, service design, servitization of manufacturing.

1. INTRODUCTION

This goal of this paper is to elaborate a new concept for creating service value using a digital twin. The aim is to design and engineer service that is derived from the customer's needs and that leverages the potential of the digital twin.

The approach discussed in this paper starts with the concept of service-dominant (S-D) logic. With the transition from products to services, the economy moves from the concept of “Goods-Dominant Logic” (GDL) to “Service-Dominant Logic” (SDL). In SDL, service is considered the fundamental purpose of economic exchange (foundational premise 1, FP 1). The focus of value creation is moved from the manufacturer as creator to co-creation through customer interaction (Vargo and Lusch 2008), whereby the quality of the service is determined by the customer’s perception rather than by the engineering on the side of the provider. Hence, value is always co-created by the customer (FP 6). Value is deployed over a period of time which exceeds the discrete moment of sales and distribution.

SDL also states that operant resources - knowledge and skills - are the fundamental source of competitive advantage for the actors in the ecosystem (FP 4). Service providers apply their knowledge and skills for the benefit of another entity or the entity itself (Lusch and Vargo 2008). In the context of industrial services, the use of a digital twin based on data-based models and analytics represents an operant resource.

When designing a new service, it is essential to first define and understand the target customers and to explore their needs for service in his specific context. The benefit realized for the customer depends strongly on the customer himself and on his individual situation and context (FP 10). Meierhofer and Meier (2017) provide an approach for the systematic development of service value given the outcomes of analytics. The paper describes how analytics-based results can systematically be deployed into service value.

From service science and service design, there is a comprehensive set of methodologies for designing relevant value for customers (Lusch and Vargo 2008, Osterwalder et al. 2014, Stickdorn et al. 2017, Brenner and Uebernickel 2016). The specific literature about service design (Osterwalder et al. 2014, Stickdorn et al. 2017, Brenner and Uebernickel 2016) describes how to design value propositions that are relevant for the customer. Service is designed in an iterative process consisting of several distinct phases. In all steps of this process, there are specific design challenges to be solved. With the data available today and the tools to analyze it, better solutions for these challenges can be found.

2. DATA-DRIVEN SERVICE DESIGN

Service needs to provide value in use to the actors (users or customers) involved. This value needs to take into account not only the functional, but also the social and emotional needs of these individuals. The literature (Osterwalder et al. 2014) provides templates and procedures for the systematic design of value propositions. The customer needs are analyzed in terms of customer jobs to be done, pains, and gains. Customer jobs to be done are tasks and problems that the individual on the customer side needs to tackle and solve. Pains are factors that annoy the customer while doing these jobs, whereas gains provide the outcomes and benefits that the customer strives for. The customer jobs, pains, and gains are shown in the so-called value proposition canvas (Figure 1). In the design of the service value proposition, features fitting with the customer jobs, pains, and gains are systematically deployed. This results in the products and services fitting with the customer jobs and the pain relievers and gain creators fitting with the pains and gains, respectively. Following this systematic approach, the resulting services are centered around the needs of the user.

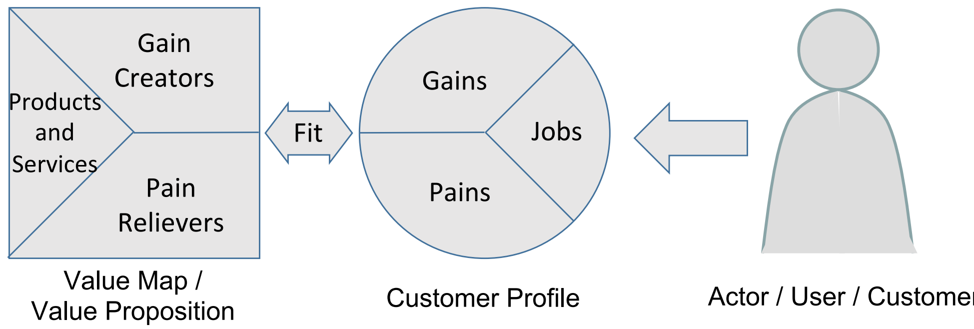

Figure 1: Designing service value propositions based on the customer's jobs, pains, and gains.

