Rigor in Applied Data Science Research Based on DSR: A Literature Review

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Abstract: Design Science Research (DSR) enjoys increasing popularity in the field of information systems due to its practical relevance and focus on design. A study from 2012 shows that DSR publications in general have a weak rigor in connection with the selection and use of research methods. At the same time, there has also been a recent increase in Data Science publications based on the paradigm of DSR. Therefore, this study analyzes the rigor and the specific characteristics of the application of DSR based on 62 publications from this field. Major deficits are observed in a large part of the sample regarding the rigorous documentation of the scientific process as well as the selection and citation of adequate research methods. Overall 77.4% of the analyzed publications were therefore characterized as weak in regard to their rigor. One explanation is the novel combination of DSR and Data Science together with the speed at which new findings are obtained and published.

1 INTRODUCTION

As a result of the digital transformation, Data Science has developed into a trending topic that has recently become important and is discussed in both, theory and practice (Jordan and Mitchell, 2015). Due to the increasing volume of available data and the easy applicability of machine learning algorithms in various areas, this technology is key to the digital transformation of a company. This leads to major productivity increases through automation (Goes, 2014; Abbasi et al., 2016). Moreover, researchers emphasize the focus on IT artifacts and their analysis, which is particularly relevant for business and society (Benbasat and Zmud, 2003; Saar-Tsechansky, 2015; Abdel-Karim et al., 2021).

Considering the research focus of information systems in the field of Data Science Research, it is not surprising that numerous publications in this context select Design Science Research (DSR) as their research paradigm. DSR has become an established research paradigm in the field of information systems in general and gained in popularity (Alturki et al., 2012). A major cornerstone for this development was laid by the authors Hevner et al. (2004), in which they position DSR as an alternative to traditional behavioral science research (Samuel-Ojo et al., 2010; Gregor and Hevner, 2013; Pascal and Renaud, 2020). The numerous parallels to Data Science research lead Saar-Tsechansky (2015) to conclude that the guidelines defined by Hevner et al. (2004) for conducting DSR research also apply to publications in the field of Data Science Research. However, due to the novelty of DSR in the field of Data Science Research and the interdisciplinary nature of this research area, there are potential ambiguities in adapting the guidelines defined by Hevner et al. (2004). For instance, the guidelines refer to practical relevance. Further, Elragal and Klischewski (2017) argue that Data Science publications often lack such practical relevance. Instead of relevant problems usually use cases with a large number of existing datasets are preferred. The rigorousness of these Big Data datasets is questioned by researchers as well, due to the unclear rigorous collection of data as well as unknown hypotheses behind (Elragal and Klischewski, 2017). In addition, Big Data creates new needs in terms of evaluating artifacts and demonstrating knowledge gain and problem solving (Elragal and Haddara, 2019).

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Consequently, it is important to pay attention to both the practical applicability and the scientific grounding of the Data Science publications. Even before the multitude of ambiguities presented in connection with Data Science, Arnott and Pervan (2012) identified in a study that two-thirds of the publications show weak rigor in connection with the selection and use of research methods. It is currently unknown whether, and if so, how, Data Science publications rigorously apply DSR to meet the demands of a scientific community and the guidelines of Hevner et al. (2004). Therefore, the following research question (RQ) arises:

RQ: How is the rigor of DSR addressed in Data Science research?

The aim of this literature review is to analyze Data Science publications from the past three years claiming the DSR approach and examining their rigor.

To achieve the objective, the following chapter lays the necessary theoretical foundations. Building upon this, the methodology as well as the selection criteria for the research data will be explained in more detail. Subsequently, the data will be analyzed on the basis of the previously defined schema in order to derive statements about the rigor. The findings of this research are summarized in a respective overview at the end of this research work. In the end, after a short summary of the results, the limitations and implications of this paper are pointed out.

2 THEORETICAL BACKGROUND

In this chapter, the terms "Data Science Research", "DSR" and "Rigor" are explicitly presented and explained to provide an overview of the theoretical foundation of this paper.

2.1 Data Science Research

Data Science is an established interdisciplinary field that combines scientific methods, systems, and processes from statistics, information science, and computer science to gain insight into phenomena about structured or unstructured data (Zhu and Xiong, 2015). According to van der Aalst (2016), Data Science is used to assign business value to data. Ethical, social, and legal aspects also play a role when considering the resulting insights (van der Aalst, 2016).

