Egusphere-2025-1715: Deciphering the drivers of direct and indirect damages to companies from an unprecedented flood event: A data-driven, multivariate probabilistic approach

Reviewer #2:

This manuscript quantifies drivers of damages to companies by rare flood events via 3 data-driven techniques, which ultimately lead to a Bayesian Network. This study could have potential, but its possible novelty is currently hidden behind a rather complicated and untransparent chain of calculations. In particular, the justification of using the 3 data-driven models is unclear. Why not less? Why not more? Why these? This could easily be arbitrary. And what does the Bayesian Network add to the variable importance analysis via those 3 models? I raise more questions below. I believe these should be addressed before the paper can be reconsidered for publication.

The authors would like to thank the reviewer for acknowledging the significance of our study and for providing valuable and constructive feedback. The comments were extremely helpful in improving the quality of the manuscript and will be acknowledged. We provide detailed responses to each comment below, with reviewer comments shown in blue and our responses in black. All references cited in our responses are listed at the end of this letter.

In the revised manuscript, we will introduce the variable selection section with a clear rationale for choosing the three machine learning techniques, as follows:

"2.2 Variable Selection

Flood damage processes vary by region, flood type, and asset type (Mohor et al., 2020; Sairam et al., 2019; Wagenaar et al., 2018). Since our analysis focuses on flash floods and covers direct and indirect damages, we use a data-driven approach to identify which variables strongly influence these diverse outcomes. We adopt three feature selection approaches that are robust to multicollinearity and capable of capturing nonlinear relationships and interactions. To this end, we employ three complementary machine learning techniques: Elastic Net (EN), Random Forest (RF), and Extreme Gradient Boosting (XGBoost). EN efficiently handles multicollinearity and performs variable selection through regularization; RF captures nonlinear relationships and complex interactions via ensemble decision trees; and XGBoost, a gradient boosting algorithm, provides high predictive accuracy and models intricate dependencies. By combining the strengths of these methods, we assume to ensure a comprehensive assessment of variable importance. To mitigate potential biases from relying on a single model, we aggregate the variable importance scores across all three methods to derive a final ranking.''

In this study, BNs are employed to complement the machine learning models by providing a probabilistic framework for analyzing multivariate dependencies and scenario-based inference. Whereas EN, RF, and XGBoost primarily emphasize predictive accuracy and variable ranking, BNs explicitly capture conditional dependencies among variables. We will revise the section to better explain this motivation as follows:

"Bayesian networks (BNs) are probabilistic graphical models that represent dependencies among multiple variables and enable multivariate predictive density estimation (Sucar, 2021). In this study, BNs are employed to complement the machine learning models by providing a probabilistic framework for analyzing multivariate dependencies and scenario-based inference. Whereas EN, RF, and XGBoost primarily emphasize predictive accuracy and variable ranking, BNs explicitly capture conditional dependencies among the variables. This is particularly valuable in flood damage analysis, where damage outcomes result from complex interactions between hazard intensity, company characteristics, and preparedness measures. Moreover, BNs are able to estimate posterior probabilities of damages given partial evidence (e.g., observed water depth or company

preparedness), thereby offering a transparent and interpretable tool for risk assessment under uncertainty".

Title: I suggest a different word than "deciphering" because that's not what is being done in this study.

We thank the reviewer for raising this point. Our analysis is a process of uncovering the drivers of direct and indirect damages to companies, which involve complex interrelationships, and extracting insights that are not immediately apparent from the raw data. This is directly reflected in our methodology and findings:

1. Multivariate modeling (Figure 5): Variable importance scores capture the combined effects of hazard, preparedness, and company characteristics on multiple damage types, explicitly accounting for interdependencies rather than isolated relationships.
2. Bayesian network analysis (Figures 7): The BN models conditional probabilities, showing how hazard intensity, company size, and precautionary measures collectively shape damage outcomes.
3. Multivariate probabilistic estimation (Figure 8): Probabilistic outcomes highlight how small and micro-companies are disproportionately affected under extreme conditions, reflecting complex interactions between hazard severity and company characteristics.

We feel that, in this context, "deciphering" is an appropriate term, as it conveys the analytical effort required to reveal and quantify underlying mechanisms that are not directly observable. We believe it best captures both the analytical depth and the objectives of our study. Therefore, we would like to keep the title as is.

