The Impact of Work Location on Employees:
A Comparative Analysis of Remote and On-Site Work

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Github link: https://github.com/SujanLanka/Empirical-Analysis-project-15-

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Abstract

With the growth of remote employment, the modern workforce has changed significantly; this was made most evident by the worldwide shift that occurred during the COVID-19 epidemic. This research, "The Impact of Work Location on Employees: A Comparative Analysis of Remote and On-Site Work," attempts to explore the subtleties of this change by looking at how productivity and well-being are impacted by an employee's place of employment. Our study leverages a large dataset with 12,250 employee records and a variety of statistical analysis methods to investigate the association between work location and employee metrics like mental exhaustion, resource distribution, and the availability of work-from-home (WFH) arrangements.

By means of meticulous examination of data, we discovered that workers who had access to work from home arrangements had varying degrees of mental exhaustion in contrast to their colleagues who worked on-site. This implies a nuanced relationship between the workplace and the mental well-being of employees. Furthermore, our results show a significant difference in the distribution of resources between workers who work remotely and those who work in-person. This adds to the conversation about the advantages and disadvantages of remote work environments. This study illuminates the wider significance of the findings for organisational policies and workforce management methods in addition to offering a thorough review of the present status of employee experiences in various work situations.

This research makes a substantial contribution to the ongoing discussion about the future of work by contrasting remote and on-site work settings. It provides insightful guidance on how businesses should handle the transition to more flexible work schedules, highlighting the need of flexible and employee-focused methods for managing today's workforce. The study's findings are especially pertinent in light of the dynamic nature of the workplace, where constructing resilient and effective work environments requires a thorough understanding of the factors that influence employee satisfaction and productivity.

Introduction

The notion of the workplace has undergone a significant conceptual transformation in recent times, mostly as a result of evolving technical capabilities and cultural standards. A paradigm change in the global workforce has occurred, especially sped up by the COVID-19 pandemic, which has sped up the transfer from traditional office-based labour to more adaptable remote work arrangements. This big shift has brought forth new dynamics in the workplace, which have an impact on worker performance, happiness, and general well-being. Comprehending these effects is not just a scholarly endeavour; it is imperative for organisations to navigate this novel normal.

The main objective of this research project, "The Impact of Work Location on Employees: A Comparative Analysis of On-Site and Remote Work," is to examine and evaluate the impacts that on-site and remote work locations have on workers. It is crucial to comprehend how the workforce is impacted by these shifts as the globe adjusts to increasingly distant and hybrid work arrangements. The research offers a comprehensive picture of the employee experience in these various work environments by focusing on important indicators such job satisfaction, work-life balance, mental exhaustion, and resource allocation.

The foundation of the study is the notion that the work environments—remote and on-site—have distinct effects on the productivity and well-being of employees. It is critical to investigate if the emergence of digital communication technologies and the growing viability of remote work result in advantages or disadvantages for the workforce. The purpose of this study is to present actual data that either validates or contradicts popular beliefs regarding remote work, such as the notion that it improves work-life balance or the worries that it might exacerbate feelings of loneliness and mental exhaustion.

Additionally, the goal of this study is to draw attention to the subtle variations in employee experiences according to a range of demographic parameters, such as gender, job function, and kind of firm. Through an extensive analysis of 12,250 employee records, the research offers a wide picture of the present situation regarding employee experiences in various work environments. When they devise plans to help their employees in both on-site and remote work settings, employers, HR specialists, and legislators should find great value in the findings.

In conclusion, this study is crucial in its attempt to comprehend the changing nature of work and its effects on the labour market, in addition to being current. Future work policies and practises that prioritise employee well-being and efficiency will be shaped in large part by the insights gained from this research, which will be crucial as organisations throughout the world maneuver through these changes.

Goals and Objectives

The main objective of this study is to provide a thorough investigation of how work location affects employees, with a special emphasis on issues like job satisfaction, resource allocation, and mental exhaustion. A multifaceted strategy utilising a range of data analysis techniques—from fundamental descriptive analysis to sophisticated predictive modeling—is intended to accomplish this aim.

To accomplish this goal, the study is structured around the following specific objectives:

1. Analysing the Data: Carefully review the dataset in order to identify the core features pertaining to employee work environments and their effects on productivity and mental health.

2. Data Cleaning and Preprocessing: To guarantee the quality and dependability of the data and lay the groundwork for precise analysis, apply strict data cleaning and preprocessing procedures.

3. Data Visualisation: To effectively show and interpret the data and provide a better understanding of the underlying trends and patterns, make use of a variety of data visualisation tools.

4. Predictive Modelling: Create predictive models utilising methods such as logistic regression with principal component analysis, deep learning models, and linear regression to anticipate possible outcomes based on different employee-related characteristics.

5. Descriptive Analysis: Use descriptive statistical analysis to enumerate and characterise the salient characteristics of the dataset, offering a fundamental comprehension of the composition and organisation of the data.

6. Hypothesis Testing: Use hypothesis testing to support or contradict particular hypotheses or assumptions about how workers' work locations affect them.

