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Concept for Digital Twin-based predictive Value Engineering

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Abstract

Competitive products must fulfill numerous requirements, including the needs of stakeholders and economic constraints, simultaneously. Considerable costs emerge in manufacturing, whereas the design has a significant impact on these costs. Design decisions are driven by multiple criteria, as many, but competing, requirements need to be met. Often, valid information for decision-making is limited in the early phases of development. The presented approach of predictive Value Engineering is based on a Digital Twin concept, which applies existing knowledge from Product Generation Engineering and provides its context-specific use during development. The goal is to support cost decisions for value-driven design and improved manufacturability.

Keywords: *Value Engineering; Product Generation Engineering; Digital Twin*

1. Introduction

New product ideas and concepts require extensive investigations, including functional feasibility and manufacturability. A relevant key is to establish new value and competitiveness by identifying future customer needs in the early development phases. Numerous functions serve as innovation drivers but enhance the product complexity and costs [1]. Mastering the innovative value creation with competitive costs, Value Engineering (VE) is utilized as a method during product development. Today, VE primarily concerns the demand-based provision of relevant functions. Decisions are based mainly on the functions. However, the decisions about context-specific impacts on functions, e.g., impacted properties on functions, require valid information that comes from historical data [2].

Often, when additional elements or attributes are integrated into new products, the function fulfillment requires many efforts for sufficient investigation. However, the knowledge here is distributed among the domains with diverse impacts on the product [3]. Predictive analytics is commonly used to draw future events based on analyzed historical data. Primarily, prediction models add value by forecasting new scenarios to improve the performance [4].

Against this background, this paper aims to provide a concept to predict VE for new products in the early development phases based on Product Generation data and context-specific VE knowledge.

1.1. Structure

Based on an overview of the fundamentals of Product Generation Engineering (PGE), Value Engineering (VE), and Digital Twin (DT) in Section 2, the contribution investigates the state of research of VE-approaches. The outcome of the third Section is a systematization of research gaps that form the concept requirements for a Digital Twin-based Value Engineering (DTVE) approach. Moreover, the DTVE requirements are presented by an industry-related evaluation of predicting VE through several criteria. Finally, the DTVE concept is discussed and reflected by an outlook.

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2. Fundamentals

2.1. Value Engineering

Since the design primarily determines many costs in the early phase, but not all, many decisions are needed to evaluate concept maturity with limited information [5]. The costs mainly refer to material and associated production processes as manufacturing costs [6].

Usually, the manufacturing costs are estimated in the early phases based on experience as a bottom-up approach, which is associated with uncertainties and subjectivity from experience. Target Costing (TC) is utilized as a strategic cost method. Derived from a target market price for the customer´s willingness to pay, the target profit margin is subtracted to receive the maximum allowable costs as a top-down approach. However, TC creates transparency for cost reduction potential but does not lead directly to cost reduction [7].

To optimize costs and values in the context of product development, Value Engineering (VE) aims to improve the design by focusing on function-related costs. As an essential VE element, the function represents the effect of a product or its components as value objects. Originally, Value Analysis (VA) was specifically implemented to improve existing products. Later, the approach evolved to new products under the term VE [2,8]. The main idea of VE is eliminating overdimensioned specifications without impacting the product's core function and finally, the value. The purpose of VE is to maximize the value-driven design and not only reduce costs [9]. Figure 1 illustrates the main VE phases according to DIN EN 12973, such as planning, data and function analysis, and idea evaluation. The functions are specified through related characteristics [2]. The Function Cost Analysis (FCA) represents the central point. As direct costs are usually allocated to components from assembly groups, the evaluation of function to costs poses a challenge. This is intended to create a balanced relation between the function for design and incurred part costs as a basis for purchasing [2,8].

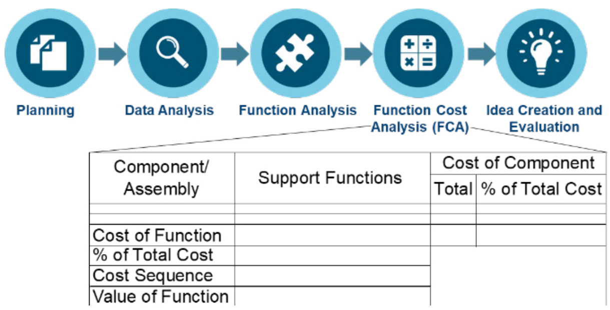

Figure 1: VE Process focusing on FCA based on [8,10].

