# Chronic Diseases as Leading Mortality Drivers: A 22-Year Statistical Analysis in Alberta*

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In this statistical analysis, we investigated mortality data from Alberta over 22 years, applying Poisson and Negative Binomial models to identify significant mortality causes. The findings indicate that chronic diseases significantly elevate mortality rates, with a notable effect size in the Negative Binomial model. This insight highlights the substantial impact of chronic conditions on public health, suggesting a need for focused interventions. Our study contributes to understanding mortality trends, emphasizing the importance of addressing chronic diseases in healthcare planning.

## 1 Introduction

The COVID-19 pandemic has profoundly impacted global health, becoming a prominent cause of mortality with over 19,700 Canadians dying to the virus in 2022, marking the highest annual death toll since the pandemic's onset (ICI.Radio-Canada.ca, n.d.). This stark statistic places COVID-19 among the leading causes of death in Canada since 2020. Beyond the pandemic, however, numerous other factors contribute to mortality rates, prompting an investigation into the primary causes of death preceding the emergence of COVID-19. This paper focuses on Alberta, a Canadian province that has maintained detailed records of mortality causes since 2001, offering a comprehensive dataset of the top 30 causes of death annually from 2001 to 2022.

This research endeavors to analyze the top five causes of death over the past 22 years in Alberta, quantifying their relative contributions to the overall mortality rate. To this end, we employ two statistical models: the Poisson distribution model and the Negative binomial distribution model. The choice of dual models allows for a nuanced analysis, accommodating

*Code and data are available at: https://github.com/peachvegetable/Alberta-mortality

the data's variability and overdispersion, with the ultimate goal of identifying the model that best combines accuracy and precision in reflecting the underlying trends.

Data for this study were sourced from the Alberta Government's open data portal, focusing on explaining the relationship between individual causes of death and the total mortality rate. This analysis seeks to determine the estimand, a statistical term denoting the quantity of interest that our models aim to estimate.

The structure of this paper is designed to guide the reader through our research journey, starting with Section Section 1, which introduces the study's context, objectives, and preliminary observations. Section Section 2 presents visualizations of the changing landscape of mortality causes from 2001 to 2022, accompanied by a detailed description of the dataset. Section Section 3 delves into the methodology, clarifying the statistical models employed in our analysis. The findings and their statistical examination are detailed in Section 4, while Section 5 discusses these results, reflecting on the study's limitations and proposing avenues for future research.

## 2 Data

Data for this study were prepared and analyzed using R (R Core Team 2023), grasping several packages including Tidyverse (Wickham et al. 2019) for data manipulation, ggplot2 (Wickham 2016) for visualization, Janitor (Firke 2023) for data cleaning, Readr (Wickham, Hester, and Bryan 2023) for data import, Dplyr (Wickham et al. 2023) for data manipulation, Knitr (Xie 2014) for dynamic reporting, Modelsummary (Arel-Bundock 2022) for summarizing model outputs, and Rstanarm (Goodrich et al. 2022) for Bayesian modeling.

Our analysis focuses on the Alberta Government's open data, encompassing annual records of the top 30 causes of death from 2001 to 2022 (Government 2015). This comprehensive dataset sheds light on mortality trends in Alberta, offering insights into the dominant health challenges before the onset of the COVID-19 pandemic. Such an extensive temporal range is crucial for identifying long-term trends and shifts in public health priorities.

The dataset's primary variables include 'calendar_year' (renamed to 'Yaer'), capturing the range from 2001 to 2022; 'cause' (renamed to 'Cause'), listing the top 30 distinct causes of death annually; and 'total_deaths' (renamed to 'Deaths'), representing the yearly mortality count per cause. Initial data cleaning involved condensing the lengthy cause-of-death labels to ensure clarity in visualization. Furthermore, our analysis strategically omits causes not consistently present over the 22-year span, such as COVID-19, to maintain a focus on long-term trends and ensure analytical consistency.