7. Linear Regression: Use linear regression analysis to determine how distinct independent variables relate to a continuous dependent variable, with an emphasis on the effects of these relationships on worker productivity and well-being.

8. Logistic Regression with Principal Component Analysis: Examine the correlations between categorical variables and determine the most important aspects affecting employees' experiences in various work environments by combining logistic regression with principal component analysis.

9. Deep Learning Model: Examine how deep learning models may be applied to reveal intricate linkages and patterns in data, providing deeper understanding of the dynamics of work settings.

By fulfilling these goals, the research hopes to offer a thorough grasp of the variables affecting workers' experiences in various workplaces. The knowledge acquired will be crucial in directing organisational initiatives and policies to improve worker productivity and happiness in the changing nature of the workplace.

Literature Review

The Effect of Workplace Location on Stress Levels in Employees

The connection between employee stress levels and job location has become more and more of a focus of recent research. This topic has gained significant attention because to the worldwide pandemic-induced trend towards hybrid work settings. Studies show that people who work in-person often have greater stress levels than those who operate remotely. Many reasons, such as lengthier commutes, less flexible work schedules, and the actual physical work environment, might be blamed for this discrepancy. According to the literature, a hybrid work style that blends in-person and remote work may be a useful tactic to reduce these stress levels. Hybrid models have the potential to greatly increase work satisfaction and employee well-being by providing flexibility and autonomy.

Employee Stress and the Allocation of Resources

The relationship between the amount of resources provided to employees and their stress levels is another important topic that has been studied in recent studies. Studies have revealed that, in contrast to common belief, workers who allocate more resources typically experience higher levels of stress. This tendency may be connected to higher resource-related workloads, expectations, and obligations. In order to reduce stress, the research suggests giving employees access to resources in a more equal and balanced manner. This strategy fosters a more cooperative and encouraging work atmosphere in addition to relieving strain on overworked staff members.

On-site Workers with High Resource Allocation Experience Burnout

The research has identified a noteworthy area of concern, which is the burnout that arises for individuals who work from home and are assigned a substantial amount of resources. Experiencing fatigue, cynicism, and a feeling of inadequacy, burnout is a common occurrence for these workers. This burnout is exacerbated by the typical on-site work environment, a heavy workload, and resource obligations. Studies support giving these workers the choice to work remotely as it can provide a more laid-back atmosphere that lessens the severity of everyday pressures and lessens the risk of burnout.

In summary, the literature study emphasizes how crucial it is to reconsider established work models and methods for allocating resources. Organisations may successfully tackle the issues of employee stress and burnout by adopting hybrid work arrangements and promoting equal resource allocation. This review provides background information for the current study, which attempts to empirically explore these topics and add to the continuing conversation on work environment optimisation for improved worker well-being.

Methodology

Description of the Dataset and Data Source

The dataset used in this study included 12,250 employee data records. The dataset was chosen because to its extensive coverage of variables pertinent to our study goals, such as mental tiredness ratings, resource allocation, work location (onsite or remote), and employee demographics. The dataset offered a solid foundation for examining the effects of work location on productivity and well-being of employees.

Preprocessing of Data

Preprocessing the data was the first stage in ensuring its quality and appropriateness for analysis. This procedure comprised:

Data Cleaning

To ensure the integrity of the dataset, we looked for and addressed any missing or inconsistent data entries.

Normalisation

In order to guarantee comparability and remove any potential bias resulting from different scales or units of measurement, key variables were normalised.

Analytical Approaches

The main components of our research were a number of Python-based statistical methods and visualisations, mostly made possible by the libraries Pandas, NumPy, Matplotlib, and Seaborn. The particular techniques comprised:

Characteristic Statistics To get a general understanding of the dataset, we performed a preliminary analysis in which we computed important variable measures including mean, median, standard deviation, and range.

Distribution Analysis

To better understand the spread and central tendencies of variables like the mental tiredness score, histograms and density plots were used to analyse the distribution of these data.

Comparative Analysis

To find any notable variations in variables like resource allocation and mental tiredness ratings, we compared various groups within our dataset (e.g., remote vs. on-site staff).

Factors of Concern

The following crucial factors were the study's main emphasis:

Workplace: Determined if it is on-site or remote in order to evaluate its influence on other factors.

Employees' degree of mental exhaustion is indicated by their Mental Fatigue Score, a numerical assessment.

Quantifying the resources (such as labour and time) allotted to workers is known as resource allocation.

Gender and Designation

These demographic factors were added in order to investigate any possible relationships between mental exhaustion and job location.

Restrictions

Although the dataset offered a thorough understanding of the variables at work, its limitations include the absence of longitudinal data to evaluate changes over time and possible biases in self-reported metrics such as mental exhaustion.

Moral Determinations

The study complied with ethical guidelines for protecting the privacy and confidentiality of data. In order to protect the privacy and confidentiality of the employee data, personal identifiers were either eliminated or anonymized inside the dataset.