Nowadays, several process models can help researchers to execute data science projects (Baijens et al., 2020). Well-known reference models are the CRoss Industry Standard Process for Data Mining (CRISP-DM) as well as the Knowledge Discovery in Databases (KDD). Based on them, several additional process models emerged over time (Martínez-Plumed et al., 2021). Taking CRISP-DM as an example the typical process activities are arranged sequentially and consist of six different phases that can optionally be iterated several times. These are (1) Business Understanding, (2) Data Understanding, (3) Data Preparation, (4) Modeling, (5) Evaluation, and (6) Deployment (Chapman et al., 2000).

2.2 Design Science Research (DSR)

A well-known methodological framework in information science that brings both practice and theory to the solution approach is DSR (Hevner et al., 2004). DSR is a problem-oriented approach that attempts to gain a profound understanding of how novel solutions, called artifacts, can be designed in the field of information science. An artifact reflects the research object under consideration and can be represented as a construct, model, method, or instantiation. The knowledge from the generated artifacts can be used for future research or for practical implementation (Hevner et al., 2004). Knowledge about the design problem can be generated through constructing and applying artifacts. In principle, the DSR framework according to Hevner (2007) is presented as a DSR cycle model with three different research cycles. These are the relevance cycle, rigor cycle and design cycle.

The cycles shown can also be abstracted as a sequential process that represents a single iteration stage after each run. Peffers et al. (2006) divided the Design Science Research Process Model into six distinct phases: problem identification, objective of solution, design and development, demonstration, evaluation, and communication. This process model also allows iterating by going back to previous phases or starting at different entry points (Peffers et al., 2006). Over time several additional process models or advancements of the presented models are made (Gregor and Jones, 2007; Vaishnavi and Kuechler, 2004; Sonnenberg and Brocke, 2012).

2.3 Rigor

Primarily due to its practical orientation, the DSR approach has been repeatedly criticized since its establishment for not meeting the demands of rigorous research (Kuechler and Vaishnavi, 2011). "In both design-science and behavioral-science research, rigor is derived from the effective use of the knowledge base - theoretical foundations and research methodologies".(p. 88) (Hevner et al., 2004) Thus, Hevner et al. (2004) set up seven guidelines ((1) design as an artifact, (2) problem relevance, (3) design evaluation, (4) research contribution, (5) research rigor, (6) design as a search process, and (7) communication of research) for constructing and applying artifacts. These guidelines are based on the fundamental principle that DSR is a problem-solving process. Within Hevner (2007) DSR cycle model, rigor is ensured in the form of a separate cycle. According to Peffers et al. (2007), rigor must be ensured in both development and evaluation. This can be ensured through the thoughtful selection and application of existing research methods and reference models (Hevner et al., 2004).

While Arnott and Pervan (2012) subdivided rigor into the theoretical foundation and the selection and use of appropriate research methods. This paper focuses mainly on applied research methods. The reason for this focus is that the original study (Arnott and Pervan, 2012) already identified a high level of theoretical rigor but a low level of rigor in relation to research methods. Several publications present possible methods that are well suited for DSR (Sonnenberg and Brocke, 2012; Peffers et al., 2012).

3 METHODOLOGY

Fig. 1 illustrates our research approach. In the first step, we conducted a literature review to identify relevant publications. For this, we followed the guidelines of vom Brocke et al. (2009) to meet the requirements for rigor in this work. Initially, the criteria for the selection of suitable literature are determined. The selection first focused on the three literature databases IEEE, ScienceDirect, and SpringerLink. Using the keyword search, relevant publications were searched with the following search string. *"Data Science" AND ("Design Science*" OR "DSR").*

Applying this, 82 publications are identified and examined for duplicates. Their suitability in terms of content is assessed on the basis of the abstracts and the respective methodological sections. Here, a publication is only classified as suitable if it actively states that it proceeds according to DSR. In addition, data science has to play at least a thematic role. Accordingly, the number of relevant publications is reduced to a final number of 62, which are subsequently analyzed in depth.

