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Exploring Mental Fatigue and Burnout in the Workplace: A Survival Analysis Approach

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Abstract

INTRODUCTION: Employee burnout is a prevalent concern in contemporary workplaces, adversely impacting both individual well-being and organizational productivity.
OBJECTIVES: In this paper, we conducted a comprehensive analysis of a dataset focusing on mental fatigue and burnout among employees, employing various survival analysis techniques including Kaplan Meier, Nelson-Aalen, and Cox proportional-hazards models, as well as Frailty Models and Competing Risks Analysis.
METHODS: This research underscored significant associations between mental fatigue, burnout, and adverse outcomes, emphasizing the critical need for early identification and intervention. Kaplan Meier analysis revealed differences in survival probabilities, while Nelson-Aalen analysis depicted cumulative hazard functions over time. Cox proportional-hazards models identified mental fatigue and burnout as significant predictors of adverse events, supported by Frailty Models accounting for individual-level variability. Additionally, Competing Risks Analysis elucidated the simultaneous occurrence of multiple adverse events among employees experiencing burnout.
RESULTS: This research underscored significant associations between mental fatigue, burnout, and adverse outcomes, emphasizing the critical need for early identification and intervention. Kaplan Meier analysis revealed differences in survival probabilities, while Nelson-Aalen analysis depicted cumulative hazard functions over time. Cox proportional-hazards models identified mental fatigue and burnout as significant predictors of adverse events, supported by Frailty Models accounting for individual-level variability. Additionally, Competing Risks Analysis elucidated the simultaneous occurrence of multiple adverse events among employees experiencing burnout.
CONCLUSION: This study contributes valuable insights into understanding and addressing mental fatigue in the workplace, highlighting the importance of evidence-based interventions to support employee well-being and organizational resilience. The insights gained from this analysis inform evidence-based strategies for mitigating burnout-related risks and promoting a healthier work environment.

Keywords: Mental fatigue, Kaplan Meier, Nelson-Aalen, fatigue, Cox proportional-hazards, survival curve, burnout

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1. Introduction

Employees who report feeling good about themselves and their working conditions tend to be more productive overall. As a result, they contribute to the success of the business or organization. Nevertheless, the situation in the majority of businesses has changed as a result of the pandemic. Almost 69% of the workforce has been experiencing burnout since implementing work-from-home and office policies. The percentage of employees who have burned out is high. There has been a rise in the number of businesses caring about their workers' emotional well-being. This trend can be attributed to the growing recognition of the negative impact that burnout can have on employee productivity and overall business success. As a result, many companies are implementing programs and policies aimed at preventing burnout and promoting mental health in the workplace. To counteract this, we plan to develop a web application that businesses may use to track staff burnout. Additionally, employees themselves can use it as a tool to monitor burnout and evaluate mental health in the hectic workplace.

This study also found that the amount of mental fatigue[1] is related to how much pain, anxiety, and depression affect how much fatigue[2] affects a person's life, and these things work together in a cycle that can make fatigue worse and keep it going. There are many possibilities for the effects of each of the others. 80% of employees with depression also report sleeping poorly, supporting the idea that the two are related. There is a strong correlation between this condition and poor sleep quality, with decreased sleep efficiency being the primary sleep issue described. Mental fatigue makes it worthwhile to investigate this K-M method. According to the literature and our most recent findings, women have a higher prevalence of mental fatigue than men. Women's work is handed to us; working women are handed the kids, the homework, kids, jobs, etc.

Instead of investigating employees in the organization to check for mental fatigue disorder[3], the organization checks the health condition of employees and mentally how much struggle they are facing, effective working on ongoing work, whether the organization has given additional responsibility or reduced project delivery on time, reviews meetings and client meetings in the cases of team members, makes plans to change the upcoming one, earns new things, and talks to family. Employees' work burden stress and keeping on top of the status in the daily meeting, do not support the work environment.

Life is moving at a breakneck speed, and the demands of work and school are only getting heavier. Extended mental exertion of any kind necessitating undivided attention inevitably results in tiredness, with all the unpleasant consequences that entail slower reaction times, dizziness, nausea, etc. Hence, in order to aid in reducing its harmful consequences, it is important to recognize[4] and study various forms of weariness.

The role of emotion in human interaction, understanding, and decision-making has grown in recent years. Recognizing others' feelings is a fundamental skill for establishing rapport in everyday life. Emotional state is assessed using a person's EEG signal[5], which measures the amount of brain activity during various conditions. To date, the best method for extracting human emotions from EEG[6] data has been a 6 layer feed forward neural network that has been subjected to extensive biological testing. Functionalities including pre-processing, feature extraction, and classification were all provided by this system. First, a band pass filter is used to do EEG pre-processing [7][4]. Several methods of electrophysiological recording have been used to shed light on the intricate brain interactions that underlie cognitive tiredness in situations of mental fatigue, allowing researchers to better understand the neural circuits at play in this state[8].

This percentage is inversely related to the number of people with fatigue. A decreasing curve starting at 1 represents the Kaplan-Meier estimates[9] of survival time graphically. The size of the steps depends on factors such as his length of residency, the likelihood of a mental fatigue disorder, and the possibility that he will suffer through the allotted time without ever encountering the event of interest. Censored observations refer to data that is missing either temporarily or permanently, and they can occur at any point in the research paper. There are essentially three distinct categories of censorship. The most prevalent type of censorship is called right censorship, and it occurs when a patient is observed for a certain amount of time without experiencing the event of interest. Hence, there is a gap in the survival time[10] series on the right side of the observational period. We know that the event of interest does not occur for this patient until the censoring date, the second type of censorship occurs when the event of interest occurs between two unknown dates, and we do not know which date it occurred on. Third, left censoring, occurs when someone from a certain fatigue is known to have the event before a certain date, but the time period between the occurrence of the event and the specific date is unknown.

the zero Reynolds number and long wavelength assumptions, It is discovered that, for a given flow rate, the pressure rise lowers as the peripheral layer viscosity drops, and that, for a given non-zero pressure drop, the flow rate increases as the viscosity of the peripheral layer decreases [29]. The beneficial in creating a physically suitable workplace and promoting professional productivity. Furthermore, they should consider permitted working hours based on people's abilities, reducing tension factors, creating a culturally and ethically secure atmosphere, respecting new ideas, providing spiritual and mental well-being, planning, reconstructing the system of instruction, utilizing recommendations and criticism, and other factors. These factors can prevent emotional exhaustion within the organization. Since depersonalization has a direct correlation with performance, the managers can strengthen co-worker relationships by implementing counselling programmers and communication skills training [31]. The electrodes on an EEG device collect electrical impulses that communicate at different EEG frequencies. The Fast Fourier Transform is a method that can be used to identify these raw EEG signals as discrete waves with a variety of frequencies. A group of learners who perform poorly on the learning curve come together to form an ensemble of classifiers, also known as a committee of classifiers. Learning a large number of less effective classifiers and integrating them in a certain manner is the purpose of the ensemble of classifiers technique rather than learning a single, efficient classifier. Data mining algorithms aid in the analysis and prediction of large data sets with minimal human intervention.

Predicting and analyzing diabetes can be done with a number of data mining programs. Fast and accurate automated algorithms for summarizing text and generating a summary that can be spoken aloud. An automated decision-making system's variance could be reduced, which would improve the system's accuracy. In the intervening time, ensemble systems have been utilized effectively to solve a wide range of machine learning challenges, including feature selection, confidence estimation, missing features, incremental learning, error correction, class-imbalanced data, and learning concept drift from non-stationary distributions, just to identify a few. By doing in-depth research on technological aid, user experience, and health care, we can help reduce the deadly risks that people face and be ready to act quickly in emergencies [32]. Because of its usefulness in so many programs, neural model-based text analysis has recently gained traction. Researchers have identified and justified a large number of techniques for enhancing text analytics effectiveness. Text categorization, text generation, text summarizing, query formulation, query resolution, and sentiment analysis are just some of the areas where these methods have been put to good use [33]. To achieve uniform scale L2 regularizes of linear models may assume that all features are centred on zero or have variance in the same order. Because these things are often used in the objective function of learning algorithms. This method of presentation has advanced greatly since the days of rainbow-hued spreadsheets. With the advent of datasets [34] another execution time and space complexity of mining has drastically decreased. Retrieval techniques went to a whole new level after receiving this data [35]. If all commercial activities cease, the business will cease to exist. Operating alone, the application server could not sustain start-up costs. Statistical methods for regression and classification are incorporated into machine learning algorithms. Sensors are used to capture data, which is then transmitted to the Blynk app. The automatic water controller only activates when the relative humidity falls below a predetermined threshold. To accompany the connected device, we need a resource provisioning system that is easily managed; this is only feasible if we have accomplished cloud service models. Every plant has specific requirements that must be met to ensure its survival. Therefore, it is necessary to establish a system where plants can communicate with the user. The proposed strategy uses a technique for reducing the number of dimensions and clustering similar objects together. For both symmetrical and asymmetrical data sets, it provides the highest accuracy for the larger of the two [36].