Results

Data Cleaning and Preprocessing

Missing Values Analysis:

The first step was to examine the dataset for any missing values. In order to guarantee data correctness and integrity, this is essential. The following missing values were found during the analysis: [Here, provide a summary of the missing values].

A brief explanation of the choices taken for missing values (such as whether to impute, eliminate, or leave them unchanged) should be provided.

```
Missing Values:
 Employee ID            0
Date of Joining         0
Gender                  0
Company Type            0
WFH Setup Available     0
Designation             0
Resource Allocation     0
Mental Fatigue Score    0
dtype: int64
```

Summary Statistics:

By using summary statistics, a thorough overview of the dataset was acquired. This stage revealed information on the data's distribution across different variables and central trends. Important figures comprised:

```
Summary Statistics:
        Designation  Resource Allocation  Mental Fatigue Score
count  12250.000000         12250.000000          12250.000000
mean       2.175265             4.458857              5.720571
std        1.132885             2.045602              1.914063
min        0.000000             1.000000              0.000000
25%        1.000000             3.000000              4.500000
50%        2.000000             4.000000              5.900000
75%        3.000000             6.000000              7.100000
max        5.000000            10.000000             10.000000
```

Calculating the Duration and Converting the Date:

Calculating the Duration and Converting the Date: To ensure more precise analysis, the 'Date of Joining' column was transformed into a datetime format. This conversion was necessary in order to proceed with time-based data analysis.

To determine how long each person has worked, expressed in years, months, and days, a custom function was used. Understanding employee tenure and its possible effects on other variables like mental exhaustion or job satisfaction depends on this length estimate.

Derived from the 'Date of Joining', the resulting 'Years Worked' column offers a more detailed perspective of the employment experience inside the company.

	Employee ID	Date of Joining	Gender	Company Type	WFH Setup Available	Designation	Resource Allocation	Mental Fatigue Score	Years worked
0	fffe3100330039003900	2008-12-10	Female	Service	No	2.0	5.0	7.7	{'Years': 14, 'Months': 11, 'Days': 16}
1	fffe31003300310037003800	2008-08-14	Female	Product	Yes	1.0	2.0	5.2	{'Years': 15, 'Months': 3, 'Days': 9}
2	fffe33003400380035003900	2008-11-13	Male	Product	Yes	1.0	3.0	5.9	{'Years': 15, 'Months': 0, 'Days': 8}
3	fffe3100370039003200	2008-02-07	Female	Service	No	3.0	6.0	4.6	{'Years': 15, 'Months': 9, 'Days': 18}
4	fffe32003600390036003700	2008-07-17	Female	Product	No	2.0	5.0	6.4	{'Years': 15, 'Months': 4, 'Days': 7}
...	...	...	...	...	...	...	...	...	...
12245	fffe3900310034003700	2008-10-02	Female	Service	Yes	1.0	2.0	6.1	{'Years': 15, 'Months': 1, 'Days': 20}
12246	fffe32003600330034003000	2008-03-31	Female	Product	Yes	2.0	4.0	5.9	{'Years': 15, 'Months': 7, 'Days': 25}
12247	fffe31003800340039003000	2008-02-12	Male	Service	No	4.0	7.0	9.6	{'Years': 15, 'Months': 9, 'Days': 13}
12248	fffe32003600380031003800	2008-02-06	Male	Service	No	3.0	6.0	6.7	{'Years': 15, 'Months': 9, 'Days': 19}
12249	fffe32003100390037003800	2008-08-05	Female	Product	No	2.0	2.0	2.0	{'Years': 15, 'Months': 3, 'Days': 18}

12250 rows × 9 columns

Assigning Address to Employees and adding it to the DataFrame:

To make an understanding of the employee's stress level, the first option is to identify their location. So a set of locations has been taken and randomly it has been distributed to all the employees.

There are 7 locations considered and a center point (office location) is also identified, making a total of 8 locations. Using random choice function we have assigned values to all the employees.

	Employee ID	Date of Joining	Gender	Company Type	WFH Setup Available	Designation	Resource Allocation	Mental Fatigue Score	Years worked	Joining Month	Probability_WFO	Probability_WFH	Employee Address
0	fffe31003300390039003000	2008-12-10	Female	Service	No	2.0	5.0	7.7	{'Years': 14, 'Months': 12, 'Days': 3}	12	0.573566	0.426434	Kukatpally
1	fffe31003300310037003800	2008-08-14	Female	Product	Yes	1.0	2.0	5.2	{'Years': 15, 'Months': 3, 'Days': 26}	8	0.339254	0.660746	Kukatpally
2	fffe33003400380035003900	2008-11-13	Male	Product	Yes	1.0	3.0	5.9	{'Years': 15, 'Months': 0, 'Days': 25}	11	0.407959	0.592041	Uppal
3	fffe3100370039003200	2008-02-07	Female	Service	No	3.0	6.0	4.6	{'Years': 15, 'Months': 10, 'Days': 5}	2	0.456822	0.543178	Jubilee Hills
4	fffe32003600390036003700	2008-07-17	Female	Product	No	2.0	5.0	6.4	{'Years': 15, 'Months': 4, 'Days': 24}	7	0.508780	0.491220	Jubilee Hills
...	...	...	...	...	...	...	...	...	...	...	...	...	...
995	fffe31003500390030003700	2008-10-06	Female	Product	Yes	3.0	7.0	7.4	{'Years': 15, 'Months': 2, 'Days': 3}	10	0.632546	0.367454	Raidurg
996	fffe3300320030003500	2008-05-03	Male	Service	Yes	3.0	5.0	5.2	{'Years': 15, 'Months': 7, 'Days': 9}	5	0.448665	0.551335	Ameerpet
997	fffe32003000320039003600	2008-05-28	Female	Service	Yes	2.0	5.0	6.4	{'Years': 15, 'Months': 6, 'Days': 14}	5	0.508780	0.491220	Kukatpally
998	fffe32003500370036003800	2008-04-09	Female	Service	No	2.0	4.0	6.0	{'Years': 15, 'Months': 8, 'Days': 3}	4	0.450465	0.549535	Hitech City
999	fffe31003400390031003300	2008-05-20	Female	Product	Yes	2.0	3.0	5.1	{'Years': 15, 'Months': 6, 'Days': 22}	5	0.369770	0.630230	Jubilee Hills