For value-based decisions, the data analysis, e.g., about costs and requirements, follows the planning. Usually, the requirements are linked to functions. In the FCA, the parts are linked to the functions in percent to create the function cost share of the total component costs. This builds the basis to illustrate cost-driving but also functions that are potentially affected to initiate the value-driven evaluation [2,8].

2.2. Product Generation Engineering

Products always consist of several elements [11]. Developing a new Product Generation is often based on reference elements from predecessors and existing solutions, according to Albers et al. (2015). The reference product (RP) can be from the company's own predecessor products, technologies, or other products on the market. The goal is to achieve differentiation characteristics to the RP [12].

Albers et al. (2019) also describe three variation types in Product Generation Engineering (PGE). In general, selected subsystems of the RP are adopted for the new Product Generation (NPG) as an information basis. While in the carryover variation (CV) the principle is not adapted, the embodiment variation (EV) focuses on modifying the subsystem with same solution principle, but with variations in relevant properties. In the principle variation (PV) the principle is adapted by removing or adding elements. In this context, the product development is reflected as a dedicated selection between reference elements and variation types [13, 14].

As a key factor, the product profile focuses on customer benefits at an early stage. Here, the variation is linked to functions, properties, requirements, and stakeholder needs. The product profile considers the technical and economic feasibility during product development with related risks. Product properties support the product similarity analysis subjectively, but also objectively to identify product differentiation [15]. Based on the PGE approach, the experience knowledge during development is drawn considering the variation types (CV, EV, PV) and the product profile.

2.3. Digital Twin

One of the fundamental tasks in product development is creating a master model with relevant data before the actual manufacturing is initiated. As the physical product does not exist in the early phases, the virtual representation of all relevant product characteristics and properties is defined as Digital Master (DM). Through the fusion with appropriate data, the DM can project the expected behavior or product properties of the Physical Twin (PT) based on real data [16]. For example, several cars of the same type were manufactured according to same drawings and production instructions. Here, all models and related data of the produced cars are defined as master [17].

Once the product has been implemented as a physical instance, the real data from the product life cycle phases can be obtained from the DM and stored in the digital shadow of the product. Extending the PT through mutual communication to a Digital Twin represents the Digital Twin Solution in Figure 2. The acquired know-how from existing DTs can be utilized as feedback for optimizing the actual product or developing NPGs. The Digital Twin can be developed from the DM with related adaptations on the PT [16,18].

The link between DM and Digital Shadow through the information flow generates an added value of the DT [17]. As an informational DT, the data are gathered from the PT and combined in a useful way. The goal is to provide a model that is based on combined data sources [19].

Especially the fusion between physical and virtual data requires data preprocessing and advanced data analysis, such as data mining [4].

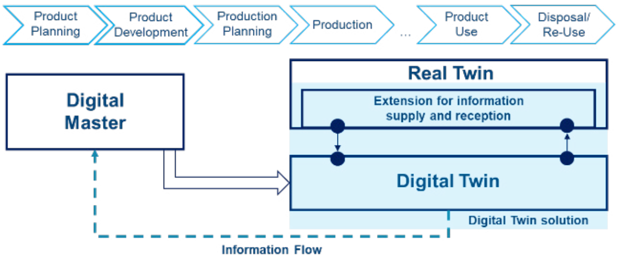

Figure 2: Digital Master within the Digital Twin Solution based on [18]

Consequently, the data are optimized through iterations to discover the evolution. Here, Tao et al. (2019) presented many DT cases in industry that lead to accurate prediction based on historical data [15].

3. State of Research

As this paper aims to provide a conceptual framework to predict VE, the research evaluation is initiated with the scope of this research (1) in Table 1. In addition, the fundamentals from VE (2), PGE (3), and DT (4) are considered (cf. Section 2) as assessment criteria to investigate the simultaneous fulfillment of the research to predict VE. From the PGE view, it is essential to identify the relation of variations to VE, as well as from the integration view through DT.

Table 1: State of research for predictive VE based on [21–28].