The value proposition needs to be designed specifically for each actor of the ecosystem and for the different phases of the life-cycle (West et al. 2018). In the case of services for business-to-business ecosystems, as considered in this paper, this means elaborating the value proposition separately for the individuals within the boundaries of the business organizations, not for the companies as a whole. These may be, for instance, individuals responsible for purchasing, installing, or operating equipment.

For taking into account the life-cycle of the product, we consider the different phases of the whole product service system (PSS) life-cycle as described by (Wuest and Wellsandt 2016), i.e., from "beginning of Life" (BOL) over "Middle of Life" (MOL) to "End of Life" (EOL) (Figure 2). The service design process describes the systematic procedure consisting of several phases from evaluation of the customer needs, over the design and testing of the value proposition (in the BOL phase), to the deployment and operations (MOL phase), and the replacement or upgrade (EOL phase) of the PSS. Although there is no standard service design process, understanding the customer needs and creating customer insights is always the starting point. This is followed by iterations of designing, testing, and improving the service (Osterwalder et al. 2014, Stickdorn et al. 2017, Brenner and Uebernickel 2016).

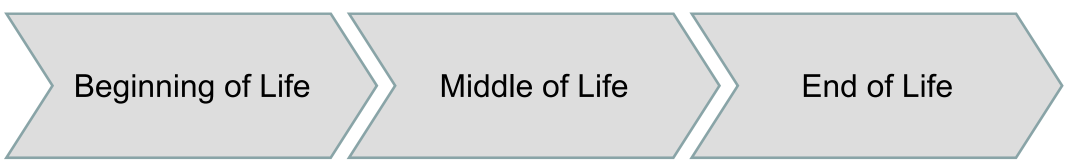

Figure 2: Phases of the product life-cycle to be covered by services.

According to the literature there is still a gap to be filled for a systematic procedure for designing data-driven services. Further research for data-driven service design is relevant and required (e.g., Peters et al. (2016), Spohrer et al. (2015)). In particular, there is a big potential for data-driven services in manufacturing and especially for SMEs. According to Taoa et al. (2018), data provides the benefits of customisation, self-organisation, self-execution, or self-learning in the data-driven smart manufacturing context. This enables data-driven smart services like maintenance, quality control, process monitoring, material logistics, planning, and smart design. Moeuf et al. (2017) note that analytics is rarely used in SMEs. However, SMEs are starting to use IoT (internet of things), which prepares a basis of data, which will be followed by analytics. The gaps in the SMEs' knowledge and competences to develop data-driven services are confirmed by the study described in Meierhofer et al. (2019). It reveals that SMEs are less familiar with data science tools than large companies; they mainly know BI (business intelligence) tools and are less likely to use advanced analytical tools. However, the study shows that SMEs are more open to the formation of partnerships and ecosystems than large companies, which paves the way for the concept of service value creation using digital twins, as discussed in this paper.

Against the background of service dominant logic, the knowledge and skills applied (i.e., the operant resources) substantially stem from the data and their analysis, which will be incorporated in the digital twin. The benefits can be structured and modelled according to Porter and Hepelmann (2014) in four increasing levels: 1) monitoring, 2) control, 3) optimization, and 4) autonomy. An example for 1) “monitoring” is monitoring the condition of machines: the service provider can remotely observe the health status of the machine running on the customer’s premises. In level 2) “control”, a feedback loop is established to control the machine, based on the outcomes of the monitoring. This may e.g., result in adapting operational parameters to improve the health status of the machine. The optimization applied in level 3) “optimization” pursues an optimization target such as energy consumption or number of units produced in a time period. Autonomous systems in level 4) “autonomy” would be e.g., fully self-organized shop floors.