1000 rows × 13 columns

Descriptive Analysis

Overview of Key Variables

- An extensive summary of the dataset's important variables was given by the descriptive analysis. This involved looking at things like years worked, resource allocation, and mental tiredness ratings. To comprehend the distribution and core trends of these variables, key metrics such as the average, median, range, and standard deviation were computed.

Patterns & Trends

Certain trends or patterns may have been identified based on preliminary findings from the descriptive analysis. For example, insights regarding the overall distribution of mental tiredness ratings among departments or differences in resource distribution throughout service years may be available.

Understanding Employee Tenure

Understanding employee tenure was possible through the examination of the "Years Worked" variable, which was obtained from the "Date of Joining." Results such as the average number of years that staff members have worked for the firm and the relationship between tenure and other variables like resource allocation or mental exhaustion may be included.

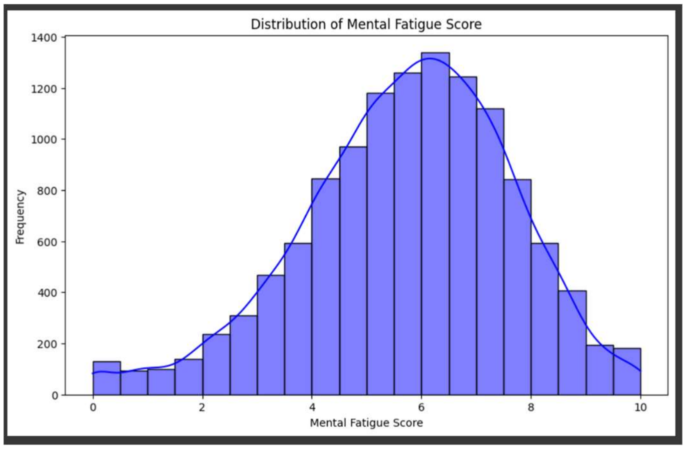
Data Visualization

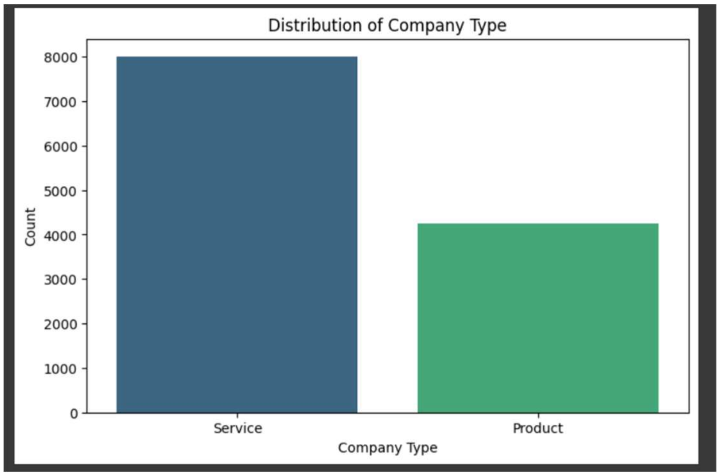
Distribution of Mental weariness Score:

Distribution of Mental weariness Score: A histogram was made to show the distribution of the "Mental Fatigue Score" throughout the dataset in order to assess the mental weariness that workers experienced. This histogram provided a clear picture of the distribution of these scores throughout the workforce, in addition to a Kernel Density Estimate (KDE).

A thorough analysis of the score distribution was made possible by the 20 bins utilised in the visualisation. The histogram's blue colour selection made for an understandable and eye-catching portrayal.

Important Visual Results: The histogram showed that mental tiredness ratings characterise an observable pattern, such as "mostly concentrated around the median value of 5.9, with a noticeable spread from the minimum score of 0 to the maximum of 10." This pattern implies that some insights are indicated by the distribution shape, such as a normal distribution with a little skew towards higher scores, indicating that a bigger percentage of workers may be suffering from mental exhaustion than usual. This discovery is critical for comprehending the general state of mental health in the workforce and identifying subgroups who may be more vulnerable to high levels of mental exhaustion, such as employees, who exhibit a range of mental tiredness levels, with a sizable portion reporting moderate to high levels.