● - addressed ◑ - partially addressed ○ - not addressed	Sahu et al. (2023)	Vijayan et al. (2019)	Bock et al. (2016)	Sadi et al. (2015)	Behncke et al. (2014)	Leber et al. (2014)	Zarandi et al. (2011)	Ibusuki et al. (2006)
1 Scope of Research								
1.1 Conceptual framework	●	○	●	●	●	◑	●	●
1.2 Planning horizon (i.e. VE prediction)	○	○	◑	○	○	○	◑	○
2 Value Engineering								
2.1 Function Cost Analysis (FCA)	●	◑	◑	●	●	●	◑	●
2.2 Target Costing (Top-down)	◑	◑	●	●	●	○	○	●
2.3 Connection of Requirements, Functions, Costs	●	●	◑	●	●	●	◑	●
3 Product Generation Engineering								
3.1 Consideration of variation types (CV, EV, PV)	◑	◑	◑	○	◑	◑	◑	◑
3.2 Product profile	◑	◑	◑	◑	◑	◑	◑	●
4 Prediction Framework								
4.1 Prediction approach (VE)	●	○	●	●	●	◑	◑	●
4.2 Digital Twin interaction (with Digital Master)	○	○	◑	○	○	○	◑	○
4.3 Decision Support	●	●	●	●	●	◑	●	◑
5 Applicability								
5.1 Phase model	●	◑	●	●	●	◑	◑	●
5.2 Stakeholder interaction	●	◑	●	●	●	◑	◑	●

To ensure the implementation of the VE conceptual transformation, the applicability (5) of the research papers is investigated. In general, the literature distinguishes research in cost prediction and VE-approaches. The research around cost prediction, among other areas, with machine learning focuses on cost prediction, while the research scope around VE extends the original process from Section 2.1.

As an example, Hennebold et al. (2022) developed a machine learning approach to predict costs in the early development phase. The research motivation was derived from the standard cost estimations with limited accuracy. Here, the research potential is identified by the required connection of requirements, functions, and costs for VE. Especially, the classification of decision criteria to predict specifically the value-related functions is not explicitly addressed in the research [29].

In the following four papers from Table 1 are presented to highlight the VE with FCA prediction.

Bock et al. (2016) developed a mathematical decision model to determine the efficient product quality program in the VE context. The goal is to maximize the contribution margin based on target costing and pricing. Here, the approach partially addressed criterion 4.2 of Digital Twin by introducing real-time VE to control variances as the concluding concept step with an iterative loop to TC and pricing. The concept also includes current database and VE knowledge. When addressing the decision-making in sales production departments, the concept does not specifically refer to predicting FCA for value-driven design. Moreover, the integration of a DM model for FCA prediction to complement criterion 4.2 is not explicitly addressed [22].

Sadi et al. (2015) present an extended framework for information distribution within VE, focusing on stakeholder analysis. The contribution addressed the VE criteria through matrix-based visualization. Although the information acquisition plays a central role, the paper does not explicitly contain the DT interaction or prediction model for NPG from RPs [21]. Besides, the model for integrated VE (IVE) by Maisenbacher et al. (2013) compares the current costs with target costs in terms of requirements, functions, and components [30]. The goal is the identification of optimization potentials throughout the domains (requirements, functions, components). However, the different variation types for NPG configuration are not explicitly addressed [21].

Behncke et al. (2014) extend the original VE by manufacturing and supply chain processes to highlight the cost-value ratio. The conceptual transformation of the VE process considers the dependencies between the determination of suppliers for components and assigned manufacturing and assembly, but the prediction of function costs for design value based on RPs is not explicitly addressed [27].

Ibusuki et al. (2006) combine FCA and TC in their methodology along the development process with stakeholder tasks. The methodology introduces VE criteria during the stages of concept, project, and validation with integrated TCs. However, the DT interaction with the prediction model for FCA is not explicitly considered [23].

Based on the state of research, the identified research gap of predicting VE, specifically the FCA throughout DT, leads to the following research question (RQ):

➔ How can the Digital Twin be integrated to predict Value Engineering in the early development phases?

Overall, the research intends to focus on elaborating a conceptual framework that supports the VE prediction. Here, the criteria in Table 1 are considered as concept requirements to transform the VE through the phases in Section 4.