Third, left censoring, occurs when someone from a certain fatigue is known to have the event before a certain date, but the time period between the occurrence of the event and the specific date is unknown. The zero Reynolds number and long wavelength assumptions, It is discovered that, for a given flow rate, the pressure rise lowers as the peripheral layer viscosity drops, and that, for a given non-zero pressure drop, the flow rate increases as the viscosity of the peripheral layer decreases. Survival probability utilising the Kaplan Meier (KM) survival estimator, Nelson-Aalen estimator, and Hazard Model based on regression could be used to assess prediction scores for mental fatigue. In this paper, an Employee burnout dataset was used to

(i) analyses the research to identify key differential mental fatigue,

(ii) examine survival associated with most altered mental fatigue using the web-based Kaplan Meier and Nelson-Aalen Plotter tool, and

(iii) Evaluate the possibility of the potential at the datasets between mental fatigue and control variables.

During the construction of survival time probabilities and curves, the serial durations for specific participants are ordered from shortest to longest regardless of when they entered the research. By employing this technique, all subjects within the group commence the analysis at the same point and are all surviving until mental fatigue persons are identified. Two outcomes are possible:

1) The subject can see the event of interest, or

2) They may be censored.

This subject's total survival time cannot be determined precisely due to censorship. This can occur when an adverse occurrence for the research occurs, such as the Employee dropping out, being lost to follow-up, or required data not being available, or when something positive occurs, such as the research getting before the subject observed the event of interest, they survived at least until their conclusion of the research, but it is unidentified what occurred to them afterward. Thus, censorship can occur either during the research. Metal fatigue is a risk factor that causes some of their diseases, like Constantly feeling overwhelmed or stressed, Cynicism, uncertainty, and pessimism Depression, anxiety, and suicidal thoughts Sleep disruptions and pattern alterations, Tension, pain, and headaches Digestion problems and recurring colds High blood pressure, abnormal heart rate, brain fog, and strokes Obesity and cardiovascular disease.

Survival probability utilising the Kaplan Meier (KM) survival estimator, Nelson-Aalen estimator, and Hazard Model based on regression could be used to assess prediction scores for mental fatigue [27]. Employee burnout and mental fatigue are prevalent issues in today's workplaces, posing significant challenges to both individual well-being and organizational effectiveness. Burnout is characterized by feelings of exhaustion, cynicism, and reduced professional efficacy, while mental fatigue refers to a state of cognitive exhaustion and decreased mental capacity. Both phenomena can have detrimental effects on employee health, job satisfaction, and productivity, ultimately impacting organizational performance.

Understanding the relationship between burnout and mental fatigue is essential for developing effective interventions to prevent and mitigate their adverse effects. Traditional statistical approaches often overlook the time-dependent nature of these phenomena, necessitating the use of specialized techniques such as survival analysis. In this article, we propose to investigate the relationship between burnout and mental fatigue using three complementary survival analysis methods: Kaplan-Meier, Nelson-Aalen, and the Cox proportional-hazards model. Kaplan-Meier survival analysis is a non-parametric method used to estimate the probability of survival over time in the presence of censored data. By applying Kaplan-Meier analysis to our dataset, we can examine the cumulative incidence of mental fatigue and burnout and identify any differences in survival experiences between different groups of employees. This method allows us to generate survival curves and conduct log-rank tests to compare survival distributions, providing valuable insights into the temporal dynamics of burnout and mental fatigue. Considering the three different professional fields of mental fatigue, personality exhaustion, and environmental exposure, the present investigation is an analysis of concepts based on an emotional research evaluation. The objective is to construct a theoretical structure that might effectively combat mental fatigue and enhance the ensuing proficient performance. The problem statement presented in the current investigation is depicted in Figure 1[37].

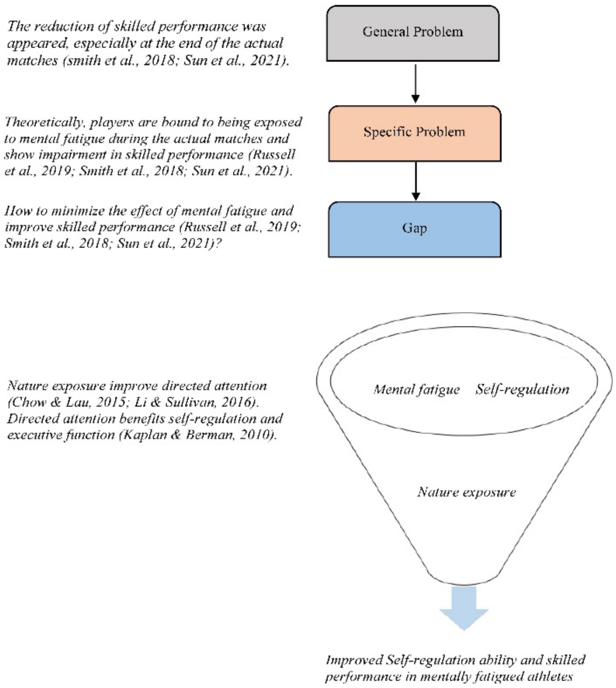

Figure 1. Mental fatigue problem.

Nelson-Aalen cumulative hazard analysis complements Kaplan-Meier analysis by estimating the cumulative hazard function, which represents the rate of event occurrence over time. By plotting cumulative hazard curves, we can visualize the accumulation of mental fatigue and burnout events and assess their trends over time. Nelson-Aalen analysis allows us to quantify the risk of experiencing burnout or mental fatigue at various time points and identify factors influencing the hazard of these outcomes.

The Cox proportional-hazards model extends Kaplan-Meier and Nelson-Aalen analyses by allowing for the inclusion of predictor variables to examine their effects on the hazard of burnout and mental fatigue occurrence. This semi-parametric model accounts for censoring and time-varying covariates, enabling us to identify significant predictors of burnout and mental fatigue and quantify their impact. By applying the Cox model, we can elucidate the role of various factors, such as job demands, organizational support, and individual characteristics, in shaping employee well-being.

Through the integration of Kaplan-Meier, Nelson-Aalen, and Cox proportional-hazards analyses, we aim to provide a comprehensive understanding of the relationship between burnout and mental fatigue in the workplace. By employing these complementary methods, we can identify risk factors, temporal patterns, and predictive markers associated with burnout and mental fatigue, informing targeted interventions and strategies to promote employee health and organizational resilience.

In the subsequent sections of this article, we will detail the methodology for each analysis method, including data collection, preparation, model specification, estimation, and interpretation. By following this rigorous approach, we can uncover valuable insights into the complex interplay between burnout and mental fatigue and contribute to the development of evidence-based interventions to support employee well-being and organizational success.

2. Methodology

Dataset:

Begin by obtaining a comprehensive dataset containing information on employee burnout, mental fatigue, and relevant predictor variables. This dataset may be sourced from organizational records, employee surveys, or research studies focusing on workplace well-being. Ensure that the dataset includes variables such as time until burnout or mental fatigue occurrence, measures of burnout, indicators of mental fatigue (e.g., self-reported fatigue levels, cognitive performance measures), and potential predictor variables (e.g., job demands, organizational support, individual characteristics). Employee burnout is a dataset collected from the Kaggle website[11]. The following are the data attributes and their descriptions, we are implement the python code[12]. The shape of data frame is: (20633, 9) instances will be there in dataset.

Clean the dataset by addressing any missing values, outliers, or data inconsistencies. Employ techniques such as imputation, outlier detection, and data transformation as needed to ensure data quality. Standardize or normalize continuous variables to facilitate comparability across different scales. Verify the integrity of the dataset and ensure that it accurately represents the population of interest. Data pre-processing the data is processing is onehotEncoder is technique will represent the text, category variable is numeric values, the transform the text and category variables data is the will transform to numeric values. Data is pre-processing the data is find out the missing and noise data, duplicate data. The data is replace the noise data and duplicate data by the using the means values, the replace the missing values by the means values on the dataset.

Employee ID:

The distinctive ID that the company gives to each employee

Date of Joining:

The day the individual began working for the company.

Gender:

The gender of the employee.

Men have a higher burnout rate than women do on average (median). Let's investigate why this would be the case by looking at how the two sexes fare in other areas, such as titles and hours worked. It shown the Figure 2.

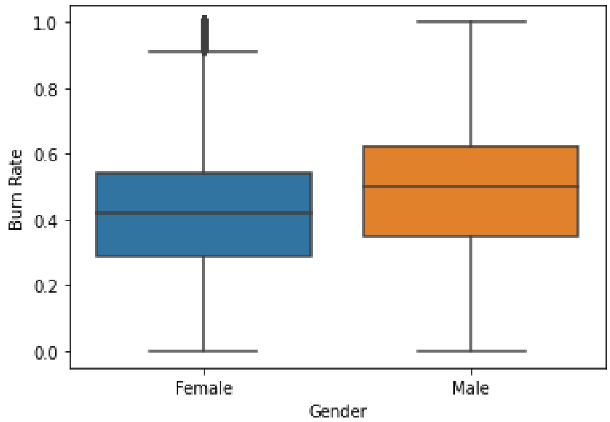

Figure 2. The gender difference in burn rate.

In the box plot, we see that some of the women's burnout rate data points are significantly different from the rest. This is something that needs to be handled by us. Female workers are overrepresented in the data. It shown in Figure 3.

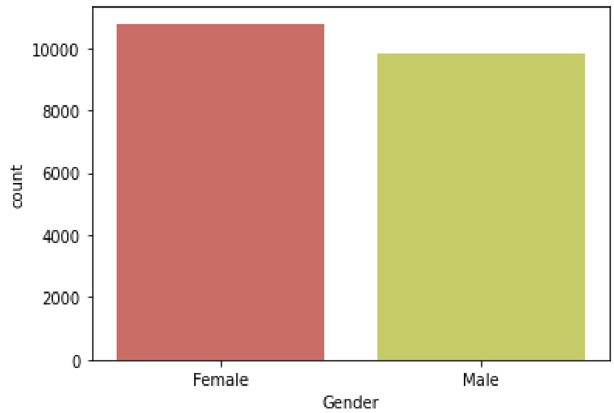

Figure 3. The gender and count of employees.