3. FIELD STUDY RESULTS

A quantitative survey with firms in manufacturing, as well as a series of in-depth interviews, were conducted in order to validate the findings from the literature. The survey with 53 responses carried out in this study showed that the areas with the most to gain were considered to be (Figure 3): operations, service, and new technology development. Also important, however smaller, benefits were anticipated in marketing and sales, logistics (out- and inbound), and procurement.

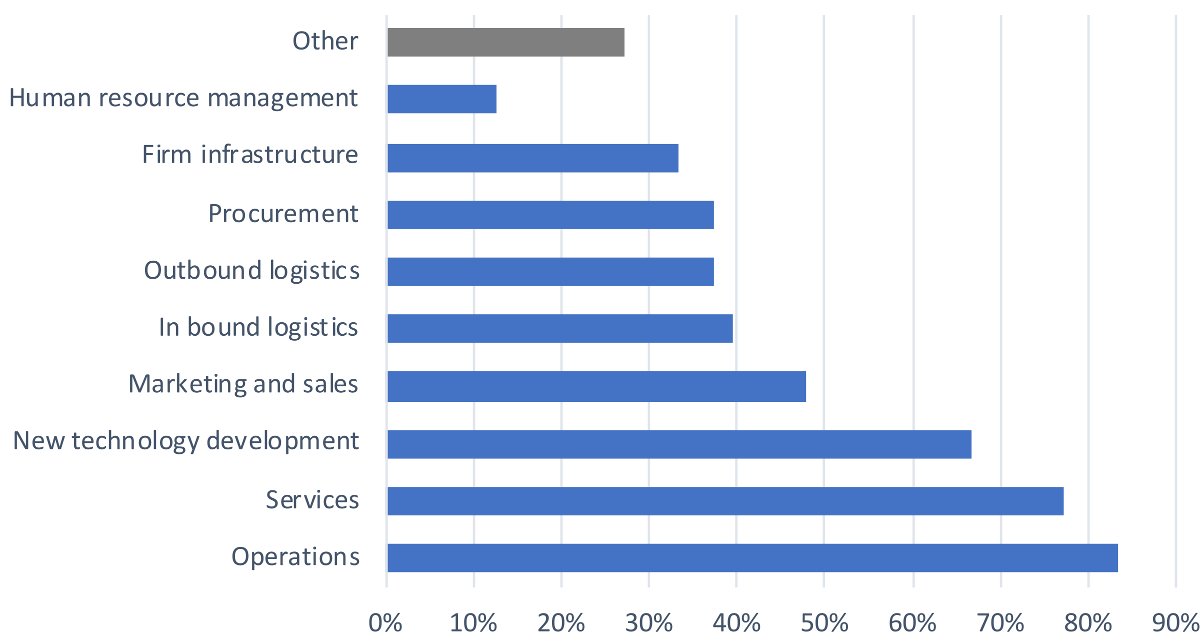

Figure 3: Beneficiaries of service value from the digital twin.

The interviews were analyzed based on four interview questions: what is a digital twin; what are its benefits; who benefits; how would you model a digital twin. The main findings of the interviews are presented in Table 1. The results here confirm the wide and varied potential use of the digital twin and what different experiences people expect. There is a general alignment with the interviews and the survey findings. The literature, survey and the interview data will be combined to a new conceptual approach in section 4.