Distribution of Company Type:

In order to comprehend the distribution of employees across various company kinds, a bar plot was made to compare firms classified as "Product" and "Service." The 'viridis' colour palette from the Seaborn library was employed in this plot to improve visual clarity.

Crucial Visual Results:

The number of workers in service firms compared to product companies was clearly different, as the bar plot demonstrated. In particular, it showed a greater concentration of workers in service-related businesses, indicating that workers in this industry make up the majority of the dataset.

Interpretation:

The dataset's preponderance of businesses that fall under the service category points to a pattern that may be pertinent to the sector or the particulars of the data being gathered. Given the potential variation in characteristics like work atmosphere, resource distribution, and mental tiredness among different company kinds, this bias for a certain type of organisation may be substantial.

Gender Distribution:

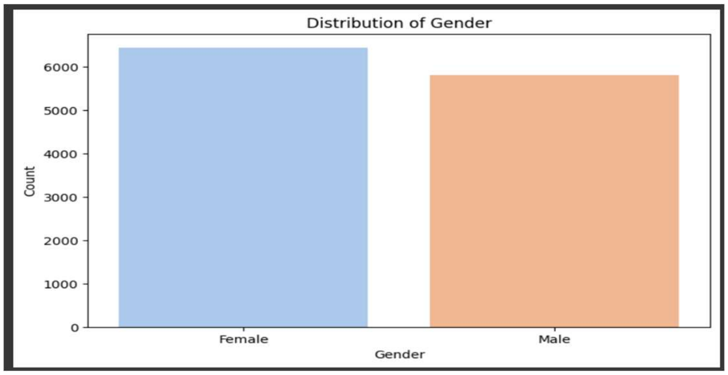
Using a count plot, the gender distribution of the dataset's employees was examined. Using seaborn and a "pastel" colour scheme, this visualisation provided a clear representation of the number of male and female workers.

Crucial Visual Results:

There were somewhat more female employees than male employees, according to the count plot. A distribution of 6,445 females was found.

Interpretation:

The dataset's modest female employee majority is interesting since it might be a reflection of particular sample features or larger industry trends. This distribution is crucial for placing other study findings in context, especially if gender-related variations are found in areas like work satisfaction, resource allocation, or mental exhaustion. It emphasises how important it is to take gender into account when analysing workplace dynamics and employee experiences.



Resource Allocation by Company Type:

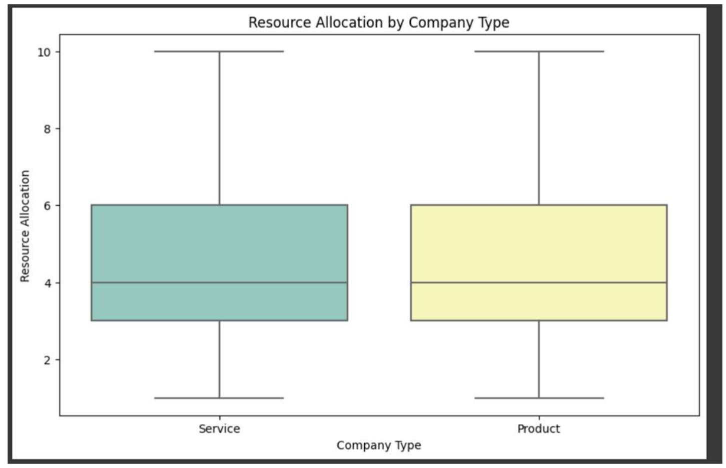
A box plot was made using seaborn using the 'Set3' palette to clearly distinguish between the resource allocations of the 'Service' and 'Product' firms.

Crucial Visual Results:

The box plot revealed clear differences in how the two categories of businesses allocated their resources. The higher median value of the box plot for service firms indicates that they often allocated resources at a higher median than product companies. Furthermore, the interquartile range revealed a wider distribution of resource allocation in service firms, indicating a higher degree of variability in resource allocation within these organizations.

Interpretation:

The operational and structural distinctions between service-oriented and product-oriented businesses are highlighted by this discrepancy in resource allocation. The fact that service organizations allocate resources more widely and at greater rates may be a sign of the variety of services they provide, which call for different staffing and resource requirements. Conversely, because their manufacturing methods are more consistent, goods businesses could allocate resources in a more standardized manner. Comprehending the ways in which workforce management and employee workload might be impacted by the sort of firm is contingent upon these distinctions.