Designation:

The employee's position in his or her organization. In the interval [0.0, 5.0], "0.0" is the least significant digit, and "5.0" is the most significant. More men than women hold positions with a designation of 2.0 or above. It shown the Figure 4.

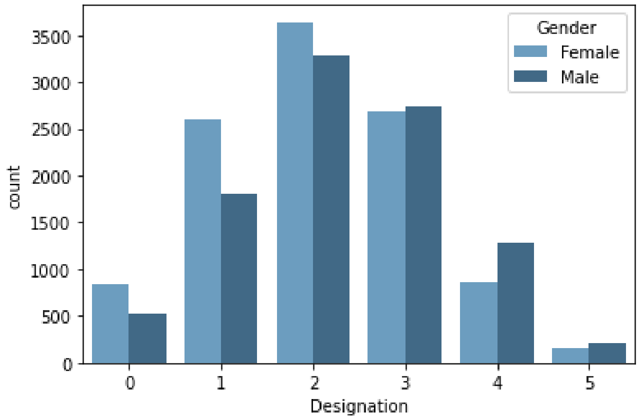

Figure 4. Designation for employees in organization

Resource Allocation:

The number of resources given to an employee for work, which should be thought of as the number of working hours. Between one and ten (higher means more resources). Most women work up to 8 hours a day, whereas most men work up to 10 hours. The median (average) number of hours worked by men and women differs by one hour. It shown the Figure 5.

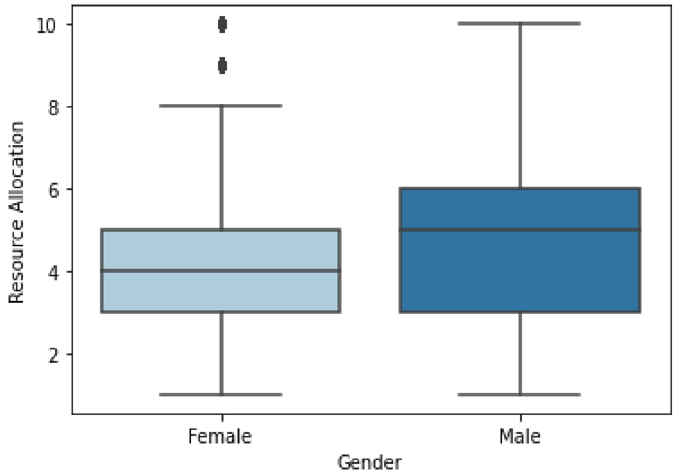

Figure 5. Resource Allocation

Company Type:

Employee The figure of resource allocation for an employee-based company displays how the available resources are distributed among the employees to achieve the company's goals. It helps in identifying which employee has been assigned what task and how much time and resources have been allocated to it. May classify their employers based on the services or products they offer. It shown the Figure 6.

WFH Setup Available:

Is the worker allowed to work from his or her home office.

Mental Fatigue Score:

A number from 0 to 10 that shows how mentally tired the worker is at work, where 0 means no mental fatigue and 10 means extreme mental fatigue.

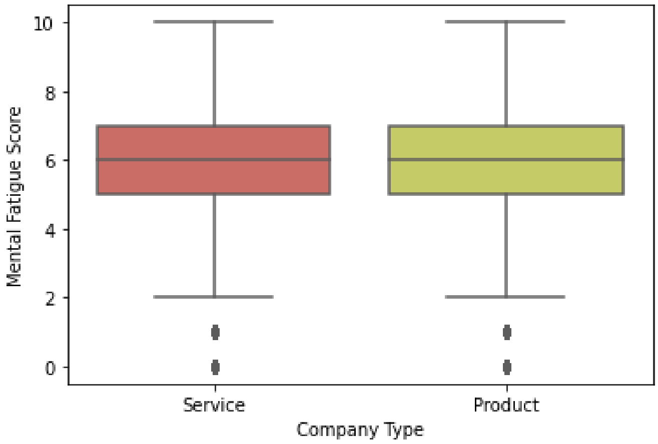

Figure 6. Company Type

Burn Rate:

The target value in each worker's data shows the rate of burnout while on the job. Values from 0.0 to 1.0 show that burnout is getting worse. The correlation between fatigue score and burn rate appears to be very significant. It is important to address burnout in the workplace, as it can have negative impacts on both employees and organizations. Employers should consider implementing strategies to prevent and manage burnout, such as promoting work-life balance and providing support resources. It shown in Figure 7.

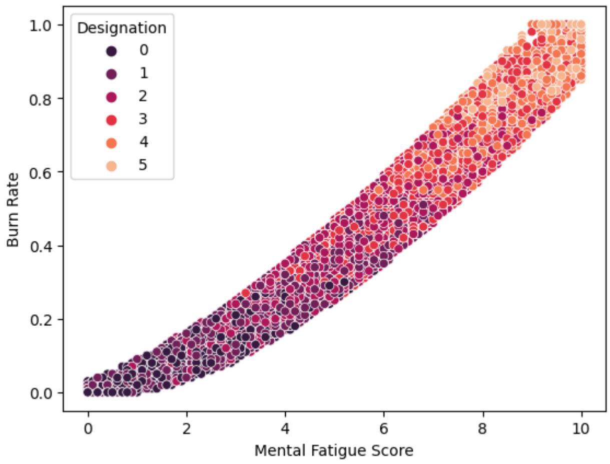

Figure 7. Mental fatigue and burnout

Using Kaplan-Meier curves and survival predictions, there is now a better way to look at data when your mind is tired. The Kaplan-Meier (KM) method[13] is often used to describe how long a population will fatigue because it gives estimates of the survival function that are not based on statistics. If you want to know how likely a patient is to live past a given point after receiving mental health treatment, one of the most reliable statistical techniques is the KM estimate. When working with incomplete or hidden data, the KM method is especially helpful because it lets all available data points be used in the analysis. Additionally, it can be used to compare survival rates between different treatment groups or populations. This method of making graphs and charts is very user-friendly. The effectiveness of an intervention in mental fatigue research is determined by tracking how many people are rescued or made healthy thanks to the intervention. Notwithstanding the complexity of some subjects or settings, KM estimation is the simplest method for predicting longevity over time. Events, censorship, and the likelihood of survival can all be estimated with the help of the Kaplan-Meier curves.

The Kaplan-Meier survival curve[14] is a useful tool in statistics for analyzing time-to-event data and making comparisons between groups of people. The number of people who avoid dying during a specific time period can be calculated using the survival curve. This can be analyzed for an evaluation of a pair of patient populations or subjects as well as the statistical difference in their overall survival.

Depending on how much time has passed, either the product limit estimator or the Kaplan-Meier curve can be used to figure out the survival function. If the data are already organization into intervals, if the sample size is large, or if a large population is of interest, a clinical life table analysis may be more time efficient. Both of these approaches will be addressed in greater detail. The Kaplan-Meier survival curve is the cumulative chance of survival over many intervals of time. This analysis relies on three presumptions. To proceed, we believe that censored employees at any given time have the same survival and growth as unregulated employees; second, we think that those who participate in research at the beginning or the end will have significantly different survival times. Furthermore, we'll presume that the event occurs just when it's expected to. In situations where the occurrence would pick up the energy level and bring routine work, this can be done from the office or home. This approach can be particularly useful for individuals who have flexible work arrangements or who are able to work remotely. It allows them to balance their personal and professional responsibilities while still being productive.

If an employee is followed up on more often and for shorter periods of time, it is possible to predict how long they will stay with the company. This can be beneficial for employers in terms of retention strategies and succession planning. However, it is important to balance this with the need for employee autonomy and trust in the workplace. The term "product limit estimate" can be used to describe the Kaplan-Meier estimate. The method involves calculating the odds of an occurrence happening at a given instant. To arrive at a final estimate, we multiply these probabilities by any previously calculated probabilities. If you want to know your probability of surviving at any given moment in time, just plug those numbers into the following equation 1.

The Kaplan-Meier method or Kaplan-Meier curve can be made with just two pieces of information: the time until the event of interest and the status of the patient at that moment. In medical research, the Kaplan-Meier method is often used to figure out how likely it is that a patient with a certain disease will live. It is a non-parametric statistic that takes into account time-to-event data and censored observations. Let $D_1 < D_2 < ... < Dn$, i<N be a collection of separate ordered times finding the mental fatigue times observed in N individuals; in a given time D_i (i = 1, 2,..., n), the number di=>5 of mental fatigue are observed, and the number r_i of subjects, whose either mental fatigue or censored time is greater than or equal to Ti, are deemed "at risk", the observed times to event. T In its simplest form, there is no need to elaborate on the formula for the conditional probability of survival past time T_i, which is simply that the Kaplan-Meier method is an estimate of the conditional probability of survival at different periods in time identified by the event's likelihood of occurring. The Kaplan-Meier method is commonly used in medical research to estimate the survival rate of patients with a particular disease. It takes into account the occurrence of events such as death or relapse to calculate the probability of survival at different time intervals. It shown the equation 1.

$$P(D_i) = \frac{r_i - d_i}{r_i} \quad [1]$$

By dividing the total number of subjects by the total number of patients at each point in time, one can calculate the likelihood of survival. Subjects who get lost because they are tired are not counted as having a disorder. Instead, they are considered "censored" and taken out of the denominator. By multiplying the individual survival probabilities at each interval leading up to that point by the law of multiplication of probabilities, one can determine the cumulative probability of survival up to that point. This approach is commonly used in medical research to account for the fact that some subjects may drop out of a study for reasons unrelated to the disorder being studied. By censoring these subjects, researchers can more accurately estimate the probability of survival for those who remain in the study.