What is a digital twin?	What are the benefits?
- It is the entireness of information in a digital form, down to individual components. - All sensor data, production data and process information over the entire life-cycle of the equipment (BOL, MOL, EOL) allowing context to be understood. - It can include (should) all process information. - Real-time data (dynamic) allowing simulation and forecasting to support decision making. - A system that allows individual machines or aggregation of assets to be viewed. - It is all technical data / it includes business data and allows business relevant information to be predicted. - It is a tool for supporting knowledge management. - It is simply a model of the physical asset that allows predictions to be made, it must be connected to the real world.	- It offers to improve current practice and support optimization along the asset's life-cycle. - It allows every machine to be a test machine. - Identification of quality assurance (QA) issues before final machine acceptance. - It offers a platform for collaboration. - It allows the machine to be offered as a service. - It allows the whole system (technical and business) to be optimized. - It supports better (more informed) decision making though better prediction. - It allows users to understand the condition of the equipment. - It allows the whole installed base to provide input for the next generation of machines. - It works better when it is not just an HMI copy. - It is a codification of knowledge.
Who benefits? - The operations and maintenance team as they can cooperate better. - The NPD team who have access to more information and at different operational parameters. - The service teams, as they have more support and can better plan their work. - Many actors up-stream and down-steam of the product/equipment. - Actors who are connected to the outcome of the business. - The service teams, as they have more support and can plan their work better.	**How would you model?** - From a simple Excel model to a complex real-time AI to machine learning (off process). - Rule-based modeling. - AI models can be used to create simple rules in the local digital twin. - Agent-based simulation and discrete event simulation. - Systems simulation, numerical Methods (CFD, FEA) - 3D modelling

Table 1: Results from the twelve interviews.

Each actor will have different jobs, pains, and gains and these are dependent on the situation in question; in effect, the actor's problem. The digital twin needs therefore to match closely with the "problem of the actor" in a systematic approach, so that the resulting services are centered around the individual needs of the actor in the particular situation. This fosters a close relationship and co-creation of value between the different actors (e.g., the providers and the customers), which contributes to long-term relationships and loyalty. There is no one single applicable value proposition but rather, many value propositions that are based around individual actors and their situational problems. In particular, the digital twin lends itself to contribute to the value propositions by supporting all of the actors around the

PSS, in particular by relieving the pains and increasing the gains of the actors. As discussed before, the digital twin is based on a combination of data, analytics, and the visualization of the insights such that they support decision-making by providing advice. Depending on the phase of the product life cycle, different components of the twin and different data are required.

<u>The BOL phase</u>

A digital twin of the existing production line and shop floor helps to simulate which model of the new machine fits in and supports the existing operations. For this, an abstract model of the machine is typically fit into a discrete event simulation model of the shop floor. Data is required about the capacity and processing times of the new and the existing machines. Furthermore, a physical 3D model of the machine may help positioning it in the environment of the shop floor using augmented reality technology. In the value model according to Porter and Hepelmann (2014), this can be considered an optimization task.

<u>The MOL phase</u>

Critical components of the new machine may be constantly observed by means of a component level digital twin. Real-time data of the component may be constantly fed back to the twin, which, by means of e.g., finite element modelling techniques, can predict the behavior of the component in the near future, can send out control commands for the machine, or issue alerts if there will be a failure or a potential loss of performance. This can be considered a monitoring, control, or optimization task in the value model according to Porter and Hepelmann (2014). For this, detailed physical data is required about the critical component of the machine. Additionally, of course, the discrete event shop floor model can also be constantly applied during the middle of life phase. Moreover, a digital twin on the level of the business ecosystem may be applied during the middle of life phase to constantly monitor, control, and optimize the logistics stream across companies. Technically, a systems dynamics model will be applied for this. Data is required about the logistics flows in the system including production and customer dynamics.

<u>The EOL phase</u>

For the end of life phase, a digital twin based on component and shop floor model can e.g., be applied to detect the optimum time for replacing a machine or its components. Additionally, the health status of individual components can be assessed using component level digital twins, typically based on finite elements modelling techniques. Detailed physical data on a component level is required here. Given this, the effectiveness of recycling or refurbishment strategies can be improved. Hence, again, there is a case for covering the value levels from monitoring to optimization according to Porter and Hepelmann (2014). The end of life phase can also benefit from a digital twin on the factory or shop floor level for assessing an adequate replacement.

4. APPLYING THE DIGITAL TWIN AS AN ENABLER FOR DATA-DRIVEN SERVICES

The approach discussed in this paper considers the digital twin as a data-driven operant resource for the design and provision of services. The twin is structured according to technical and business hierarchies. The product which is in the focus of the industrial service on the one hand consists of sub-components and on the other hand is part of a larger system. Therefore, the objects may range from physical components, over integrated machines, up to shop floors, factories, and systems of factories (Porter and Hepelmann, 2014).