4. Conceptual Framework

In this Section, the concept of Digital Twin-based predictive Value Engineering (DTVE) is introduced as decision support for design and purchasing in the early development phases. The DTVE is shown through concept phases in Figure 3 by focusing on target costs (cf. 2.1) to avoid overspecification in design with corresponding component prices for purchasing. The goal is to predict the function costs of a new Product Generation (NPG) as G_{n+1} based on the Digital Twin-driven VE of G_n as the reference product (RP). As decision support, the DTVE intends to improve the quality of VE results during the development of G_{n+1}. The objective is to provide a better and earlier basis for valid cost decisions. In the following, the FCA (cf. 2.1) is considered as a basis to provide the component price from the view of purchasing.

Phase 1: Physical Twin

As a starting point for the VE prediction, the Physical Twin (PT, cf. 2.3) builds the basis with relevant historical data and context-specific VE knowledge over Product Generations. Focusing on the VE prediction of G_{n+1}, the planning and actual data from G_n serve as input. The planning data includes mainly context-specific models (master) and documents for VE, while the actual data represents the G_n after production. The identification of value drivers (cf. 2.1) over Product Generations in Phase 1 serves as input for the VE prediction.

As the DTVE aims to support cost decisions in the early development phases, the FCA cannot be carried out by linking functions to physical parts and costs (cf. 2.1). Based on top-down target costs, the function weighting needs to be derived from context-specific VE knowledge.

For example, the customer requires a variation of the displacement as an engine characteristic to differentiate from the RP (cf. 2.2), but also a specific power as a property. Both competing requirements have impacts on the functions, e.g., storing oil in the oil sump as a component. As value drivers, variations in engine displacement and power impact the design of the oil sump to realize its functions. The scope is on determining the importance of function weighting with target costs, especially for the EV and PV of G_{n+1} (cf. 2.2). In the context of predicting VE, the value drivers intend to highlight the product differentiation over Product Generations. The context-specific view of value drivers for G_{n+1} aims to support cost decisions holistically by reflecting the function importance of impacted domains in the early development phases.

Based on the goal of providing valid cost decisions, the link between the Digital Shadow and the DT, but also to the DM, is crucial for context-specific VE knowledge and Product Generation data.

Phase 2: Digital Shadow

The Digital Shadow (cf. 2.3) is generated from related data according to the value drivers of existing reference products, as well as from development data of Gn+1. The data serve as a basis for identifying the value drivers with related data. This Phase aims to prepare the DTVE after data collection from various sources at two levels: Processing (I) and Mining (II). The G_n data from Phase 1 is processed for the DT, while the data mining combines G_n and G_{n+1} data for the prediction model in Phase 3.

Data Processing (Level 1)

Due to different data formats, Level 1 aims to transform the raw data into qualitative and quantitative information for the FCA. Essentially, the dependencies of the value drivers from G_n are considered. The function weighting is processed according to context-specific VE knowledge.