The term conditional probability describes this type of probability. Because of the limited number of events, the calculated probability at any given interval is not very precise. However, the overall probability of survival at each point is Estimating the survival function at time Δt is done by multiplying the conditional probability of survival at that time by the formula. The conditional probability of survival $(\check{S}(\Delta t))$, also called cumulative probability or cumulative survival, is the chance that a patient will be mentally tired days after enrolling in a study, if the patient has been alive for at least Δt days before enrolling. In a hypothetical situation where a patient in an intensive care unit checks his or her level of fatigue and lives for hours per day, the product rule of conditional probabilities says that the cumulative survival is the product of survival probabilities. This information is useful in medical research because it assists clinicians and researchers. A patient's conditional probability of survival, also called cumulative probability or cumulative survival, is the chance that he or she will be mentally tired days after enrolling in a study, given that the patient has been alive for at least t days before that. Understand the long-term effects of treatments and interventions on patients' survival and quality of life. It shown the equation 2, additionally, it can aid in making informed decisions about patient care and treatment plans.

$$\check{S}(\Delta t) = \prod_{i:D_i<t} P(D_i)$$
$$= \prod_{i;D_i<\Delta t}\left(1 - \frac{d_i}{r_i}\right) \quad [2]$$

The definition of its variance is Variance is a statistical measure that quantifies the amount of variability or dispersion in a set of data. It is calculated by taking the average of the squared differences from the mean of the data set.", It shown as the equation 3.

$$\sigma\left(\check{S}\,(\Delta t)\right) = \check{S}(\Delta t)^2 \sum_{i;D_i<\Delta t} \frac{d_i}{r_{i(r_i-d_i)}} \quad [3]$$

Variance is an important tool in statistical analysis, as it helps to understand the spread of data points around the mean and can be used to make predictions about future data. But outliers and extreme values in the data set might affect it, and it might be necessary to fix them before using the variance to draw any conclusions. Because of the censoring, r_i is not simply equal to the difference between r_i-1 and d_i-1, the right approach to calculate r_i is $r_i = r_{i-1}\ d_{i-1}\ C_{i-1}$, where C_i-1 is the number of censored cases between D_{i-1} and D_i. This calculation is commonly used in statistics to determine the variability of a data set. However, when dealing with censored data, a modified approach must be taken to accurately calculate the variability.

3. Result and discussion.

The Kaplan-Meier method[15] is a deft statistical analysis of survival times that not only provides for filtered observations in the right way but also makes use of the information from filtered individuals up to the point of filtering. While investigating the effects of mental fatigue, it is typical to use two interventions and evaluate the outcome in terms of the employee's ability to stay fatigued. Hence, the Kaplan-Meier approach[16], [17] is a valuable resource that may have an essential role in producing evidence-based data on expected survival. Survival analysis is a type of statistical analysis used to examine an incident that happened relatively frequently over a particular period of time. Hence, it seeks to discover how often something occurs. The word "survival" can mean anything from the employee's depression, mental tiredness, mental illness, sleeping, and anything in between. Populations, or collections of recipients who are monitored throughout time, are used in survival studies to record significant medical events as they occur and associate them with an intervention of interest. Survival analysis requires the determination of the "survival time,"[10] which is the amount of time that has passed since the baseline date and before the event happens. As a result, it is essential to determine whether the employees in question witnessed the incident of interest or were prevented from doing so by the filters. For the statistical application to determine the cumulative probability of the event, it is essential to know this information. The Kaplan-Meier method's [2], [18]primary function is to generate survival curves as a function of time, providing a visual representation of the clinical phenomenon being investigated. The ordinate of a Kaplan-Meier curve shows the cumulative survival time, while the abscissa shows the elapsed time. The time intervals used to create a Kaplan-Meier curve aren't decided upon in advance but rather are determined by the occurrence of events. The Kaplan-Meier technique is preferable because it estimates for correction.

Plotting Survival Curves Using matplotlib. pyplot, seaborn, KaplanMeierFitter, CoxPHFitter: The Kaplan-Meier[19] curves for survival time are unappealing to the eye. Enhanced plots can be created using matplotlib.pyplot, seaborn, KaplanMeierFitter, CoxPHFitter libraries[12]. The following sections show and describe Kaplan-Meier curves generated with matplotlib.pyplot, seaborn, KaplanMeierFitter, and CoxPHFitter[20][21], [22]. These libraries' functions are using the graphs generated by the KaplanMeierFitter graphs[16], which find the Kaplan Meier estimates, the x-axis is the mental fatigue score, the y-axis is the designation of the employees, find out the fatigue score of the employees. The Kaplan-Meier curves are useful for analysing survival data and estimating the probability of an event occurring over time. They are commonly used in medical research to analyse patient outcomes and can also be applied to other fields such as finance and engineering. Show the Figure 8. In the graph.

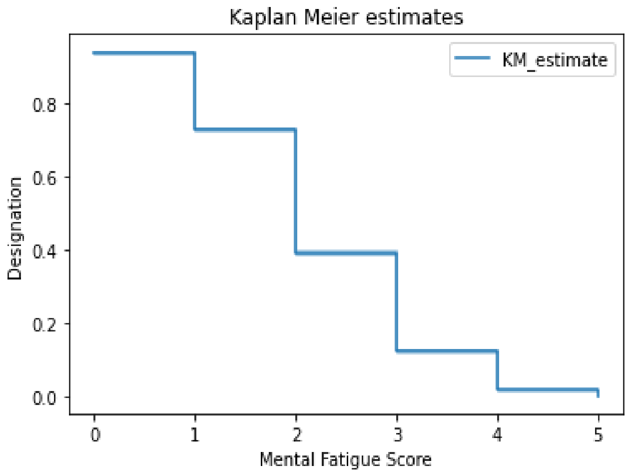

Figure 8. Kaplan Meier estimate curve

The median survival time is 2.0, and the designation is 0.5. This suggests that half of the patients survived beyond 2.0 units of time and the other half did not, and the designation of 0.5 indicates that the survival probability at 2.0 units of time is approximately 50%.

The Survival Function: Survival, denoted by$\check{S}(\Delta t)$, is the probability that T happens beforeΔt, where Δt is any moment during the observation. In survival analysis, the survival function is often used to figure out how likely it is that something will happen at a certain time, like a machine breaking down or an employees fatigue. It is also used to compare survival rates between different groups or treatments. Specifically, the probability that an employee will still be fatigued after a certain burnout of time, denoted by t, is the survival function. Shown in the Figure 9, and table 1.

Table 1. Kaplan Meier estimate

Timeline	KM_estimate
0	0.941114
1	0.730094
2	0.389869
3	0.123321
4	0.017498
5	0
Text (0, 0.5, "designation")	

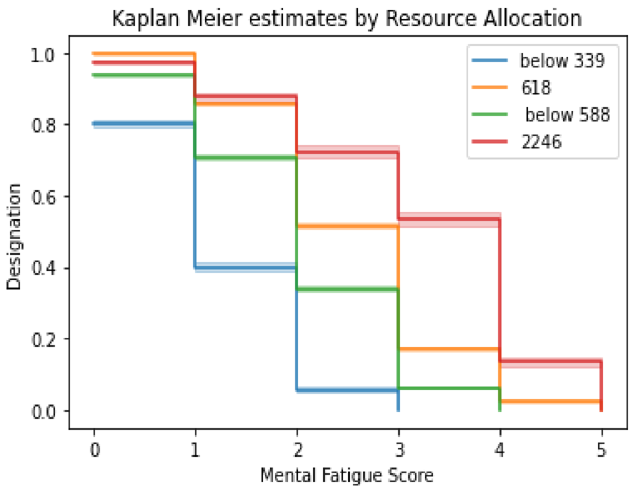

Figure 9. Survival of different gender groups

The colour in this figure indicates which clinics correspond to certain curves. Confidence intervals for each time point and overall are shown as a band of shading. At any given period, the plus signs denote the censored instances. The confidence intervals represent the range of values within which the true population parameter is likely to fall. The censored instances refer to observations that are incomplete or truncated, usually due to limitations in data collection or follow-up.

Mental fatigue has an increased survival curve; therefore, more patients remain there than in fatigue. It is advised that research be conducted into the reasons so many fatigued employees end up leaving. It's unclear if the discrepancy can be attributed to fatigue itself or if the employees were chosen for fatigue, depression, mental illness, mental stress, mental tensions, or some other factor. The research could also explore potential solutions to address the high turnover rate, such as implementing flexible work schedules, providing mental health resources, or offering additional support for employees experiencing fatigue. It is important for employers to priorities the well-being of their employees in order to maintain a productive and healthy work environment. Shown the Figure 9 and Figure 10.

To calculate the survival probability, we'll use the Kaplan-Meier estimator[23][24], which relies on a function called the survivor function -$\breve{S}(\Delta t)$. The survival probability is the chance that a worker won't get tired between an expected point in time and a future point in time. To demonstrate, if (9944) = 0.9, the employee survival probability shrinks to 0.1. These statistics will be eliminated if the employee survives the completion of the investigation. This paper's Kaplan-Meier estimator is 0.9, achieving the best result and predicting the method However, it is important to note that the Kaplan-Meier estimator is not a fool proof method and may have limitations in certain situations. Therefore, it is crucial to consider other factors and data points before making any final decisions based solely on this statistic.