Table 1: Top 10 causes of deaths in 2022, Alberta

| Year | Cause | Ranking | Deaths | Years |
|---|---|---|---|---|
| 2022 | Organic dementia | 1 | 2,377 | 22 |
| 2022 | All other forms of chronic … | 2 | 2,098 | 22 |
| 2022 | Other ill-defined and unkno… | 3 | 1,714 | 4 |
| 2022 | COVID-19, virus identified | 4 | 1,547 | 3 |
| 2022 | Malignant neoplasms of trac… | 5 | 1,523 | 22 |
| 2022 | Acute myocardial infarction | 6 | 1,240 | 22 |
| 2022 | Accidental poisoning by and… | 7 | 1,200 | 10 |
| 2022 | Other chronic obstructive p… | 8 | 1,183 | 22 |
| 2022 | Diabetes mellitus | 9 | 730 | 22 |
| 2022 | Stroke, not specified as he… | 10 | 650 | 22 |

Table 1 presents data from Alberta for the year 2022, focusing on the top 10 causes of death. Each row in the table lists a specific cause of death, its rank in terms of mortality for that year, the number of deaths attributed to that cause, and the number of years that particular cause has appeared in the top 10 list out of the 22-year period studied.

For instance, the top cause of death for 2022 is listed as "Organic dementia," which caused 2,377 deaths and has been among the top 10 causes for all 22 years analyzed. The fifth cause is "COVID-19, virus identified" with 1,547 deaths, but it has only been in the top 10 causes for 3 years, corresponding to the recent years of the pandemic.

We can use this table for quickly identifying the most significant health concerns in Alberta in 2022 and assessing their persistence over time.

Figure 1 shows a multi-line graph depicting the annual number of deaths in Alberta for various causes from 2001 to 2022. Acute Myocardial Infarction (Heart Attack): The line appears relatively flat, which indicates that the number of deaths from heart attacks has remained consistent over the 22-year period. There is no significant upward or downward trend, suggesting stable incidence or improvements in treatment may be offsetting the risk factors in the population. All Other Forms of Chronic Diseases: This category shows a slight downward trend, indicating a small decrease in the number of deaths over time. This could be due to better management of chronic diseases or changes in diagnostic criteria and classification. Malignant Neoplasms of Trachea, Bronchus, and Lung (Lung Cancer): The line is fairly stable with a slight increase, suggesting a small rise in mortality from lung cancer over the years. This could reflect population growth, aging, or lifestyle factors influencing disease rates. Organic Dementia: There is a noticeable upward trend in deaths due to organic dementia. This is likely reflective of an aging population and increased diagnosis rates, as well as potentially increased prevalence of the disease. Other Chronic Obstructive Pulmonary Diseases (COPD): The trend for COPD is relatively stable with a very slight increase, indicating mortality rates from COPD have remained somewhat constant, potentially reflecting better treatments balancing out any