The second step is to analyze the characteristics of publications. Therefore, qualitative content analysis according to Mayring (2000) is used. The publications are systematically analyzed on the basis of previously developed coding guidelines. Through an inductive category development process, two new dimensions are identified. These are extended by two further dimensions that are deductively derived

1. The use of research process models. Both in the area of DSR and Data Science. In the context of the analysis, only those sources were taken into account where the authors state that they follow a DSR approach.
2. The role of Data Science in the publications. Here it is inductively identified on the basis of the literature examined that Data Science
   (a) appears as an **enabler** and is only considered from a meta-perspective. No implementation or detailed explanation of Data Science concepts follows.
   (b) appears as an **demonstrator** within the framework. For example, as a prototype in the demonstration while the actual main artifact is a framework.
   (c) appears as an **artifact** itself and is thus the main component of the publication. Here, for example, a prediction model is developed for a problem and its performance is subsequently validated.
3. The type of artifact developed according to the classification of Hevner et al. (2004).
4. The research methods used or cited are classified according to Sonnenberg and Brocke (2012).

If such a concept is identified in a publication, this is indicated by an X in the concept matrix. A finer distinction is made for the research methods in order to assess the rigor of Data Science Research as mentioned in section 2.3. If the use of a research method is only mentioned, a blank circle is filled in. If a suitable publication is referenced and justified, a full circle is used as a symbol instead.

In the third step, an assessment based on the publication by Arnott and Pervan (2012) is made. For this purpose, the classification is broken down into the areas *Weak, Adequate, and Strong*. As the original paper did not provide a comprehensive definition of the assessment categories, the following guidelines are made for the purpose of this paper.

- **Weak:** The rigor of a publication is classified as *Weak* if it (1) does not mention any research methods (2) mentions research methods but does not give any references and justifications for the choice of methods or (3) appropriately references and justifies less than 50 % of the chosen research methods.
- **Adequate:** The rigor of a publication is classified as *Adequate* if (1) it uses at least one research

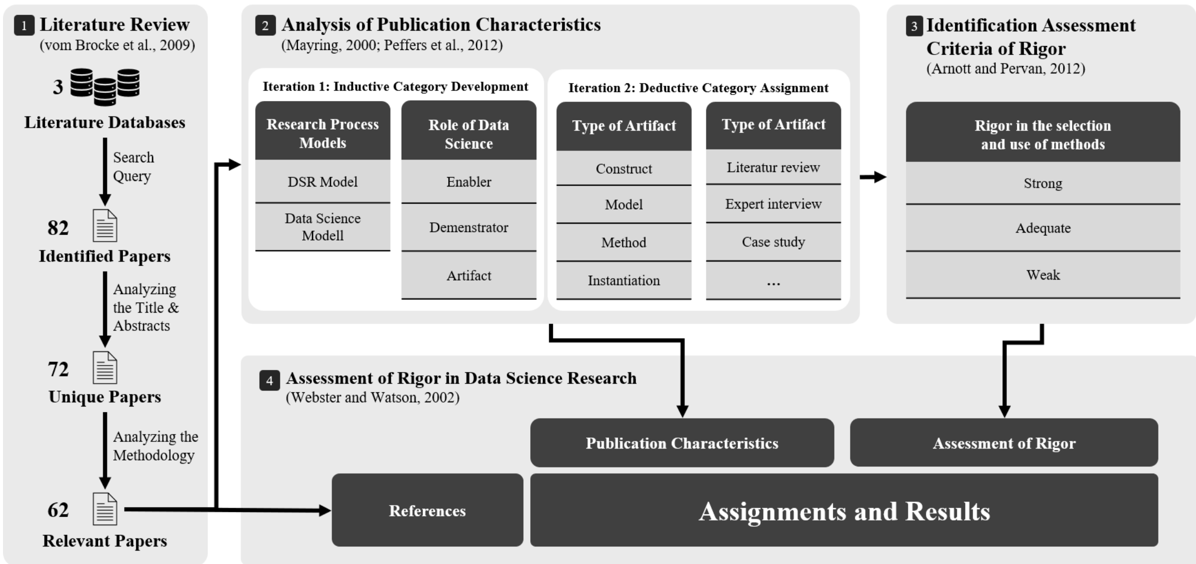

Figure 1: Overview of the Research Approach.

method and (2) justifies and supports the choice of research methods with appropriate references in 50 % or more of the cases.