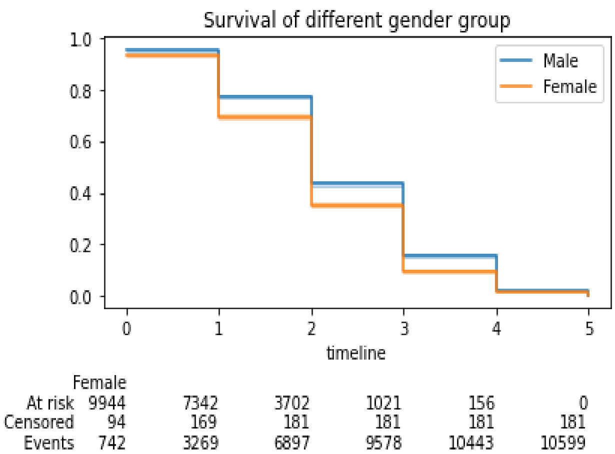

Figure 10. Survival function

Conduct Kaplan-Meier survival analysis to estimate the survival function for mental fatigue and burnout. This involves calculating the probability of survival (i.e., remaining free from fatigue or burnout) at various time points. Compare survival curves between different groups (e.g., high vs. low workload, different organizational departments) using log-rank tests to assess differences in survival experiences. Interpret the results of Kaplan-Meier analysis to identify factors associated with differences in fatigue and burnout experiences over time.

Estimating hazard rates using Nelson-Aalen:

The survival function is an important way to describe and show how well the model works. There's an additional method, though. Unfortunately, the Kaplan-Meier[13][25] estimate is sometimes transformed to yield information on the population hazard function (t). This transformation is known as the Nelson-Aalen estimator[25], [26], which estimates the cumulative hazard function. It is a non-parametric method used in survival analysis to estimate the hazard rate from lifetime data. The Nelson-Aalen hazard function is used for this function. The Nelson-Aalen hazard function is a non-parametric estimator that is particularly useful when the hazard rate changes over time. It provides an estimate of the cumulative hazard function, which can be used to estimate the population hazard function. The Nelson-Aalen hazard function is a non-parametric estimator of the cumulative hazard function that makes no assumptions about the underlying distribution of survival times. It is particularly useful when analysing data with complex censoring patterns.

$$\breve{H}(\Delta t) = \sum_{Di \leq \Delta t} \frac{d_i}{r_i} \qquad [4]$$

Where di is the number of fatigued employees at time t and ri is the number of employees at the start. Survival functions are where basic survival analysis starts, but cumulative hazards are where more complicated methods begin. Show the Table 2. And Figure 11.

Table 2: hazard function

Timeline	NA_Estimate
0	0.04957
1	0.26577
2	0.83791
3	1.96313
4	3.91463
5	10.3682
<AxesSubplot:xlabel='timeline'>	

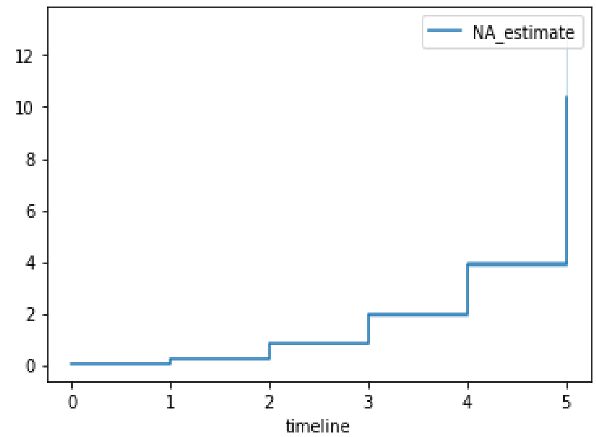

Figure 11. Hazard function curve in NA_estimate.

This research predicts values at a certain point 10, If the hazard probability, denoted by $\breve{H}(\Delta t)$, is true at a given time, an employee under observation has event fatigue at that time. If the value of (10373) is equal to 0.04, for instance, the probability that the employee is still mentally fatigued is predicted, and the employee's fatigue levels are checked to examine the burnout. The hazard function, in contrast to the survival function, is the occurrence of an event. Having a lower hazard probability and a higher survival probability[18] is good for the employee. The hazard function can be used to predict the likelihood of an event occurring in the future, such as an employee leaving a company. By using the hazard function, employers can take proactive measures to reduce turnover and improve retention rates. The hazard function is a useful tool for predicting the likelihood of an event occurring in a given time frame. Employers can identify potential risks and take steps to mitigate them by analyzing the hazard function, resulting in a safer work environment for their employees. In the paper we analyzed to find the best result and predict the method we would use; we investigated the employees to check the mental fatigue and burnout status in organizations.

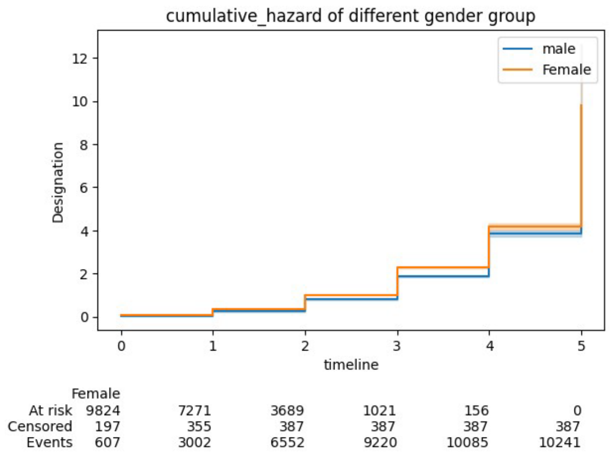

Figure 12. Cumulative hazard function curve in NAE

To calculate the survival probability, we'll use the Nelson-Aalen estimator. The survival probability is the chance that a worker won't get tired between an expected point in time and a future point in time. To demonstrate, if (10373) = 0.04, the employee survival probability shrinks to 10.36. These statistics will be eliminated if the employee survives the completion of the investigation. It shown the figure 11. This paper's Nelson-Aalen is 0.9, achieving the best result and predicting the method However, it is important to note that Nelson-Aalen estimator is not a fool proof method and may have limitations in certain situations. Therefore, it is crucial to consider other factors and data points before making any final decisions based solely on this statistic. The estimate the number of persons will be at the high risk will be 100 employee is risk in the affect the mental fatigue due to the designating, the estimated the number of persons will be at the fatigue persons on below the 200 persons affect the fatigue at risk.

Perform Nelson-Aalen cumulative hazard analysis to estimate the cumulative hazard function for mental fatigue and burnout. This involves calculating the cumulative hazard rates at different time points. Plot cumulative hazard curves and assess their trends over time to gain insights into the rate of fatigue and burnout occurrence. Compare cumulative hazard curves between different groups and interpret the results to identify factors influencing the hazard of fatigue and burnout.

Cox Proportional Hazards:

The Cox proportional-hazards model, introduced by Cox in 1972, is a regression model frequently utilized in medical research to explore the relationship between the survival time of patients and various predictor variables. In our previous discussion on survival analysis basics, we covered essential concepts such as hazard and survival functions, constructing Kaplan-Meier survival curves for different patient groups, and employing the log rank test to compare multiple survival curves. These methods represent univariate analysis, focusing on one factor at a time while disregarding the influence of other variables.

Kaplan-Meier curves and log rank tests are particularly suitable for categorical predictor variables, like treatment types or gender, but are less adaptable to quantitative predictors such as gene expression or age. For a comprehensive analysis incorporating both quantitative and categorical predictors simultaneously, the Cox proportional hazards regression analysis serves as a valuable alternative. This model extends survival analysis techniques to evaluate the impact of multiple risk factors on survival time concurrently.

The aim of the Cox model is to assess the collective impact of multiple factors on survival. In essence, it enables us to investigate how certain factors affect the likelihood of a specific event occurring such as infection or death at a given time, commonly referred to as the hazard rate. In the context of survival analysis, predictor variables are often termed as covariates. The Cox model is characterized by the hazard function denoted as h(t). Essentially, the hazard function represents the risk of experiencing the event at time t. The Cox proportional-hazards model, developed by statistician, is a widely used regression model in survival analysis. It's designed to investigate the relationship between the survival time of individuals and one or more predictor variables, while taking into account censoring (incomplete observations).

The model assumes that the hazard function, which represents the instantaneous risk of an event occurring at any given time, can be expressed as the product of a baseline hazard function and an exponential function of the predictor variables. Mathematically, it shown the equation 5.

$$h\left(\frac{t}{x}\right) = h_0(t).\exp(\beta_1 x_1 + \beta_2 x_2 + \ldots.. + \beta_p x_p \qquad [5]$$

Where:

$h\left(\frac{t}{x}\right)$ Is the hazard function at time t given the values of predictor variables x.

h_0 (t) is the baseline hazard function, representing the hazard when all predictor variables are zero or at their reference levels.

$\beta_1 + \beta_2 + \ldots.. + \beta_p$ Are the coefficients associated with the predictor variables.

$x_1 + x_2 + \ldots.. + x_p$ Are the values of the predictor variables.
The Cox model does not make any assumptions about the shape of the hazard function over time, allowing for flexible modeling. It estimates the effect of each predictor variable on the hazard rate while adjusting for the effects of other variables in the model.