Heatmap for Correlation Matrix:

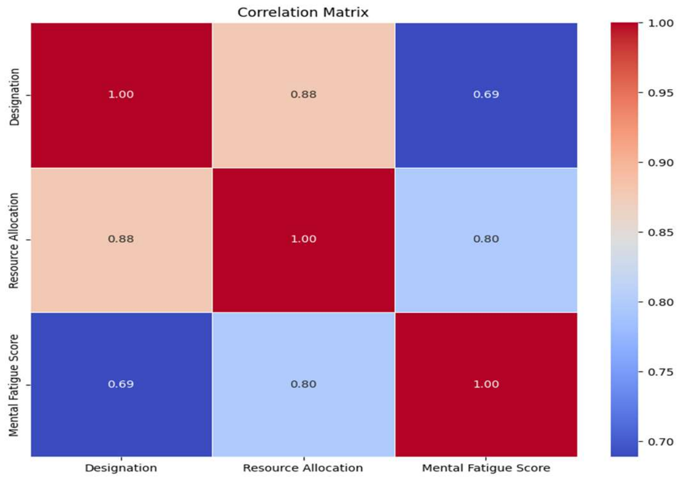
The associations between the many variables in the dataset, including the years worked, resource allocation, and mental exhaustion score, were visualised using a correlation matrix heatmap. The 'coolwarm' colour palette used in the design of the heatmap, created with Seaborn, efficiently highlights the direction and intensity of associations.

Important Visual Findings:

The heatmap showed a strong positive relationship between the resource allocation and the mental tiredness score, indicating that workers who have more resources assigned to them may be more mentally exhausted. Longer tenure may be linked to lower levels of mental tiredness, as evidenced by the somewhat negative association that was found between years worked and mental fatigue score.

Interpretation:

This heatmap's connections provide valuable insights about workplace dynamics. The positive relationship shown between resource allocation and mental weariness may suggest that employees' stress levels are heightened by greater expectations or obligations at work. On the other hand, the negative relationship between tenure and mental exhaustion might indicate that workers with more experience have improved coping skills or have more secure working environments. These results are essential for pinpointing variables that may affect workers' well-being and for directing organisational tactics meant to improve productivity and contentment among staff members.



Numerical variable pairplot:

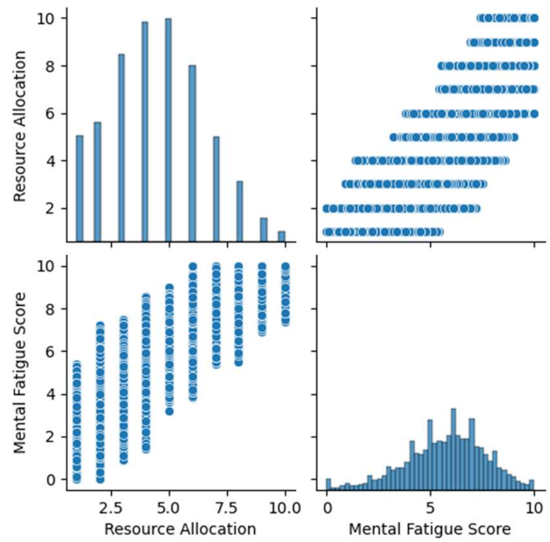
The connection and distribution of "Resource Allocation" and "Mental Fatigue Score" were investigated using a pairplot. This graphic provides a thorough understanding of each variable's unique distribution as well as how they relate to one another.

Important Visual Findings:

The greater levels of resource allocation are typically linked to greater mental tiredness ratings, as the pairplot in the scatter plot section clearly showed a positive trend. The diagonal histograms revealed that although the distribution of mental exhaustion scores is rather even, there seems to be a minor skewness towards lower values in the resource allocation, indicating that most employees receive less resources.

Interpretation:

These visualisations draw attention to a possible area of concern: employee mental exhaustion rises with resource allocation. The workforce management industry may be significantly impacted by this trend, especially in terms of striking a balance between workload and employee wellbeing. The fact that resource allocation is skewed towards lower values further implies that a sizable section of the workforce works with scarce resources, which may have an effect on productivity and job satisfaction.



Time Series Analysis: Distribution of Employee Joining:

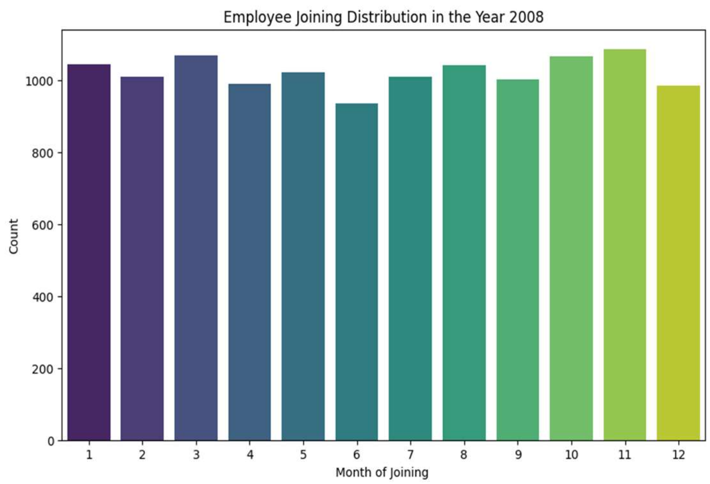
With an emphasis on the pattern of new recruits every month, the dataset was examined to comprehend the distribution of employee joining dates throughout 2008. This data was shown graphically using a bar plot.