- **Strong:** The rigor of a publication is classified as *Strong* if it justifies and references each chosen research method, in contrast to Adequate.

According to Peffers et al. (2012), a four- or multi-eye principle is applied. In this way, an appropriate and consistent assessment is attempted. In a fourth step, the identified dimensions are presented in a concept matrix according to the approach of Webster and Watson (2002), based on the presented assessment rules. The findings can be derived from the matrix and will be presented in the following chapter.

4 FINDINGS

The rigor assessment of the 62 publications according to the procedure already described yields different findings. These are mapped in the concept matrix below and then subsequently explained. For this purpose, this section is subdivided according to dimensions in the concept matrix.

4.1 Assessment

Looking at the assessment of the entire sample of this study, three (4.8 %) publications are in the category strong, eleven publications (17.7 %) are adequate and 48 (77.4 %) are weak. According to the study conducted by Arnott and Pervan (2012) about 10 years ago, 3.3 % were Strong, 22.1 % were Adequate, and 74.6 % were Weak. Thus, it can be seen that within this sample the ratio of publications seems to remain the same. In the context of data science publications, therefore, the weak rigor with regard to the selection, justification, and citation of appropriate research methods continues to be clearly evident.

4.2 Research Methods

During the analysis numerous research methods could be identified. A detailed overview of all methods as well as which publications use specific methods can be found in the concept matrix 1. Upon closer examination of the research methods used, the most common one is literature analysis followed by expert interviews. Although they are used in 33 and 24 cases respectively, the concrete application is seldom explained and supported by research method references.

A distinct portion of the sample did not mention any applied research method in the context of DSR. In eight cases, it was not possible to observe any research method. Consequently, these cases completely omit the mention of adequate research methods. They limit themselves to the naming of DSR in general. In addition to this, eight further cases only mentioned a single research method for their research approach. In both of those cases, this automatically resulted in classification as weak.

There are publications that merely mention the use of research methods without referencing them. This applies to 41 cases (66.1 %) after classification. This percentage does not allow for a general conclusion on the mention of methods since publications in this group also mention using more than four methods.

Table 1: Overview of Publication Characteristics and Assessment Results.