The research question in this study requires framing within the context of data-driven product service systems so that the complexities of the B2B (business to business) environment and digital twins can be investigated in the industrial world. Around this framing the research question is: “In a complex data-driven product service system, what service value can the digital twin provide, who is the provider, who is the beneficiary, and which data and analytics are required?”

Layered Approach for Service Value Creation using the Digital Twin

In this section, we discuss a structure of the digital twin that lends itself to the design of industrial services along the product life-cycle. From the perspective of the product life-cycle management phases (BOL, MOL and EOL), systematic service design delivers customer value in all these phases (Figure 4). The actors in the ecosystem, i.e., the diverse users along the product life-cycle, require value propositions that fit their jobs to be done, pains, and gains. These diverse instances of value propositions are generated by the family of twins, consisting of several sub-twins each serving a specific sub-set of jobs to be done, pains, and gains, and using specific elements of data and models.

According to Qi and Tao (2018), value creation based on data and analytics is very similar to that based on the digital twin. Data and analytics can be considered as an enabling part of the digital twin. Although technical discussions of the digital twin predominate in literature, there are also sources that illuminate the object from the perspective of services and value contribution. According to Tao and Zhang (2017), the integration of the digital twin and service represents a promising research direction which should be addressed in future paradigms. Boschert and Rosen (2016) as well as Qi et al. (2018) and Tao and Zhang (2017) discuss the application of the digital twin along the product life-cycle. It can provide value in the form of services in product design and engineering, in the design and optimization of the shop floor, in product operations and usage monitoring, and in after-sales services and prognostics and health monitoring of the product.