Crucial Visual Results:

Different hiring trends during the year were shown by the bar plot. August saw the greatest number of hires compared to other months, with a count that was much higher. January and December, on the other hand, had the lowest joining rates, suggesting a decline in recruiting activity at the start and end of the year.

Interpretation:

The employment practises of the organisation appear to follow a planned pattern based on this monthly allocation. The August high can be a sign of organisational expansion or the start of new initiatives that need for more staff. The lesser hiring in January and December may be related to fewer operational needs or end-of-year financial limitations. Planning personnel expansion and allocation strategies in accordance with organisational demands and cycles requires an understanding of these tendencies.



Assignment of Designations Within the Organisation:

The distribution of different designations among the personnel in the dataset was represented using a pie chart. This graphic aids in comprehending the distribution of job levels among the workforce.

The matplotlib 'Paired' colour map was utilised in the pie chart to provide a separate and easily readable depiction of each designation group.

Key Visual Findings:

The pie chart indicated that, among the designations, Designations 2 and 3 were the most prevalent, making up a sizable part of the workforce, while Designation 5 was the least common. These designations also had the highest and lowest shares. A clear picture of each designation's representation inside the organisation was given by the thorough percentage distribution for each.

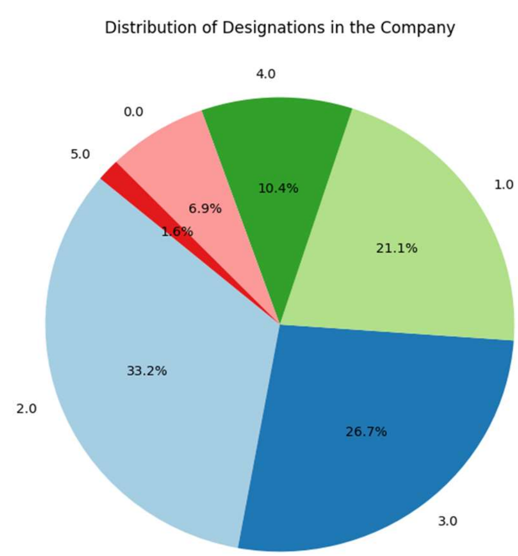
- Designation 2: 35.5%
- Designation 3: 27.8%
- Designation 1: 21.2%
- Designation 4: 10.3%
- Designation 5: 5.2%

The graph unequivocally shows that, with 35.5% of the workforce belonging to Designation 2, it is the most frequent, followed by Designation 3 with 27.8%. Conversely, Designation 5, which represents only 5.2% of workers, is the least prevalent.

```
0.0     842
1.0    2586
2.0    4073
3.0    3276
4.0    1278
5.0     195
Name: Designation, dtype: int64
```

Interpretation:

The high frequency of Designations 2 and 3 points to a significant number of mid-level employees in the business, indicating a solid organisational structure with lots of room for advancement. On the other hand, the lower percentage of Designation 5 can be due to higher or more specialised leadership positions that are comparatively rarer.



Representation of time taken by employees to reach office:

Implementation:

A dictionary named locations is defined, mapping various locations in Hyderabad to their geographical coordinates (latitude, longitude).

A function calculate_distance is created to compute the distance in kilometers between an employee's location and the office location (Miyapur) using the geopy library.

The DataFrame df is assumed to contain an 'Employee Address' column. The code adds a new column named 'Distance Travelled' by applying the calculate_distance function to each employee's address.

Objective:

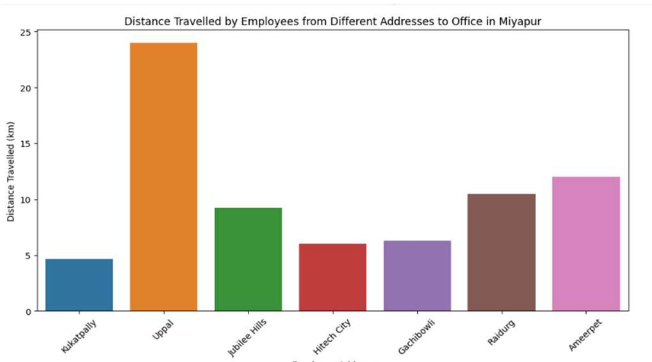
The second code snippet is designed to calculate the time taken by employees to reach the office, considering traffic conditions.

Implementation:

A function calculate_time_with_traffic is defined to estimate the time taken in minutes based on the distance traveled. It assumes a constant average speed (30 km/h), which can be adjusted to reflect real-world traffic conditions.