	Process Models		Role of Data Science			IT Artifact (Hevner et al. 2004)				Research Methods (Sonnenberg and vom Brocke 2012)										
References of Research	DSR	Data Science	Enabler	Demonstrator	Artefact	Construct	Model	Method	Instantiation	Case Study	Content Analysis	Experiment	Expert interview	Conceptual models	Literature review	Prototyping	Scenario	Survey	Results of Assessment	
(Hacker and Riemer 2021)	X	X	X					X		●				●					Strong	
(Schwaiger et al. 2021)	X				X				X	●	●		●		●				Strong	4,8%
(Warsinsky et al. 2022)	X		X				X								●			●	Strong	
(Brunk et al. 2021)	X				X				X			○		●					Adequate	
(Bunnell et al. 2020)	X			X				X						○		●			Adequate	
(Joubert et al. 2021)	X		X			X									○		●		Adequate	
(Khalil and Rambech 2022)	X				X				X					●			●	○	Adequate	
(Schuster et al. 2021)	X		X				X							●	○				Adequate	
(Schwade 2021)	X	X	X					X		●				○	○			●	Adequate	17,7%
(Schweiger et al. 2020)	X		X					X		●			●	○	●			●	Adequate	
(Simonofski et al. 2021)	X		X					X					●	●	○				Adequate	
(Volk et al. 2020)	X			X				X		○					●				Adequate	
(Vössing et al. 2022)	X			X			X			○			●			○		●	Adequate	
(Zschech et al. 2020)	X				X				X			○			●				Adequate	
(Abkenar et al. 2022)	X			X			X						○		○				Weak	
(Andrews et al. 2020)	X			X				X				○	○		○	○			Weak	
(Assarandarban et al. 2021)	X		X				X												Weak	
(Baijens et al. 2020)	X		X					X			○		○	○	○			○	Weak	
(Bokolo 2022)	X				X				X	○									Weak	
(Chasupa 2021)	X		X					X					○		○			○	Weak	
(Clapham et al. 2022)	X			X				X		○				○	○				Weak	
(van Dun et al. 2022)	X				X				X							○			Weak	
(Fabian et al. 2021)	X				X			X				○		○					Weak	
(Fatima et al. 2022)	X		X				X			○	●		○	○	○				Weak	
(Feio and dos Santos 2022)	X		X					X		○			○		○	○			Weak	
(Ferro et al. 2020)	X			X			X						○	○	○				Weak	
(Filipiak et al. 2020)	X			X			X					○		○	○				Weak	
(Fischer et al. 2020)	X			X				X							●	○		○	Weak	
(Förster et al. 2021)	X		X					X					●	○				○	Weak	
(Fussl and Nissen 2022)	X			X			X			○									Weak	
(Graafmans et al. 2021)	X			X				X					●		○	○	●	○	Weak	
(Górtowski and Lewanska 2020)	X		X					X						○	○				Weak	
(Huang and Buss 2020)	X		X					X							○				Weak	
(Hunke et al. 2020)	X			X				X			○		●		○	○		●	Weak	
(Johnson et al. 2022)	X				X				X	○					○				Weak	
(Kaymakci et al. 2021)	X			X			X			○			○	○	○				Weak	
(Korntmann et al. 2022)	X			X				X											Weak	
(Krasikov et al. 2021)	X		X					X								○		○	Weak	77,4%
(Kratsch et al. 2022)	X			X			X								○	○		●	Weak	
(Kregel et al. 2021)	X		X					X		○		○		○				○	Weak	
(Löhr et al. 2022)	X			X				X					○					○	Weak	
(Maheswaran et al. 2022)	X				X				X										Weak	
(Mar-Raave et al. 2021)	X				X				X				○			○	●	○	Weak	
(Martin et al. 2020)	X		X					X					○		○				Weak	
(Miah et al. 2020)	X				X				X				○		○	○		○	Weak	
(Molnar et al. 2020)	X		X				X												Weak	
(Mombini et al. 2020)	X				X				X				○		○				Weak	
(Monteiro et al. 2022)	X			X			X									○			Weak	
(Odu et al. 2022)	X				X				X										Weak	
(Pan and Zhang 2021)	X				X		X			○						○			Weak	
(Panzner et al. 2022)	X			X		X													Weak	
(Peixoto et al. 2022)	X	X			X				X	○									Weak	
(Pohl et al. 2022)	X			X				X											Weak	
(Romanov et al. 2022)	X				X				X						○				Weak	
(Soares et al. 2022)	X		X						X				○	○	○	○			Weak	
(Spanaki et al. 2021)	X		X					X						○			○		Weak	
(Truong et al. 2021)	X			X				X					○			○			Weak	
(Unhelkar and Askren 2020)	X		X					X					○						Weak	
(Venkata et al. 2022)	X				X				X			○			○	○			Weak	
(Vereno et al. 2022)	X		X			X				○				○					Weak	
(Xia 2022)	X			X				X											Weak	
(Yang et al. 2020)	X		X					X					○	○	○			○	Weak	

Nevertheless, according to the rules of rigor defined before, all these publications are rated as weak. The delta of these cases to all weak cases is represented by publications that make references in less than half of the cases.

4.3 IT-Artifact and Role of Data Science

A dedicated examination of rigor considering the Data Science role within this publication did not reveal any relation. The same applies to the differentiation per artifact type. However, independent of the research question, the distribution of the individual classes is nevertheless interesting.

4.4 Process Model

Since the sample was selected based on the use of DSR, it is not surprising that each publication mentions a process model. A corresponding reference is always given as well. Overall, a variety of sources is used. Sometimes publications referenced several sources for the used methodology. However, when considering data science process models, only three models mention CRISP-DM. In this sample other Data Science process models are not applied. The extended concept matrix showing all process models is available from the authors upon request.

5 DISCUSSION

The study reveals significant weaknesses in connection with the selection and citation of suitable research methods. As a result, over 77 % of publications are rated as weak in regard to the rigorous selection and application of research methods. When publications lack rigor, it can lead to results that are not replicable by other researchers, unreliable, or even incorrect. This can lead to incorrect conclusions being drawn which can have implications for further research and practice. Although each publication specifies a DSR methodology and provides evidence of it through widely used references, this still does not infer a fundamental rigor in the approach. Peffers et al. (2007), indicated by 29 publications (46.7 %), also confirmed that the citation of research methods contributes to better understanding, increased validity and generalizability of the results. A possible explanation might be that the researchers work conscientiously and structured in the background, but do not document it in the paper. Moreover, researchers may be unaware of the actual use of the research methods (e.g. experiment, survey, case study) and the need to explicitly validate the results from them.