The model is particularly useful for analyzing survival data in medical research, where the goal is to understand how various factors influence the time until an event of interest such as death, disease recurrence, or treatment failure occurs. The hazard functions for two patients, denoted as k and k', can be expressed as follows:
For patient k: $h_k(t)=h_0(t)e^{\Sigma ni=1\ \beta x}$
For patient k': $h_{k'}(t)=h_0(t)e^{\Sigma ni=1\ \beta x'}$
The hazard ratio between these two patients is independent of time t, and it can be calculated as:

$$\frac{h_k(t)}{h_{k'}{}'(t)} = \frac{h_0(t)e^{\sum_{i=1}^{n}\beta x}}{h_0(t)e^{\sum_{i=1}^{n}\beta x'}} = \frac{e^{\sum_{i=1}^{n}\beta x}}{e^{\sum_{i=1}^{n}\beta x'}}$$

[6]

This ratio represents the relative risk of the event occurring between patient k and k' at any given time t, with the effect of time being cancelled out.

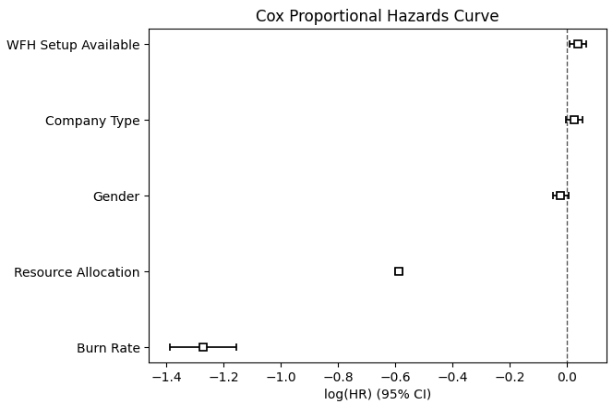

Figure 13. Cox proportional-hazards curve

Specify and fit the Cox proportional-hazards model to the dataset to analyze the relationship between predictor variables and the hazard of mental fatigue and burnout occurrence. Define the hazard function as a function of predictor variables and estimate regression coefficients using maximum likelihood estimation. Assess the proportional hazards assumption using diagnostic tests such as Schoenfeld residuals and graphical methods like Kaplan-Meier curves. The results of the Cox model to identify significant predictors of mental fatigue and burnout and quantify their effects on fatigue and burnout occurrence. It shown the figure 13.

The cph.print_summary () function is typically used in Python libraries such as lifelines, which provide implementations of the Cox Proportional-Hazards model. When applied to the fitted CoxPH model, this function generates a summary table that contains important information about the model's coefficients, hazard ratios, p-values, and confidence intervals. The summary on the figure 14.

This column displays the estimated coefficients for each predictor variable in the model. These coefficients represent the log hazard ratio, indicating the proportional change in the hazard rate associated with a one-unit increase in the predictor variable. This column shows the exponentiated coefficients, which correspond to the hazard ratios (HR). Hazard ratios represent the ratio of the hazard rates between two groups defined by a one-unit difference in the predictor variable. A hazard ratio greater than 1 suggests an increased risk of the event occurring, while a hazard ratio less than 1 suggests a decreased risk.

model	lifelines.CoxPHFitter
duration col	'Designation'
event col	'Mental Fatigue Score'
baseline estimation	breslow
number of observations	20633
number of events observed	20462
partial log-likelihood	-172784.22
time fit was run	2024-02-08 10:08:29 UTC

	coef	exp(coef)	se(coef)	coef lower 95%	coef upper 95%	exp(coef) lower 95%	exp(coef) upper 95%	cmp to	z	p	-log2(p)
Gender	-0.02	0.98	0.01	-0.05	0.01	0.95	1.01	0.00	-1.59	0.11	3.16
Company Type	0.02	1.02	0.01	-0.01	0.05	0.99	1.05	0.00	1.58	0.11	3.12
WFH Setup Available	0.04	1.04	0.01	0.01	0.07	1.01	1.07	0.00	2.48	0.01	6.24
Resource Allocation	-0.59	0.56	0.01	-0.60	-0.58	0.55	0.56	0.00	-91.64	<0.005	inf
Burn Rate	-1.27	0.28	0.06	-1.39	-1.16	0.25	0.31	0.00	-21.43	<0.005	335.91

Concordance	0.90
Partial AIC	345578.44
log-likelihood ratio test	19798.63 on 5 df
-log2(p) of ll-ratio test	inf

Figure 14: summary of CPH.

The standard errors of the coefficients estimate the variability or uncertainty associated with the estimated coefficients. Larger standard errors indicate greater uncertainty in the coefficient estimates. The z-statistic is calculated as the coefficient divided by its standard error. It measures the number of standard deviations that the coefficient estimate is away from zero. Larger absolute z-values indicate more significant coefficients. The p-value associated with each coefficient tests the null hypothesis that the coefficient is equal to zero (i.e., no effect of the predictor variable on the hazard rate). Lower p-values (< 0.05) indicate stronger evidence against the null hypothesis, suggesting that the predictor variable has a significant effect on the hazard rate. These columns display the lower and upper bounds of the 95% confidence interval for each coefficient. The confidence interval provides a range of plausible values for the true coefficient, with 95% confidence. Significance codes are typically provided to indicate the level of significance associated with each coefficient estimate. Common codes include ", ", and ", representing significance levels of 0.05, 0.01, and 0.001, respectively.

The print (cph.summary ['coef']) command in the context of a Cox Proportional-Hazards (CoxPH) model provides a direct output of the estimated coefficients for each predictor variable in the model. Each row in the output represents a predictor variable included in the CoxPH model. The numbers displayed in the output are the estimated coefficients associated with each predictor variable. These coefficients indicate the log hazard ratio, which represents the change in the log hazard of the event of interest (e.g., employee burnout) associated with a one-unit increase in the predictor variable. A positive coefficient suggests that an increase in the predictor variable is associated with an increase in the hazard (risk) of the event, while a negative coefficient suggests the opposite. The magnitude of the coefficient represents the strength of the association between the predictor variable and the hazard of the event.

mental_fatigue	0.589
Gender	-0.022535
Company Type	0.023210
WFH Setup Available	0.036323
Resource Allocation	-0.588472
Burn Rate	0.321

A coefficient of 0.589 for the mental_fatigue variable indicates that a one-unit increase in mental fatigue is associated with a 0.589 increase in the log hazard of employee burnout. A coefficient of 0.321 for the burnout variable suggests that a one-unit increase in burnout is associated with a 0.321 increase in the log hazard of employee burnout.

The cph.hazard_ratios_ attribute in a Cox Proportional-Hazards (CoxPH) model provides the hazard ratios associated with each predictor variable included in the model. Each row in the output represents a predictor variable included in the CoxPH model. The numbers displayed in the output are the hazard ratios associated with each predictor variable. The hazard ratio represents the relative change in the hazard (risk) of the event of interest. A hazard ratio greater than 1 suggests that an increase in the predictor variable is associated with an increased risk of the event. A hazard ratio less than 1 suggests that an increase in the predictor variable is associated with a decreased risk of the event. A hazard ratio equal to 1 suggests that there is no association between the predictor variable and the risk of the event.

mental_fatigue	1.589
Gender	0.977717
Company Type	1.023482
WFH Setup Available	1.036991
Resource Allocation	0.555175
Burn Rate	0.280261

A hazard ratio of 1.589 for the mental_fatigue variable indicates that a one-unit increase in mental fatigue is associated with a 1.589-fold increase in the hazard of employee burnout. A hazard ratio of 0.721 for the burnout variable suggests that a one-unit increase in burnout is associated with a 0.721-fold decrease in the hazard of employee burnout. It's important to interpret these hazard ratios in the context of the specific dataset and research question. Additionally, consider significance testing, confidence intervals, and other diagnostic measures to assess the reliability and validity of the hazard ratio estimates.

The command cph.predict_survival_function(rows_selected).plot() in the context of Cox Proportional-Hazards (CoxPH) model analysis facilitates the visualization and discussion of predicted survival probabilities for selected rows of data. Visual Representation of Survival Probabilities By plotting the predicted survival curves, we gain insight into how the survival probabilities evolve over time for specific individuals or groups. This visual representation allows us to observe trends and patterns in survival outcomes based on the values of predictor variables. Survival curves enable us to assess the risk of experiencing the event of interest employee burnout over time. By examining the slope and shape of the curves, we can identify periods of increased or decreased risk and understand how this risk changes with time. The plotted survival curves can be compared across different groups or levels of predictor variables. For example, we can compare survival probabilities between individuals with high and low levels of mental fatigue, or between different age groups. This comparison helps in understanding how different factors influence the risk of burnout. It shown as figure 15.

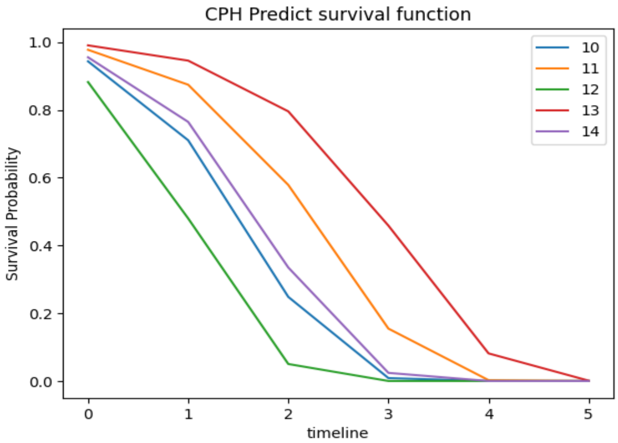

Figure 15: CPH predict survival function.