L44-52: The message needs to be streamlined here with regard to rare/high-impact events.

We will revise the explanation as follows:

"*The severity of indirect damages can be equally significant and, in the case of rare and high-impact flood events, may even exceed direct damages (Koks et al., 2015; Pfurtscheller and Vetter, 2015; Sieg et al., 2019). For instance, Pfurtscheller and Vetter (2015) reported that indirect damages are often underestimated by companies, despite sometimes exceeding direct damages during rare flood events. Using an Input-Output (IO) model, Li et al. (2018) showed that business interruptions and operational restrictions in Shanghai's manufacturing firms can propagate along interlinked value chains, with indirect damages under extreme storm flood scenarios reaching up to $60 billion. Similarly, Sieg et al. (2019) employed a supply-side IO model and identified the manufacturing, and financial sectors vulnerable to indirect damages. It should be noted, however, that not all studies classify business interruptions or operational restrictions as indirect damages. The definition of indirect damage varies across the literature. In this study, we specifically focus on business interruptions and restrictions as a key component of indirect flood damages. Altogether, these studies underscore that indirect damages, especially during low-probability, high-impact flood events, can be substantial and warrant systematic investigation to better understand the processes*".

L107, 109, 119 and elsewhere: Consider something like "rare" in place of "unprecedented", because there now is a precedent.

We thank the reviewer for this helpful comment. In lines L107 and L109, we will replace the word "unprecedented" with "rare" as suggested. In L119 we will revise the text as follows:

"The July 2021 flood in Germany has been widely described as extraordinary in terms of its hydrological magnitude, spatial extent, exceeding the scale and severity of previously recorded floods

in the affected regions (Mohr et al., 2023; Thieken et al., 2023; Zander et al., 2023) *and it caused an estimated €33.1 billion in direct damages and €7.1 billion in indirect damages (Trenczek et al., 2022)".*

L141, L214: The analyses for each damage type could have been combined, as they are also internally related, via a multivariate regression. Why employ this more elegant solution making optimal use of all information (by not considering the responses as independent)?

We thank the reviewer for this question. Although there is to some extent interdependency across the addressed damage types, we analyzed them individually for two main reasons. First, it allowed us to capture asset-specific processes and identify distinct drivers for each category (e.g., buildings, equipment, goods & stock, business interruption), which can behave differently in a rare flood event and can also vary across company sizes and sectors. Second, the dataset had varying levels of completeness across damage types. By analyzing them separately, we were able to make use of larger subsamples, rather than restricting the analysis to the smaller set of companies with complete data across all damage types.

We will add the following lines in the revised manuscript:

"Although there is to some extent interdependency across the addressed damage types, we analyzed them individually for two main reasons. First, this approach allowed us to capture loss-specific processes and identify distinct drivers for each category (e.g., buildings, equipment, goods & stock, business interruption), which can behave very differently during a rare flood event and can also vary across company sizes and sectors. Second, the dataset had varying levels of completeness across damage types: some companies reported only building damages, while others provided data on equipment or business interruption. By analyzing them separately, we were able to make use of larger and more reliable subsamples, rather than restricting the analysis to the smaller set of companies with complete data across all damage types".

As a future scope we will mention it in the conclusions section as follows:

"Future research could explore the interrelations between different types of damages, for example by applying multi-level models, to better understand how direct, and indirect damages interact."

L143: Across what scale where the missing data imputed, i.e. how far were they apart on average.

We will clarify this in the revised manuscript. We used the Gower distance to calculate similarity between observations, which is ideal for a dataset with different types of variables (continuous, nominal, and ordinal) (Kowarik and Templ, 2016). For rows with missing data, the average distance to their 5 nearest neighbors was approximately 0.09, indicating that imputation was performed among relatively similar observations.

The following lines will be added in the revised manuscript:

"We used the Gower distance to calculate similarity between observations, which is ideal for a dataset with different types of variables, i.e. continuous, ordinal and nominal (Kowarik and Templ, 2016). We calculated the average Gower distance between each row with missing data and its 5 nearest neighbors. The mean of these distances across all rows with missing values was approximately 0.09, indicating that imputation was performed among observations that were relatively similar in terms of their characteristics."

L155: J(beta) is not in the equation.