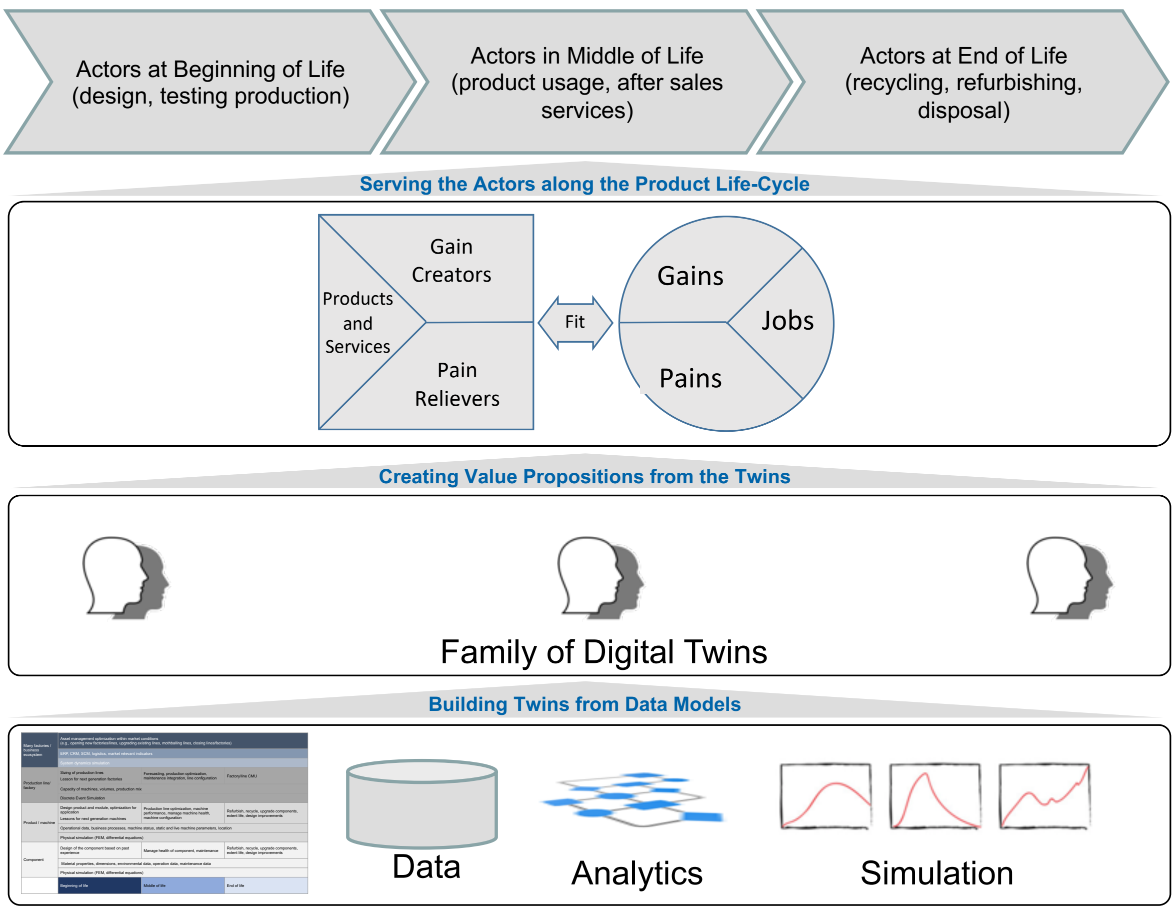

Figure 4: Data-driven value creation framework of the digital twin

Given the wide range of interpretations of the term “digital twin”, it becomes evident that further dimensions of structuring are required in order to get a differentiated perspective on the value contribution. Sources (Qi et al. 2018), (Hartmann et al. 2018), (Malakuti and Grüner 2018), (Malakuti et al. 2018), (Wagner et al. 2018) suggest dividing the twin into different levels e.g., component / system / system of systems. Suitable modeling tools included: based on physical-law (e.g., FEM), rules, statistical information, machine learning, system dynamics, as well as others. However, it becomes evident that these approaches to layering are not yet sufficiently lending themselves to a structured approach for describing the service value contribution. A hypothesis for a layer elaborated in the current study is shown in Figure 5.

Many factories / business ecosystem	Asset management optimization within market conditions (e.g., opening new factories/lines, upgrading existing lines, mothballing lines, closing lines/factories)		
	ERP, CRM, SCM, logistics, market relevant indicators		
	System dynamics simulation		
Production line/ factory	Sizing of production lines Lesson for next generation factories	Forecasting, production optimization, maintenance integration, line configuration	Factory/line CMU
	Capacity of machines, volumes, production mix		
	Discrete Event Simulation		
Product / machine	Design product and module, optimization for application Lessons for next generation machines	Production line optimization, machine performance, manage machine health, machine configuration	Refurbish, recycle, upgrade components, extent life, design improvements
	Operational data, business processes, machine status, static and live machine parameters, location		
	Physical simulation (FEM, differential equations)		
Component	Design of the component based on past experience	Manage health of component, maintenance	Refurbish, recycle, upgrade components, extent life, design improvements
	Material properties, dimensions, environmental data, operation data, maintenance data		
	Physical simulation (FEM, differential equations)		
	Beginning of life	Middle of life	End of life

Figure 5: Layers of the digital twin with design objective, data used, and simulation technique applied.

5. CONCLUSIONS AND FURTHER DEVELOPMENT

The study showed that the digital twin can be considered a data-driven enabler/support for providing services. The structuring of the twin along the phases of the product life-cycle as well as in the hierarchy of the technology and the business decisions leads to the concept of the family of twins. The field study conducted confirms the potential of the digital twin for services. In each of the phases BOL, MOL, and EOL, the digital twin can provide service value to specific actors in the product service system.

It also becomes clear from the field study that more foundations are needed for clear structuring and for realizing the operational benefits. For example, integrating the data based concepts across the layers and the phases of the life-cycles requires further investigation. E.g., the appropriate granularity of the family of twins given a service purpose needs to be determined. Additionally, the importance of contextual data integration requires further studies. Moreover, the generalizability of the concept to different industries must be examined more closely.

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