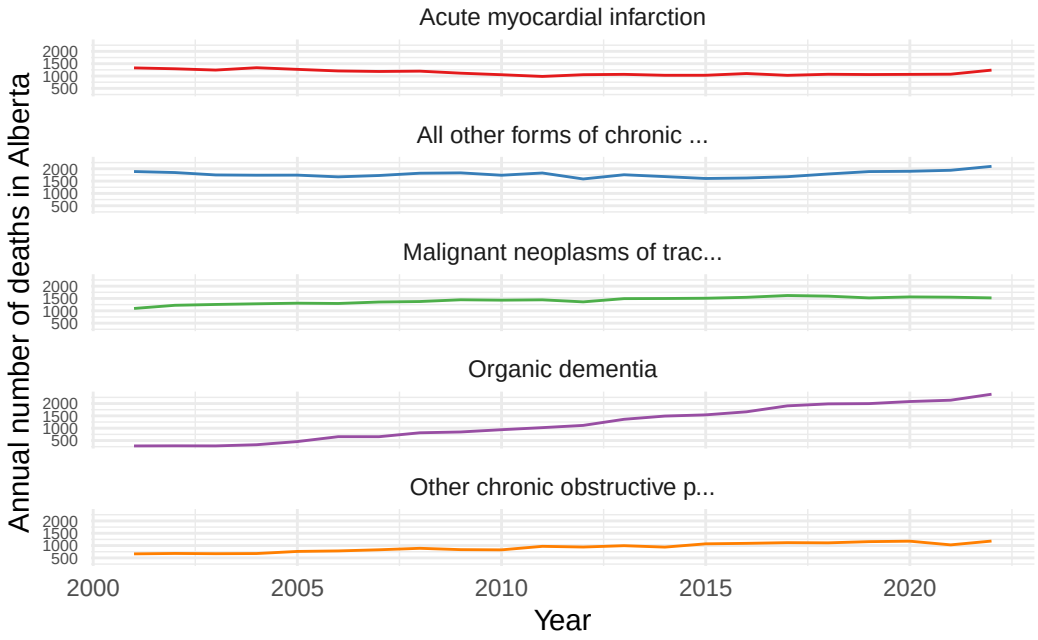



Figure 1: Top 5 causes of deaths from 2000 to 2022, for Alberta, Canada

increases in prevalence. When comparing the slopes of the lines, organic dementia shows the most significant increase, potentially indicating it is becoming a more prevalent cause of death. Acute myocardial infarction and COPD display relative stability compared to other causes, suggesting that the impact of these conditions on mortality rates has not changed markedly. The slight decline in 'All Other Forms of Chronic Diseases' could reflect effective public health interventions or improvements in healthcare delivery.

# 3 Model

## 3.1 Model set-up

Two models generated, one follows poisson distribution and another follows negative binomial distribution. We are interested in how total number of deaths differs by different causes of deaths.

Define $y_i$ as the total number of deaths for the i-th observation. Then $\beta_0$ is the expected log count of total deaths when none of the causes in the model are present. It's the starting point of the model's prediction.

$$
\begin{aligned}
y_i|\lambda_i &\sim \text{Poisson}(\lambda_i) \\
\log(\lambda_i) &= \beta_0 + \beta_1 \times \text{cause}_i \\
\beta_0 &\sim \text{Normal}(0, 2.5) \\
\beta_1 &\sim \text{Normal}(0, 2.5)
\end{aligned}
$$

Define $y_i$ as the total deaths for the i-th observation. $\theta$ is the additional parameter to model overdispersion. $\mu_i$ is the mean of the Negative Binomial distribution for the i-th observation, $\beta_0$ is the intercept, and $\beta_1$ represents the effect of each cause of death.

$$
\begin{aligned}
y_i|\lambda_i, \theta &\sim \text{NegativeBinomial}(\mu_i, \theta) \\
\log(\mu_i) &= \beta_0 + \beta_1 \times \text{cause}_i \\
\beta_0 &\sim \text{Normal}(0, 2.5) \\
\beta_1 &\sim \text{Normal}(0, 2.5)
\end{aligned}
$$

We run the model in R (R Core Team 2023) using the rstanarm package of (Goodrich et al. 2022).

We calculate the total number of deaths by the formula:

$$
\text{total deaths} = e^{\beta_0 + \sum_{i=1}^{5} \beta_i X_i} \tag{1}
$$

Where $X_1$, $X_2$, $X_3$, $X_4$, and $X_5$ represent $X_{\text{Acute myocardial infarction}}$, $X_{\text{All other forms of chronic}}$, $X_{\text{Malignant neoplasms}}$, $X_{\text{Organic dementia}}$, and $X_{\text{Other chronic}}$ respectively.

## 3.2 Model justification

The choice of the Poisson and Negative Binomial models stems from their suitability for count data. The Poisson model is a natural starting point for modeling count data, assuming that each event occurs independently and the mean rate of occurrence is constant.

However, the Poisson model's restrictive assumption that the mean equals the variance often does not hold in real-world data, prompting the use of the Negative Binomial model. The Negative Binomial model relaxes the equal mean-variance assumption by introducing a dispersion parameter, making it well-suited for modeling overdispersed count data that is common in mortality records.