We will correct the notation for consistency. $J(\beta)$ will be replaced with $Obj(\beta)$ to match the notation used in Equation 1.

L157: What does use of the MAE as objective function imply about the nature of the residuals given a response which is between 0 and 1 or counts between 0 and 540?

We thank the reviewer for this insightful question. The use of MAE as the objective function implies that residuals are treated symmetrically, without giving extra weight to large deviations. This is particularly suitable for our flood damage data, where responses range from 0 to 1 or 0 to 540 days, ensuring that both small and large errors are proportionally considered.

Our choice of MAE was based on two main considerations:

- MAE is robust to outliers, which is particularly important as flood damage data often contain extreme values. Unlike Mean Squared Error (MSE), which disproportionately penalizes large errors, MAE treats all deviations proportionally, providing a more stable and representative measure of overall model performance.
- Second, for the Permutation Variable Importance (PVI) analysis, MAE provides a direct and interpretable measure of error. The performance loss is in the same units as our response variables—relative loss (0 to 1) and duration (0 to 540 days). This allows for a clear, tangible assessment of how each variable's permutation affects predictive accuracy. While other metrics are appropriate for specific distributional assumptions, MAE is model-agnostic and ideal for generating comparable PVI scores across our different modelling approaches.

We will include the following lines in the revised manuscript:

"*The use of MAE as the objective function treats residuals symmetrically, ensuring that both small and large errors are proportionally considered. This metric is robust to outliers and provides an interpretable measure of error in the same units as the response variables i.e., relative loss (0–1) and duration (0–540 days)".*

L159: It's not entirely true that the model cannot handle nonlinearities – it can do so via transformations or in Generalised Linear Model form.

We agree that Elastic Net can, in principle, handle nonlinear relationships if appropriate transformations of the predictors are included. However, in our study, we applied Elastic Net in its standard linear form without additional transformations, and therefore it primarily captures linear associations between predictors and the response. Nonlinear effects were instead captured by the Random Forest and XGBoost models, which can model complex nonlinear relationships directly.

We will rephrase the sentence in the revised manuscript as follows:

"*Elastic Net is a powerful linear model that is effective in handling multicollinearity. However, in its standard application without explicit transformations as used in this study, it primarily captures linear associations and cannot model complex nonlinear relationships directly*".

L201: What are the implications of combining the variable importance across the 3 models?

By combining the variable importance scores across Elastic Net, Random Forest, and XGBoost, we are combining the complementary strengths of each model. This approach mitigates potential biases that could arise from relying on a single model and provides a more robust and comprehensive assessment of the variable importance. The aggregated ranking reflects variables that consistently influence predictions across multiple modelling frameworks, offering greater confidence in identifying key drivers of flood damages.

We will included the following lines in the revised manuscript:

"*By combining the strengths of these methods, we ensure a comprehensive assessment of variable importance. To mitigate potential biases from relying on a single model, we aggregate the variable importance scores across all three methods to derive a final ranking*."

Eq9, L219, Appendix: It's conditional probabilities, not fractions in Bayes Rule! I.e. X_i|E and E|X_i.

The notation will be updated throughout the manuscript and in the Supplementary information.

L222: Why not leave it discrete rather than introducing another layer of assumptions?

Thank you for this constructive feedback. We will revise the manuscript to clarify the rationale for using a continuous distribution as follows:

"The posterior probability of flood damage given the observed evidence E is discrete in nature. However, this discrete representation is limited by the binning of the data and does not allow precise estimates or a meaningful characterization of predictive uncertainty. To address this, we derived a continuous distribution of direct and indirect damages by fitting a probability distribution based on weighted sampling of the empirical damage data, following the approach of Schoppa et al., (2020). This allows for a more precise representation of uncertainty and predictions at finer scales beyond the original bins"

The following figure was developed to illustrate this process and is provided for reference, but will not be included in the manuscript:

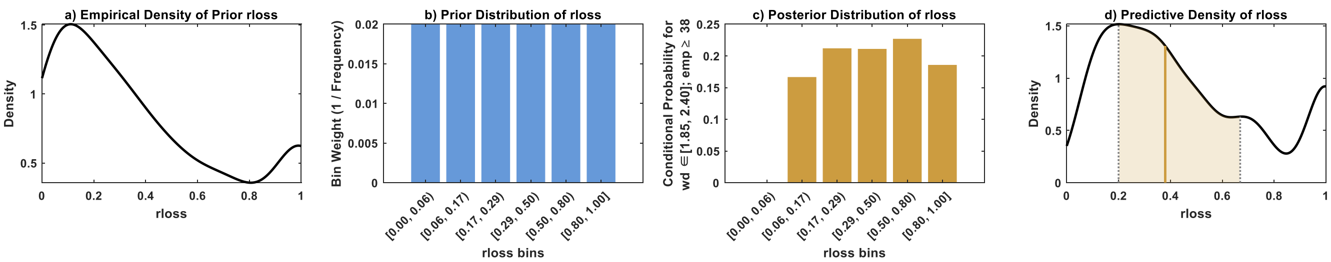

Figure: Visualizations of the prior, posterior, and predictive distributions of rloss (a) Empirical kernel density estimate of the prior rloss based on collected data (b) Prior distribution of rloss represented as bin weights (inverse frequency) across discretized intervals (c) Posterior distribution of rloss conditioned on wd ∈ [1.85, 2.40) and emp ≥ 38 (d) Predictive distribution of rloss generated by resampling 1000 values using the prior bin weights and the posterior probabilities. The solid vertical line indicates the median (50th percentile), while the dotted vertical lines represent the 25th and 75th percentiles, representing the predictive uncertainty. The shaded area highlights the interquartile range.

L228: How do the five models relate to the Bayesian Network?

Based on the Line indicate (L228), we interpret that the reviewer meant 3 models (EN, RF and XGB) and not 5.

In this study, BNs are employed to complement the machine learning models by providing a probabilistic framework for analyzing multivariate dependencies and scenario-based inference. Whereas EN, RF, and XGBoost primarily emphasize predictive accuracy and variable ranking, BNs explicitly capture conditional dependencies among variables. We will revise the section to better explain this motivation as follows:

"Bayesian networks (BNs) are probabilistic graphical models that represent dependencies among multiple variables and enable multivariate predictive density estimation (Sucar, 2021). In this study, BNs are employed to complement the machine learning models by providing a probabilistic framework for analyzing multivariate dependencies and scenario-based inference. Whereas EN, RF, and XGBoost primarily emphasize predictive accuracy and variable ranking, BNs explicitly capture conditional dependencies among the variables. This is particularly valuable in flood damage analysis, where damage outcomes result from complex interactions between hazard intensity, company characteristics, and preparedness measures. Moreover, BNs are able to estimate posterior probabilities of damages given partial evidence (e.g., observed water depth or company preparedness), thereby offering a transparent and interpretable tool for risk assessment under uncertainty".

L230-242: This part is redundant – see above. The function of the 3 models, despite factor selection is unclear. And why 3 models and not more or less?

In the revised manuscript, we will introduce the variable selection section with a clear rationale for choosing the three machine learning techniques, as follows:

"2.2 Variable Selection

Flood damage processes vary by region, flood type, and asset type (Mohor et al., 2020; Sairam et al., 2019; Wagenaar et al., 2018). Since our analysis focuses on flash floods and covers direct and indirect damages, we use a data-driven approach to identify which variables strongly influence these diverse outcomes. We adopt three feature selection approaches that are robust to multicollinearity and capable of capturing nonlinear relationships and interactions. To this end, we employ three complementary machine learning techniques: Elastic Net (EN), Random Forest (RF), and Extreme Gradient Boosting (XGBoost). EN efficiently handles multicollinearity and performs variable selection through regularization; RF captures nonlinear relationships and complex interactions via ensemble decision trees; and XGBoost, a gradient boosting algorithm, provides high predictive accuracy and models intricate dependencies. By combining the strengths of these methods, we assume to ensure a comprehensive assessment of variable importance. To mitigate potential biases from relying on a single model, we aggregate the variable importance scores across all three methods to derive a final ranking.''

Results & discussion: Too much time is spent describing univariate results. And the bivariate correlations defeat the purpose of multivariate analysis.