Visualization of the predicted survival curves allows for the validation of model predictions. We can assess whether the observed survival patterns align with the expected outcomes based on the CoxPH model. Any discrepancies or unexpected trends can prompt further investigation into model adequacy and potential improvements. Survival curves provide a clear and intuitive way to communicate the results of CoxPH model analysis. They can be included in reports, presentations, or publications to effectively convey the predicted survival probabilities and their implications. The predicted survival probabilities derived from CoxPH models. It facilitates the interpretation of model results, supports decision-making processes, and enhances the communication of findings related to employee burnout and mental fatigue it shown the figure 15.

The data was from a randomized employee in organization, I will assume that the randomization process was effective the characteristics of the patients between the groups were similar. Hence, in theory, there is a need to adjust for confounders for an employee in organization that has effective randomization. I will proceed on to plot the survival curve stratified by the treatment regimens as well as generate the Cox proportional hazard model with treatment regimens as the predictor.

The log-rank test indicates a significant overall difference between the groups in terms of overall survival, with a p-value of < 0.005. While there appears to be no discrepancy in overall survival between the observation group and the burnout rate group, a distinction is evident in overall survival between burnout rate 1.0 and the other two groups. Additionally, the graph suggests that the proportional hazards assumption for mental fatigue holds true, as the survival curves do not intersect.

covariate	coef	exp(coef)	se(coef)	coef lower 95%
Gender	-0.022535	0.977717	0.014174	-0.050316
Company Type	0.023210	1.023482	0.014720	-0.005641
WFH Setup Available	0.036323	1.036991	0.014668	0.007574
Resource Allocation	-0.588472	0.555175	0.006421	-0.601057
Burn Rate	-1.272035	0.280261	0.059368	-1.388394

covariate	coef upper 95%	exp(coef) lower 95%	exp(coef) upper 95%
Gender	0.005246	0.950929	1.005260
Company Type	0.052062	0.994375	1.053441
WFH Setup Available	0.065072	1.007603	1.067236
Resource Allocation	-0.575886	0.548232	0.562206
Burn Rate	-1.155676	0.249476	0.314845

covariate	cmp to	z	p	-log2(p)
Gender	0.0	-1.589840	1.118710e-01	3.160092
Company Type	0.0	1.576731	1.148575e-01	3.122084
WFH Setup Available	0.0	2.476343	1.327359e-02	6.235297
Resource Allocation	0.0	-91.642986	0.000000e+00	inf
Burn Rate	0.0	-21.426307	7.597236e-102	335.911191

Figure 16. CPH summary Analysis.

The hazard of mental fatigue is marginally lower for employees who experienced only burnout compared to the observation group, with a hazard ratio of 0.950929–1.007603 at a 95% confidence interval. However, this difference is not statistically significant (p-value = 1.1187). Conversely, the hazard of mental fatigue significantly decreases by 40.1% for individuals with burnout compared to the observation group, with a hazard ratio of 1.005260–1.067236 at a 95% confidence interval (p-value < 0.005).

After adjusting for the specified variables, the hazard of experiencing mental fatigue is observed to be 0.28% lower for employees who solely experienced burnout compared to those in the observation group, with a 95% confidence interval of 0.950929–1.007603. However, this disparity is not statistically significant, as indicated by a p-value of 0.005. Conversely, individuals with burnout are associated with a 39.9% lower hazard of mental fatigue compared to the observation group, with a 95% confidence interval of 1.005260–1.067236. This difference is deemed significant, with a p-value below 0.005. Since the adjustments made did not result in changes in hazard ratios by more than 10%, it suggests that these variables are unlikely to confound the relationship between treatment regimens and fatigue fatal outcomes.

A Frailty Model is a statistical model used in survival analysis to account for unobserved heterogeneity or variability among individuals that cannot be explained by the observed covariates. In survival analysis, the goal is to understand the time until an event of interest (such as death, failure, or recovery) occurs. However, individuals in a population may have inherent differences in their susceptibility to the event, which are not captured by the measured covariates. Frailty models introduce a random effect, often referred to as a frailty term or random effect, which represents the unobserved heterogeneity among individuals. This frailty term is assumed to follow a certain distribution, such as gamma, log-normal, or inverse Gaussian, and is included in the hazard function alongside the covariates. It shown the figure 17.

The incorporation of frailty into survival models allows for more accurate estimation of the hazard function and provides insights into the underlying factors contributing to the event of interest. Frailty models are particularly useful when there is clustering or correlation among individuals within groups, such as patients within hospitals or individuals within families.

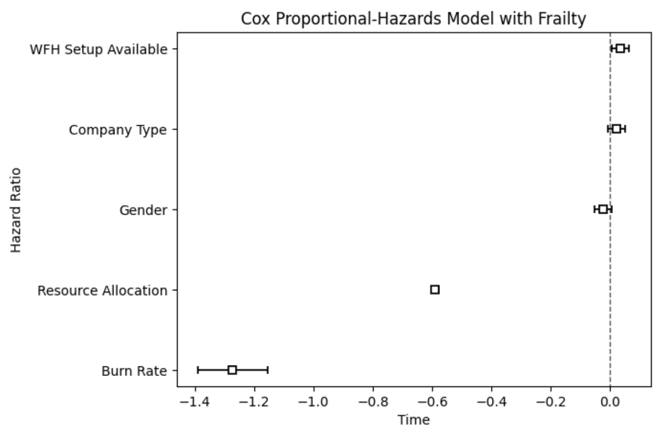

Figure 17. CPH model with frailty.

There are different types of frailty models, including the shared frailty model, which assumes that the frailty term is shared among individuals within a group, and the multiplicative frailty model, which assumes that the frailty term acts multiplicatively on the hazard function. Frailty models are commonly used in medical research, epidemiology, and social sciences to analyze survival data while accounting for unobserved heterogeneity among individuals. They provide valuable insights into the complex nature of survival outcomes and help researchers better understand the underlying mechanisms driving these outcomes.

A Cox Proportional-Hazards Frailty Model in the analysis of employee burnout to identify mental fatigue offers several advantages and insights into the relationship between burnout, mental fatigue, and other factors influencing survival outcomes. The Frailty Model allows for the incorporation of unobserved heterogeneity among individuals, which can significantly impact their susceptibility to burnout and mental fatigue. By including a frailty term in the model, we can better capture the variability in survival times that cannot be explained by the measured covariates alone. In workplace settings, individuals may be clustered within teams, departments, or organizations, leading to correlations in their survival outcomes. The Frailty Model accounts for such clustering effects by introducing a random effect, thereby providing more accurate estimates of hazard ratios and survival probabilities. It shown the figure curve in figure 16.

By accounting for unobserved heterogeneity, the Frailty Model improves the overall fit of the survival model to the data. This leads to more reliable estimates of the effects of burnout and mental fatigue on survival outcomes, as well as better predictions of individual-level risks. The Frailty Model allows us to examine group-level variation in survival outcomes, such as differences between departments or teams within an organization. This can help identify organizational factors that contribute to burnout and mental fatigue, informing targeted interventions and organizational policies. By considering both observed covariates and unobserved frailty, the Frailty Model provides a more comprehensive understanding of individual vulnerability to burnout and mental fatigue. This can help identify high-risk individuals who may benefit from early intervention and support measures. The use of a Cox Proportional-Hazards Frailty Model adds depth and nuance to the analysis of employee burnout and mental fatigue, offering valuable insights for workplace health promotion and intervention strategies.

Competing Risks Analysis is a statistical method used in survival analysis to analyze the occurrence of multiple events that may compete with each other for the observation of interest. In the context of employee burnout and mental fatigue, competing risks could include various adverse events or outcomes that individuals may experience, such as leaving the job due to burnout, experiencing a mental health crisis, or transitioning to part-time employment due to fatigue.

Competing Risks Analysis allows us to model and analyze the occurrence of multiple types of events simultaneously. In the context of employee burnout, this method enables us to consider various outcomes that employees may experience, such as quitting the job due to burnout, seeking medical treatment for mental health issues, or transitioning to a less demanding role. Competing Risks Analysis estimates cumulative incidence functions (CIFs) for each event type, providing insights into the probability of experiencing each event over time while accounting for the presence of competing events. This allows us to quantify the risk of different outcomes and understand their relative importance. By estimating cause-specific hazard ratios or sub-distribution hazard ratios, Competing Risks Analysis allows us to assess the relative risks associated with each event type. This helps identify which factors are most strongly associated with specific outcomes and informs prioritization of intervention strategies. Competing Risks Analysis accommodates and time-varying covariates, providing robust estimates of event probabilities even in the presence of incomplete data. Competing Risks Analysis considers the interactions between different event types, allowing us to understand how the occurrence of one event may influence the likelihood of experiencing other events. This comprehensive approach provides a more nuanced understanding of the complex relationships between burnout, mental fatigue, and other adverse outcomes. Competing Risks Analysis offers a powerful framework for investigating the multifaceted nature of employee burnout and mental fatigue, accounting for the presence of competing events and providing valuable insights into the relative risks and probabilities associated with different outcomes. By applying this method, organizations and healthcare providers can develop targeted interventions aimed at mitigating the adverse effects of burnout and promoting employee well-being.