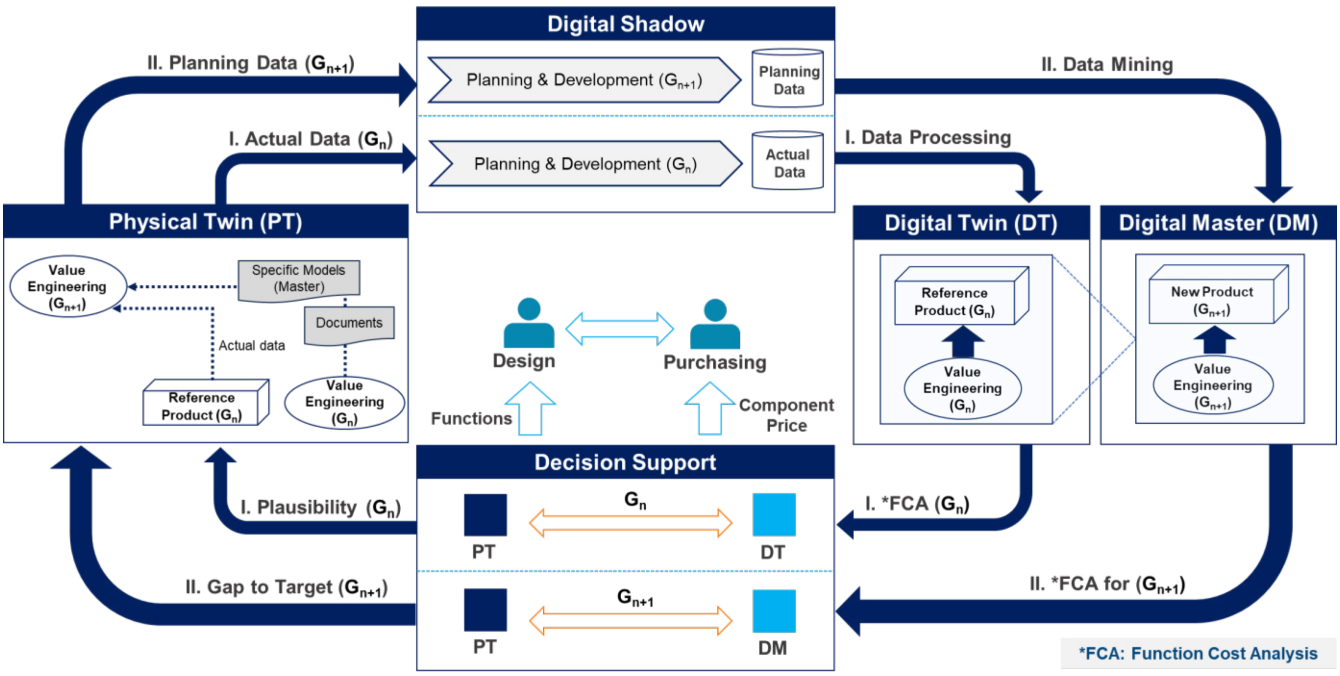

Figure 3: Conceptual Framework of Digital Twin-based predictive Value Engineering (DTVE).

Data Mining (Level 2)

Due to many uncertainties from the G_{n+1} development, it is crucial to investigate interdependencies within historical data. The main goal is to identify impacting measures for value-driven design from historical data. Especially for the EV and PV (cf. 2.2) of the G_{n+1}, it is essential to investigate the importance of the function. For CV parts, the results are gathered from Level 1. Analyzing correlations between Product Generation data in terms of value drivers intends to highlight the importance of the function.

Phase 3: Digital Twin Model (a)

The DT (cf. 2.3) evolves from processed data in Level 1. The goal is to determine the function weighting through simultaneous processing of value drivers from Phases 1 and 2. In contrast to the sequential mapping of functions, requirements, and costs (cf. 2.1), the value drivers are processed from context-specific VE knowledge across domains on (sub-) system and component-level. Through the interoperability of multiple domains, the DT aims to provide the basis for analyzing the value-driven design of processed dependencies. Here, the outcomes are the function costs per component of the G_n.

Digital Master (DM) Model for VE prediction (b)

The DM (cf. 2.3) goal is to predict VE for G_{n+1} based on the DT results as input, but also historical data from the database of various reference products (RPs). From the example of displacement variation, the effect on impacted value drivers as cost decision criteria is investigated as the DM considers the dependencies across domains of the engine. Mastering the model-based VE prediction requires value drivers from the database of reference products to identify the effects of new elements on the importance of functions. Overall, the DM model intends to provide the function weighting for the G_{n+1}, especially in the case of EV or PV, and map with the target costs accordingly.

Phase 4: Decision Support

From the results of the DT and DM, the main stakeholder interaction is between design and purchasing in this Phase. The DT provides VE as descriptive output, which presents Level 1. Especially for existing CV parts, the DT generates insights from a design view of hidden dependencies between the value drivers. From the DM, the VE is predicted as Level 2 for the G_{n+1}, especially for the estimated EV and PV. In contrast to Phase 1, the DT and DM provide a holistic view of the dependencies between the value drivers that support the functions based on Product Generation, VE knowledge, and data. For purchasing, the corresponding allowable component price is given based on the target costs of G_{n+1} in relation to the function weighting. Consequently, the results from the decision Phase are compared iteratively with Phase 1. In the case of DT, the function costs are compared with the actual G_n.