We thank the reviewer for this comment. While some univariate correlations are described in the manuscript, these serve primarily to provide context on the dataset and highlight potential relationships between influencing factors and damage types. The main focus of our study is on multivariate relationships, which are addressed extensively through:

1) Multivariate model variable importance: Figure 5 and the corresponding discussion present variable importance scores derived from multivariate models, capturing the combined effects of hazard, preparedness, and company characteristics on all five types of flood damage. This approach identifies key drivers while accounting for interdependencies among variables.
2) Bayesian network analysis: Figures 7 and 8, along with the associated discussion, illustrate the probabilistic dependencies among the top influencing factors and damage types. The BN explicitly models conditional relationships in a multivariate framework, highlighting interactions between hazard variables (e.g., water depth, flow velocity), company-specific factors (e.g., size, employees), and preparedness measures (e.g., precaution, emergency measures).

3) Multivariate probabilistic damage estimation: Figure 8 shows the distributions of damage outcomes under different hazard, exposure, and preparedness scenarios, estimated using the Markov blankets of the Bayesian networks. These results reflect the combined influence of multiple variables and quantify uncertainty, demonstrating the practical implications of the multivariate analysis.

The discussion explicitly addresses how hazard intensity, company characteristics, and precautionary measures jointly influence direct and indirect damages (e.g., business interruption and restriction durations). For instance, small and micro-companies are disproportionately affected under extreme flood conditions, highlighting the interplay of hazard severity and company size. Precautionary measures substantially mitigate business restriction durations, particularly under higher water depths, illustrating the multivariate impact of preparedness and hazard exposure.

In the revised manuscript, we will rewrite the results in a more tangible way to emphasize these multivariate findings as follows:

"The duration of business interruption varies with velocity and company size. Micro-companies (1–9 employees) show a consistent pattern under low and moderate flow conditions, with median interruption durations of around 22 days. Under torrential flow conditions, the interruption duration rises sharply to nearly 60 days. Small companies (10–49 employees) exhibit a similar trend, though their interruption duration under torrential flow is slightly lower. Medium and large companies (>49 employees) demonstrate greater resilience, with median interruption durations ranging from about 11 to 33 days across all flow conditions. The results indicate that small companies, especially micro-companies, are disproportionately affected by the 2021 unprecedented flood event.

The analysis of business restriction duration, based on the Markov blanket, further shows that companies without precautionary measures experience the longest restrictions. For instance, the median restriction duration for companies without precautions increases from roughly 102 days when water depth < 1 meter to about 210 days for water depth > 2 meters. Implementing medium precautionary measures (see variable precaution in Table A1) results in a modest reduction in restriction duration, particularly for deeper water, where the 75th percentile decreases from 368 days to 330 days. A more substantial reduction is observed in companies with strong precautionary measures, where the median restriction durations remain below 150 days. For shallow water depth (< 1 meter), effective precautionary measures reduce the 75th percentile to 178 days, compared to 238 days in companies without precautions. These results highlight the effectiveness of precautionary measures in reducing business restriction durations".

L394: Purpose of sentence unclear.

The sentence was intended to justify the use of a multivariate approach. We will revise the sentence as follows:

"*Furthermore, significant correlations exist between several influencing factors, underscoring the importance of a multivariate modelling approach*".

L373: Who's expert knowledge?

We thank the reviewer for the comment. The original mention of "expert knowledge" referred to the combined input of the study authors, who have domain expertise in flood risk assessment and damage modeling. To clarify and simplify, we will revise the sentence as follows:

"*Based on the data availability, 19 potentially relevant influencing factors were selected, covering hazard characteristics, emergency measures, precautionary actions, and company characteristics (Table 1)."*

Fig6: What is it's function for the manuscript?

As described in the manuscript (P19/L426–430), Figure 6 presents the kernel density estimations of the top four influencing factors considered for multivariate probabilistic damage modelling across five different types of damage. The violin plots illustrate the probability density of scaled variables (ranging from 0 to 1), with quartile lines indicating central tendencies and variability. The presence of skewed distributions and multimodal characteristics highlights the complexity of flood damage relationships across different damage types.