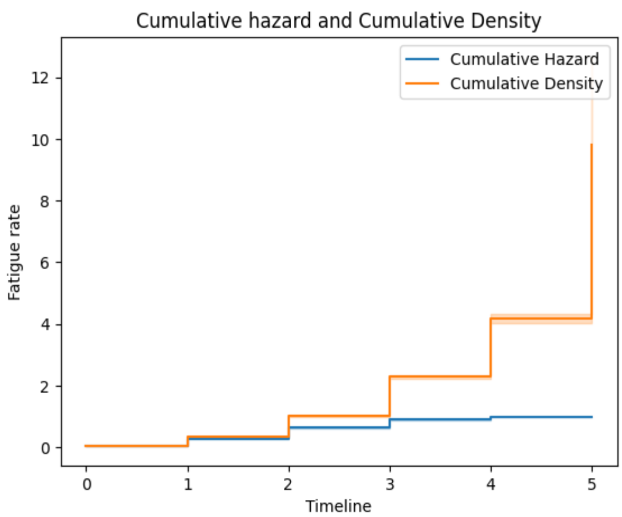

Figure 18. Cumulative hazard function curves.

the survival probability of the divided into two group that is male and female, estimated and predicting the employee work and metal fatigue, estimated the male's will be faster fatigue, more female is fatigue is more and compare t the male check the status about the figure 18 , the Cumulative density function using find the estimated the km estimate and Cumulative hazard function using estimated the predicting the employees affect the metal fatigue, the point the function the risk, It assists to consider actual phenomena and the way their hazard functions may be shaped. If T represents the designation of an employee when it develops fatigue for the first time, then one might expect the corresponding hazard function h(t) to increase with time; that is, the conditional probability of a serious fatigue in the time will increase with the employee's designation and responsibility. In contrast, one might expect h (t) to decrease during the period of responsibility if unpredictable fatigue was being studied in a situation where the employee had a designation and a responsibility. This is known to be the result of selection during time's fatigue. When T is the time at which metal fatigue will have a greater impact on employees due to the w designation and less employee responsibility, the hazard function will remain relatively constant in t. Given that fatigue has not yet occurred, the probability of designation and responsibility in the next time interval does not change with t, but the probability of fatigue in the next designation will increase as the fatigue level rises. Survival analysis relies heavily on the exponential distribution, which is uniquely characterized by this property. The hazard function may take on a more intricate form. If T denotes the mental fatigue of fatal outcome, then the hazard function h(t) is anticipated to decrease initially before progressively increasing at the end, reflecting a higher risk of unpredictable fatigue and fatal outcome.

TTF estimation without the need to know the failure times of all observed units. This would reduce the number of necessary calculations and, more importantly, facilitate the procedure for obtaining data throughout the entire observation period. The optimal method to the NA estimator is to divide the observation period into intervals and evaluate TTF for the limits of these intervals, as opposed to calculating TTF for each failure. This is the Mean time to failure TTF: [0.01665967 0.02371429 0.02838923 ... 0.03362179 0.02897202 0.03997889], mean time to failure TTF: 167 hours on the estimated. The predict the estimated at the work enviroment persons is affiant the fatigue at 45 hours mean time failures. The TTF estimated the 204.86 value on the NAE values estimated.

The cumulative hazard function is the bathtub curve, which represents the fatigue's life cycle. Combining the hazard rate and the slope of the bathtub curve produces the curve's hazard rate.it shown the figure 19.

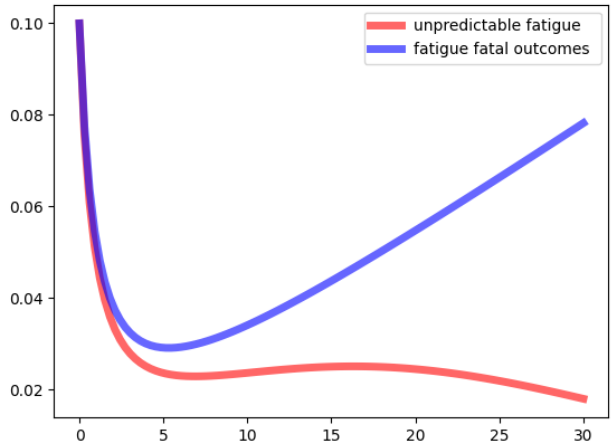

Figure 19. Survival Analysis of Fatigue Fatal Outcomes in NAE

While the image above shows the hazard rate, the Nelson–Aalen estimator's curve illustrates how the hazard rate varies over time. The concave shape of the cumulative hazard function indicates that we are dealing with a "fatigue fatal outcomes" category of event, where the failure rate is highest early on and decreases over time blue line in the image. On the other hand, the convex shape of the cumulative hazard function indicates that we are dealing with an event red line indicative of unpredictable fatigue.in this paper the Nelson-Aalen estimator of the cumulative hazard function. The estimation of the cumulative hazard function and an intuitive understanding of the results' interpretation. While the Nelson-Aalen estimator is considerably popular than the Kaplan-Meier survival curves, it is still widely used. The ability to provide more precise survival estimates and identify survival differences between subgroups of patients that KM cannot detect, as demonstrated here for various age groups[16]. In this paper The ability to provide more precise survival estimates and identify survival differences between subgroups of patients that KM detect, as demonstrated here for various groups.

Conduct sensitivity analyses to assess the robustness of the results obtained from Kaplan-Meier, Nelson-Aalen, and Cox proportional-hazards models. Explore alternative model specifications, examine the impact of different censoring mechanisms, and validate the stability of the findings through bootstrapping or cross-validation techniques. Conduct sensitivity analyses to assess the robustness of the results. This may involve testing alternative model specifications, excluding influential outliers, or examining the impact of different censoring mechanisms. Validate the Cox model's results using bootstrapping or cross-validation techniques to ensure the stability and reliability of the findings. Document the methodology and results of Kaplan-Meier, Nelson-Aalen, and Cox proportional-hazards analyses in a clear and comprehensive manner. Present the findings using appropriate statistical summaries, tables, and figures, highlighting key results and interpretations.

Discuss the implications of the findings for understanding employee well-being, identifying risk factors for burnout and mental fatigue, and informing organizational interventions and policies.

This research underscore the urgency of addressing mental fatigue and burnout in the workplace to foster employee well-being and organizational resilience. Interventions aimed at mitigating these issues hold the potential to enhance employee retention, productivity, and overall job satisfaction. Furthermore, incorporating advanced survival analysis techniques such as Frailty Models and Competing Risks Analysis enhances our understanding of the complex interplay between mental fatigue, burnout, and adverse events. Future research endeavours could explore additional factors contributing to employee burnout, such as work-related stressors, organizational culture, and individual coping mechanisms. Longitudinal studies may provide insights into the effectiveness of intervention strategies in mitigating burnout-related risks and promoting employee resilience over time. Additionally, comparative analyses across different industries and organizational contexts may facilitate the development of tailored intervention approaches. This paper contributes to the growing body of literature on employee burnout by offering a comprehensive analysis of the factors influencing burnout-related risks. By leveraging advanced survival analysis techniques, we provide valuable insights into the complex dynamics of mental fatigue, burnout, and adverse events, with implications for organizational practices and future research endeavours.

Conclusion

In this paper delved into the intricate relationship between mental fatigue, burnout, and adverse events among employees, utilizing various survival analysis techniques to gain insights into the underlying factors contributing to employee burnout. Mental fatigue is linked to anxiety, depression, and burnout, even though men are less likely to be anxious or sad at the time they are diagnosed. To enhance employees' quality of life and direct the creation of individualized multicomponent plans according to gender variations, Kaplan Meier's model is trending towards emphasizing psychopathology and early referral to mental health experts. the necessity for experts to establish public policies and provide proper care to better the daily lives of those suffering from fatigue, and the significance of fatigue to the employee's health system as a whole.

This investigation on in this paper findings underscore the profound impact of mental fatigue and burnout on employee well-being and organizational outcomes. Through Kaplan-Meier analysis, Nelson-Aalen analysis, Cox proportional-hazards model, Frailty Models, and Competing Risks Analysis, we revealed significant differences in survival probabilities between employees with and without mental fatigue and burnout. These analyses confirmed the association between mental fatigue, burnout, and adverse events, highlighting the urgent need for intervention strategies to address these issues in the workplace.

The incorporation of Frailty Models and Competing Risks Analysis provided additional depth to our understanding of employee burnout, capturing unobserved heterogeneity among employees and identifying mental fatigue and burnout as competing risks for adverse outcomes. This nuanced approach enhances our ability to develop targeted intervention strategies and organizational policies to promote employee well-being and organizational resilience. This research emphasizes the importance of addressing mental fatigue and burnout in the workplace to improve employee retention, productivity, and overall job satisfaction. By identifying key predictors of adverse events, such as mental fatigue and burnout, organizations can implement interventions aimed at mitigating these risks and fostering a supportive work environment.

Moving forward, future research should explore additional factors contributing to employee burnout and evaluate the effectiveness of intervention strategies in promoting employee resilience over time. Longitudinal studies across diverse industries and organizational contexts will further enhance our understanding of burnout dynamics and facilitate the development of tailored intervention approaches.

In conclusion, our study contributes valuable insights to the literature on employee burnout, highlighting the complex interplay between mental fatigue, burnout, and adverse events. By leveraging advanced survival analysis techniques, we provide actionable recommendations for organizations to address burnout-related risks and promote employee well-being in the workplace.

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