Here, the decision support aims to improve existing products by prioritizing function importance in the sense of VA (cf. 2.1). For the DM, the predicted function costs are compared as gap-to-target to the function costs of G_{n+1} as expert-based estimation during planning in Phase 1. This is intended to avoid design overspecification by comparing the function importance with the mapping target costs of G_{n+1}.

5. Concept Evaluation

In this Section, an industry-related utility analysis is presented based on the DTVE concept. The purpose of the evaluation is to assess the potential for industrial application. Initially, criteria were collected from experts of an engine manufacturer to compare the original VE process in 2.1 with the DTVE in Table 2. The criteria are evaluated first on a scale of 1-5, where 1 is the lowest and 5 the highest. After the criteria are weighted in percentage to indicate their importance. According to the first criterion of adaptivity and changeability, the VE should provide flexibility to examine changes during development. Since the DTVE was introduced as an iterative framework, it is estimated to have the highest score. For the usability either as a developer of DTVE or as a user to acquire efficient investigation, the DTVE outweighs. From the user's view of analyzing VE results, the original VE requires expert know-how to understand sequential process steps and data.

Further, the interoperability between elements plays a significant role from an industrial view, according to expert-based knowledge from Simulation. However, the interoperability needs to be applied to use cases, not across projects. For instance, larger pins will impact the connecting rod and several interfaces. These impacts are linked to the solution space flexibility, where the evaluation between original VE and DTVE is nearly balanced. For example, a thermodynamics calculation uses scenarios regularly, but structural simulation requires parameterization; the function costs need to be calculated separately. In this case, the DTVE shows a higher score, which explains the next criterion of early decision support by predicting VE than sequential processing. predicting VE than sequential processing.

Table 2: Industry-related utility analysis between DTVE and VE.

Utility analysis rating: 1 - lowest; 5 - highest	Weighting		Original VE		DTVE	
Assessment Criteria	**(1-5)**	**(%)**	**(1-5)**	**Score**	**(1-5)**	**Score**
Adaptivity, Changeability	5	16,13%	2	10	5	25
Usability	5	16,13%	2	10	5	25
Interoperability	3	9,68%	2	6	5	15
Solution Space flexibility	4	12,90%	3	12	4	16
Early Decision Support	5	16,13%	2	10	4	20
Data Management	5	16,13%	1	5	5	25
Procedure Costs	1	3,23%	5	5	2	2
Operational Complexity	1	3,23%	3	3	5	5
Integration of interfaces	2	6,45%	3	6	5	10
	31	100,00%		67		143

Moreover, the data management was evaluated higher for the DTVE as several data can be processed and mined simultaneously. In case of procedure costs, the DTVE incurs higher costs initially for the implementation, but could decrease costs in the long term. Similarly, the operational execution complexity is higher until the computational interfaces are linked together. Primarily, the DTVE can be standalone and not necessarily integrated with existing systems and processes in projects. Overall, the utility analysis results strengthen the implementation of DTVE.

However, the added value was emphasized for the prediction model rather than the virtual representation of RPs during the industry evaluation.

6. Summary and Outlook

This paper presented a framework as support for design and purchasing through predictive Value Engineering (VE) to avoid overspecification in the early development phases. The framework introduced value drivers as guiding criteria for cost decisions during the new development. The conceptual integration of the Digital Twin solution allows the analysis of value driver dependencies for an existing product to investigate the function importance through simultaneous processing of impacted domains. Moreover, the framework extends the model-based prediction as the Digital Master interacting with the Digital Twin. In the case of adapting properties or principles for new Product Generations, the Digital Master supports the main goal of predicting VE based on context-specific VE knowledge and Product Generation data.

Through the guiding concept phases between the physical spaces and virtual prediction model, the output for design represents the function importance in relation to the component price as support for purchasing from the target costs. The introduced framework allows the iterative comparison between predicted function costs and expert-based estimations during the early development phases.

Further research should investigate the relation between impacted domains and the context-specific value drivers. The structure between the value drivers and function dependency needs to be analyzed. The methodology for identifying impacts between function weighting and adapted properties or principles in the early development phases needs to be developed. Besides, the impact of value drivers on Product Generation data requires further analysis on implementation procedures. As the goal of value-driven design, which also highlights improved manufacturability, is achieved through simultaneous processing of Product Generation data, it is essential to evaluate and structure the data with an assessment of appropriate methods.

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