Furthermore, it can be seen in the concept matrix that only in three cases name a Data Science process model. The referenced CRISP-DM, which is popular in knowledge and practice, has fundamental similarities to DSR. Both approaches focus on the development and validation of solutions to practical problems using similar phases and methods. This could be a reason for the low number of Data Science process models while the number of DSR models is high.

Especially in publications in which the role of Data Science is a demonstrator or artifact, metrics such as accuracy are often used. One explanation for the omission of specific justifications and references could be that for many metrics in the field of Data Science no foundation papers are available. Furthermore, authors could assume that the methods used are generally known and therefore refrain from citing them.

Moreover, mathematical constructs such as an accuracy score are often used for evaluation in the field of Data Science. While Sonnenberg and Brocke (2012) argue that logical reasoning and mathematical proofs can also be a method for evaluating, this was not considered as a research method itself in this work. These metrics usually have a practical origin and are generally known in the community. Nevertheless, a reference to the work that justifies the selection and describes the metrics is usually omitted. Furthermore, the results still can be considered valid, because this does not excuse the absence of referencing chosen research methods or the absence of research methods in other phases of DSR at all. In addition, these metrics are only used for quantitative evaluations. A qualitative perspective is therefore completely missing if no other evaluation method is conducted. For this reason, the procedure can generally be regarded as well-suited to answer the research question.

6 CONCLUSION

Based on the findings of Arnott and Pervan (2012), many publications have a shortcoming in rigorously describing the selection, application, and justification of appropriate research methods. This motivates this study to re-validate these findings after ten years. For this purpose, the focus lies on the increasingly popular field of Data Science. Other publications have already shown that DSR is a suitable methodology for Data Science publications. According to the search criteria, 62 publications in the investigated time period were based on a DSR approach.

6.1 Summary

This paper examined the rigorous use of research methods and systematically maps them through a concept matrix 1 to answer the research question. Based on the research methods mentioned in each case, as well as on the corresponding references provided, an assessment of rigor is made. In summary, 77.4 % of these publications were categorized as weak in terms of rigor. Consequently, the ratio remains nearly similar to the data from the 2012 study of Arnott and Pervan (2012). Looking at the analysis of Data Science Research, 66.1 % do not reference or justify the research methods with appropriate literature references at all. At the same time, eight publications completely abstained from mentioning further research methods. Only three publications could be identified as strongly rigorous. The main reason for this assessment is the consistent use of research methods for all activities within the various phases of DSR. In each case, references are cited that prove that it is an established research method whose success can be expected. Hereby it can be concluded that after using the methods in a comprehensible and promising way in many contexts, the results are also valid for this publication.

6.2 Limitations

We need to acknowledge some limitations to our research. First, it must be taken into account that during the data collection and classification, despite maintaining a dual control principle, the absence of errors cannot be guaranteed. Due to the diversity of this research area and the missing separation precision provided by the search string used, it cannot be guaranteed that all publications matching the topic could be determined. In Addition, the differentiation by concepts and role of Data Science did not lead to any findings due to the small sub-sample size in some cases. In addition, the rigor applied by researchers can only be assessed based on what was written in the publications. This means that only explicitly mentioned research methods can be considered. Researchers may omit (intentionally) details or steps for different reasons. It is important to acknowledge the limitations in assessing the rigor based solely on the written documentation in form of publications.

6.3 Future Work

To validate this work as well as for further analysis, a replication of the study with additional Data Science publications, even if they may not explicitly state that they proceed according to DSR, would be useful. In future studies, an exploration of DSR in the domain of Data Science may benefit from adopting a qualitative methodology. By analyzing Data Science research more in-depth the rigor can be assessed beyond the applied research methods described in the corresponding publications. Another possibility for further work would be to develop a DSR process model, tailored to the specific needs of Data Science research. In order to take into account the characteristics of Data Science Research, the authors propose future work about the integration of a Data Science process model like CRISP-DM into DSR.

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