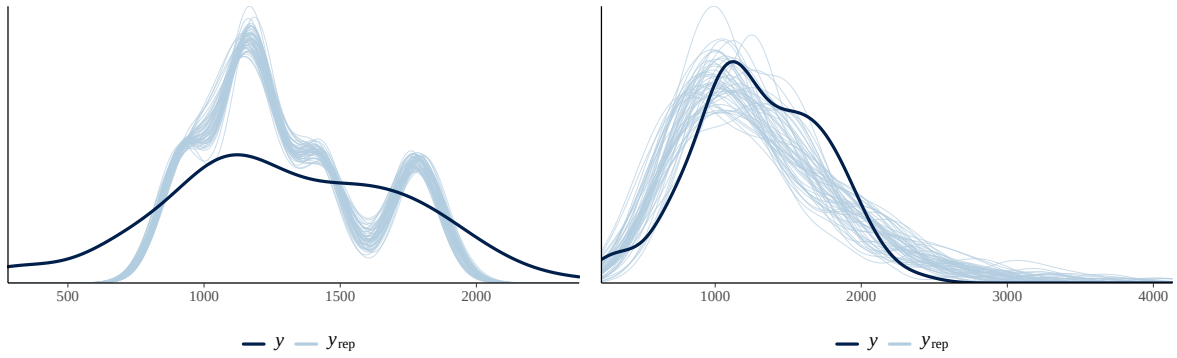
Table 2 illustrates a significant disparity between the mean(509.2) and the variance(201414.1) of total deaths over a span of 22 years, indicating the presence of overdispersion. Such a

Table 2: Showing the mean and variance of total deaths in each year from 2001 to 2022, in Alberta

Table 3: Mean and Variance of Total Number of Deaths Over 22 Years

| Estimate | Variance |
|---|---|
| 509.2 | 201414.1 |

finding suggests that the Negative Binomial model may be more appropriate than the Poisson model for this dataset. The Poisson model operates under the assumption that the mean and variance are equal, an assumption not supported by our data. In contrast, the Negative Binomial model can accommodate the observed overdispersion by allowing for a variance that is greater than the mean, thus providing a potentially better fit for the data. We also compare how the two models fit the real dataset using ppcheck in the bayesplot package (Gabry et al. 2019).




(a) Poisson model

(b) Negative binomial model

Figure 2: Comparing Poisson and negative binomial models

Figure 2 displayes a graphical comparison of posterior predictive checks for Poisson model and Negative binomial model. Figure 2a shows the fit for the Poisson model. The simulated "y_rep" lines show the spread and central tendency of the predictions that the Poisson model makes for the observed data. The replicated data lines seem to spread out and fluctuate more around the observed data, which suggests a lesser fit, particularly if the spread is wider and doesn't track the shape of the observed data closely. Figure 2b shows the fig for the Negative binomial model. The replicated data lines appear to follow the observed data line more closely, suggesting that the Negative binomial model captures the central tendency and variability of the observed data better than the Poisson model.

Table 4 shows a model comparison using the expected log pointwise predictive density (ELPD) for two models: a Poisson model and a Negative binomial model. Negative binomial model has an ELPD difference of 0.0, which serves as the baseline because it's the model with the

Table 4: LOO Comparison between Poisson and Negative Binomial Models

| Model | ELPD diff | SE diff |
|---|---|---|
| Negative binomial model | 0.0 | 0.0 |
| Poisson model | -5091.2 | 1201.6 |

higher (or equal) ELPD. Poisson_model shows an ELPD difference of -5091.2 compared to the Negative binomial model, with a standard error of the difference of 1201.6. The large negative ELPD difference suggests that the Negative binomial model has a much higher ELPD than the Poisson model, which means it is better at predicting new data according to this metric. The standard error of 1201.6 indicates the uncertainty around this ELPD difference estimate. A high standard error relative to the ELPD difference can indicate less confidence in the model comparison, but in this case, the magnitude of the difference (-5091.2) is much larger than the standard error, suggesting the result is quite robust. In summary, the table suggests that the Negative binomial model is significantly better at predicting the observed data than the Poisson model in this particular analysis.

Therefore, the visual evidence Figure 2 and the observed overdispersion beyond what the Poisson model can adequately handle Table 2, and the ELPD Table 4 indicate that the Negative binomial model may be more appropriate for this dataset.