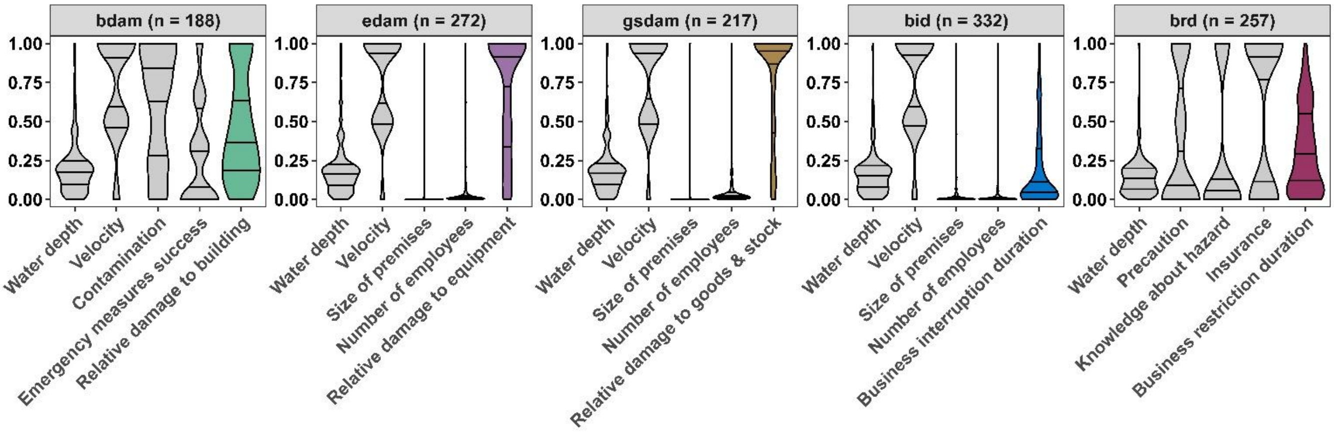

Figure 1: Kernel density estimations of influencing factors and damage types, with all variables scaled between 0 and 1. The lines in the violin plots indicate the quartiles.

Fig7: The directions matter here, no? And some of them are not intuitive!

We thank the reviewer for this question. In the Bayesian network, arrow directions indicate conditional dependencies between variables but do not imply causality. Some directions may seem unintuitive because the structure is derived from a score-based learning algorithm that optimizes overall network fit to the data, rather than reflecting causality.

We will clarify this in the revised manuscript as follows:

"The direction of the arrows represents conditional dependencies between variables but does not imply causality (Schröter et al., 2014). Some directions may appear unintuitive because the structure is derived from a score-based learning algorithm that optimizes the overall network fit to the data, not necessarily causality."

Conclusion: Too short and doesn't add sufficient novelty.

We thank the reviewer for the feedback. In the revised manuscript, we will emphasize the novelty, limitations and future scope in the conclusions section as follows:

"The July 2021 flood in Germany highlighted the significant vulnerability of companies to extreme floods, with both direct and indirect damages resulting in substantial financial costs. A central question of this study was whether the influencing factors behind flood damage during the extreme July 2021 event differ from those in earlier floods from 2002 to 2016. Our findings indicate that core hazard related variables, including water depth, flow velocity, and contamination, remain consistent predictors of damage across different events. Similarly, company characteristics such as size of the premises and number of employees continue to play an important role. What sets the 2021 flood apart is the elevated importance of emergency preparedness and behavioral responses, particularly in shaping indirect damages such as business restriction duration, while the sector was not that important. A novel insight from this study is the demonstrated link between knowledge about flood hazard and amount of precaution taken, highlighting its relevance in reducing business restriction

duration. Small and micro-companies that implemented very good precaution measures experienced notably shorter restriction durations.

While the study has deciphered the drivers of company damages during the 2021 flood event, it does have some limitations. First, the sample size for some company categories, particularly large companies, was small, which limits the generalization of findings. Second, survey participation was voluntary, which may have introduced self-selection bias. Although 431 responses are a notable sample size given the challenges of post-disaster data collection, future studies should aim for more diverse representation across different company sizes and sectors. This would further strengthen the generalizability of the findings. Moreover, comparative analyses across multiple extreme flood events in different geographical regions and socio-economic contexts, for instance, in Belgium and the Netherlands in the case of the 2021-event would allow for broader generalization of findings. Finally, future research could explore the interrelations between different types of damages, for example by applying multi-level models, to better understand how direct, and indirect damages interact. Overall, the results underscore the critical role of emergency preparedness and risk communication during extreme events, serving as essential complements to structural protection measures that may be less effective under extraordinary conditions."

We hope that the reviewer is satisfied with the changes proposed. Again, we thank for the valuable comments that helped us to improve the manuscript.

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