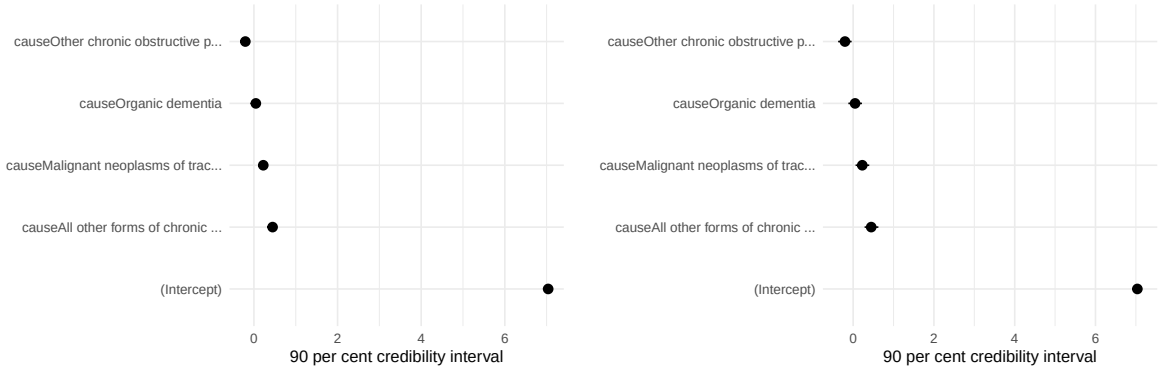
### 3.3 Model summary

Table 5 displays a model summary of Poisson and Negative binomial models, used to model the cause of deaths in Alberta from 2000 to 2022. Since we've decided that negative binomial model is a better model to use in the model justification section, we are only to describe the coefficients of the negative binomial model. "Acute myocardial infarction" used as the intercept, estimated at 7.037, represents the expected log count of the baseline category of deaths when all other factors are held constant. The coefficient for "All other forms of chronic diseases" (0.448) suggests that these conditions are associated with an increase in the log count of deaths. This implies that, when occurrences of such chronic diseases are present, there is a higher incidence of deaths. For "Malignant neoplasms of the trachea" the coefficient of 0.226 indicates a positive association with the log count of deaths, though its magnitude is smaller than that of other chronic diseases. It still represents a notable increase in the mortality count due to these types of cancer. "Organic dementia" has a coefficient of 0.048, signifying a slight increase in the log count of deaths when organic dementia is the cause, which highlights its impact on mortality, albeit less pronounced than the other conditions. Conversely, "Other chronic obstructive pulmonary diseases" has a negative coefficient (-0.202), indicating that these conditions are associated with a lower log count of deaths compared to the baseline. The coefficients are accompanied by standard errors (in parentheses), which are reasonably small, indicating that the estimates are made with a degree of precision. These coefficients and their

Table 5: Modeling the cause deaths in Alberta, 2000 - 2022

| | Poisson | Negative binomial |
|---|---|---|
| (Intercept) | 7.037 | 7.037 |
| | | (0.070) |
| causeAll other forms of chronic ... | 0.446 | 0.448 |
| | | (0.101) |
| causeMalignant neoplasms of trac... | 0.223 | 0.226 |
| | | (0.102) |
| causeOrganic dementia | 0.046 | 0.048 |
| | | (0.101) |
| causeOther chronic obstructive p... | −0.206 | −0.202 |
| | | (0.101) |
| Num.Obs. | 110 | 110 |
| Log.Lik. | −5718.182 | −810.965 |
| ELPD | −5906.6 | −815.4 |
| ELPD s.e. | 1211.7 | 10.5 |
| LOOIC | 11 813.2 | 1630.9 |
| LOOIC s.e. | 2423.5 | 21.1 |
| WAIC | 11 965.6 | 1630.8 |
| RMSE | 325.38 | 325.38 |

standard errors inform us about the relationship between each cause of death and the overall mortality rate, with the negative binomial model accounting for the overdispersion.




(a) Poisson model

(b) Negative binomial model

Figure 3: 90% Confidence Interval

Figure 3 displays the 90% credibility intervals for the coefficients estimated from a Poisson model and a Negative binomial model. Each dot represents the point estimate of the coefficient for a given variable, and the horizontal lines represent the intervals within which we are 90% confident that the true value of the coefficient lies. For both the Poisson and Negative binomial models, we can see: the intercept has the highest point estimate, with a very narrow interval, indicating a high degree of certainty about its value. The coefficients for "All other forms of chronic diseases", "Malignant neoplasms of trachea", and "Organic dementia" are all positive and have intervals that do not cross zero, suggesting these are statistically significant factors that increase the log count of deaths. The coefficient for "Other chronic obstructive pulmonary diseases" is negative and its interval also does not cross zero, indicating a statistically significant decrease in the log count of deaths. The intervals are symmetrical and relatively narrow, which shows a high degree of precision in the estimates.

## 4 Results

The analysis of the causes of death and their impact on the total mortality reveals a clear hierarchy of influences. Among the top causes, "All other forms of chronic diseases" exerts the most substantial increase in mortality rates, with a coefficient of 0.448, suggesting a significant and persistent impact on public health over the studied period. This cause of death represents the most considerable burden on mortality rates in Alberta, distinctly standing out when compared to other leading causes. In contrast, conditions grouped under "Other chronic obstructive pulmonary diseases" are associated with a reduced impact on mortality, as evidenced by the negative coefficient of -0.202. This indicates that, while still a top cause of death, its relative effect on increasing the total number of deaths is lesser than that of the

chronic diseases category. As we interpret these coefficients, it is critical to note that they measure the log change in the death count, which reflects a multiplicative change in the total deaths for a one-unit increase in the cause-specific predictor.

Table 2 provides a concise summary of these overall statistics: the mean number of deaths across all years was found to be 509.2, with a considerable variance of 201,414.1, underscoring the fluctuations in annual death tolls. The marked difference between the mean and variance suggests substantial overdispersion, a pivotal factor in our model selection. These summary statistics are the bedrock upon which our modeling efforts were built, justifying the choice of the Negative Binomial model over the Poisson model for our dataset.

Advancing to the model results, we found distinct trends among the top causes of death. Figure 1 illustrates the annual death counts for the five leading causes over the 22-year period. Notably, organic dementia shows a pronounced increasing trajectory, indicating a growing impact on mortality over time. In contrast, deaths from acute myocardial infarction and other chronic obstructive pulmonary diseases exhibit relative stability.

Collectively, these results paint a detailed statistical landscape of mortality in Alberta, with the Negative Binomial model providing a robust framework for understanding the dynamics of death causes over the two-decade span of our study.

# 5 Discussion

## 5.1 Overview of Findings

Our study rigorously quantified the influence of various causes on mortality in Alberta, leveraging Poisson and Negative Binomial models. The statistically significant coefficient of 0.448 for "All other forms of chronic diseases" in the Negative Binomial model illuminates the pronounced effect these diseases have on elevating mortality rates, surpassing other causes in their impact.

## 5.2 Insights into Chronic Diseases

The upward trend in deaths attributed to organic dementia, indicated by a coefficient of 0.048, statistically confirms the increasing burden of dementia. This trend is particularly concerning given the aging demographic and suggests a growing public health challenge that demands focused research and intervention strategies.

### 5.3 Pulmonary Diseases

The analysis presented a nuanced view of pulmonary diseases, with COPD showing a negative coefficient of -0.202. This stability, while indicative of effective management strategies, also highlights the continuous presence of these diseases as a significant cause of mortality. The data suggests that while progress has been made, pulmonary diseases remain a critical area for public health focus.

### 5.4 Choice of model

The posterior predictive checks displayed in Figure 2 provide a visual comparison between the Poisson and Negative Binomial models' fits to the observed data. The Negative Binomial model demonstrates a closer alignment with the actual data, as indicated by the tighter clustering of the 'y_rep' lines around the observed values.

A numerical comparison between the models is presented in Table 4, where the Negative Binomial model distinctly outperforms the Poisson model, with an ELPD difference indicating better predictive accuracy.

### 5.5 Limitations and Considerations

The exclusion of transient causes like COVID-19 due to data limitations underscores a methodological constraint that could skew the understanding of recent mortality trends. Moreover, the reliance on the Negative Binomial model, while addressing overdispersion, introduces assumptions that may not fully capture the complexity of mortality data, particularly in the presence of significant variance (201,414.1) observed across the dataset.

### 5.6 Future Directions

The findings advocate for an expanded statistical framework in future research, incorporating a broader array of causes, including pandemic-related mortality, and potentially employing more sophisticated models to better handle data complexities. Further, integrating demographic and socio-economic variables could offer a more comprehensive statistical analysis, uncovering deeper insights into the multifaceted nature of mortality determinants.

In summary, our detailed statistical analysis has explained the dominant role of chronic diseases in shaping mortality trends, with dementia emerging as a growing concern. The stable impact of pulmonary diseases, while reflecting some measure of control, underscores the need for sustained public health efforts. Moving forward, embracing more complex statistical models and broader datasets will be pivotal in advancing our understanding of mortality dynamics and informing public health strategies.

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