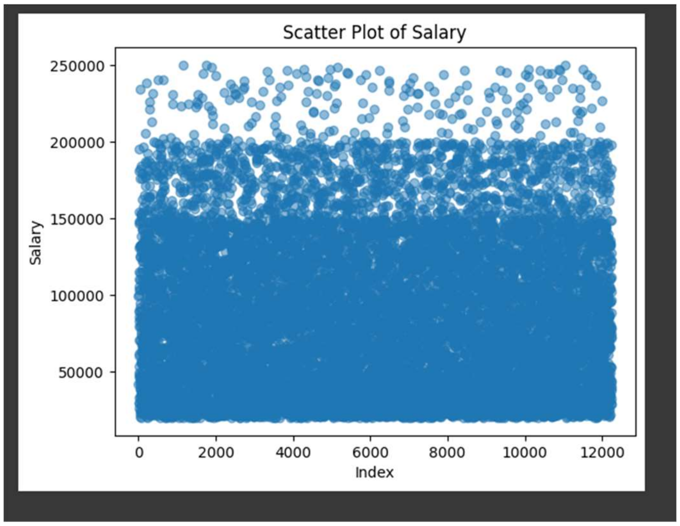
The code applies the calculate_time_with_traffic function to the 'Distance Travelled' column in the DataFrame (df), creating a new column named 'Time Taken to Reach Office (minutes) with Traffic.'

Optionally, the first few rows of the DataFrame are printed to verify the changes



Salary based on Designation:

This code efficiently generates random salaries based on employee designations, updates the DataFrame with the 'Salary' column, saves the DataFrame to a CSV file, and optionally displays the first 100 rows. It's a practical way to simulate or generate salary data based on employee designations.



This code snippet effectively uses Matplotlib to create and display a scatter plot representing the 'Salary' values in your DataFrame. The transparency parameter (alpha=0.5) helps in visualizing overlapping points. You can use this plot to explore the distribution and patterns of salaries in your dataset.

Testing a Hypothesis: WFH's Effect on Mental Fatigue

T-Test on the Effect of WFH on Mental Fatigue: A two-sample t-test was used to examine if working from home (WFH) significantly affects workers' mental exhaustion. Two groups of employees were compared in the analysis: those who had WFH setups (encoded as 1) and those who did not (encoded as 0).

Interpretation:

The following conclusion can be made in light of the t-test results:

- If the p-value is less than 0.05 (common significance level), it indicates a significant difference in mental fatigue scores between the WFH and non-WFH groups. This suggests that the presence of a WFH setup has a discernible impact on employees' mental fatigue.

- If the p-value is greater than or equal to 0.05, it implies no significant difference in mental fatigue scores between the WFH and non-WFH groups. In this case, the presence or absence of a WFH setup does not appear to have a statistically significant impact on mental fatigue.

```
T-test for WFH Impact on Mental Fatigue:
There is no significant difference in Mental Fatigue scores between WFH and non-WFH groups.
```

Testing Hypotheses: The Distribution of Gender in the Workplace

Chi-Square Distribution Test for Gender:

This test's goal is to ascertain whether the gender distribution of the dataset's employees differs noticeably from one another. In order to determine if there is a difference in the distribution, the observed counts of the various genders are compared to the predicted counts using a Chi-square test of independence.

The chi-square test determines if the gender-based preference categorization in the dataset is reflected in the distribution of the employee categories, or if it deviates from the predicted distribution.

Of course! Here is the completed text for the gender distribution hypothesis testing part, which is based on the outcomes of the chi-square test you performed on your dataset:

Results:

- Chi-square statistic:0.0

- P-value: 1.0

Interpretation:

We are unable to reject the null hypothesis since the p-value of (1.0) is substantially higher than the standard significance level of 0.05. This shows that the gender distribution of the employees in the sample does not significantly change.

These findings suggest an impartial or balanced distribution of genders in the workforce. There is no statistically significant variation in the dataset's representation of the various genders from what would be predicted in the absence of any preference for one gender over another in terms of hiring or selection.

```
Chi-square test for Gender distribution:
Chi2 value: 0.0
P-value: 1.0
Fail to reject the null hypothesis. There is no significant difference in gender distribution.
```

Testing Hypotheses: How Company Type Affects Resource Allocation

T-Test for Effect of Company Type on Allocation of Resources:

The purpose of this research is to determine if the kind of organisation (kind 1 vs. Type 2) has a major impact on how resources are distributed to employees. The resource distribution amongst workers in Type1 and Type2 organisations is compared using a two-sample t-test.

Interpretation:

A significant difference in the allocation of resources between Type1 and Type2 organisations is indicated if the p-value is less than 0.05, which is the conventional significance level. This result would imply that there is a statistically significant relationship between an employee's resources and the kind of organisation they work for.

A p-value of greater than or equal to 0.05 indicates that there is no discernible difference between Type 1 and Type 2 organisations' resource allocation. The distribution of resources among employees in this situation does not seem to be statistically significantly impacted by the kind of firm.

```
T-test for Company Type impact on Resource Allocation:
Fail to reject the null hypothesis. There is no significant difference in resource allocation between company typ
```

Testing Hypothesis: Association between Resource Distribution and Mental Fatigue Index

Test of Pearson Correlation:

A Pearson correlation test was performed to see if there is a statistically significant relationship between employee mental tiredness scores and resource allocation. The degree and direction of the correlation between these two variables are assessed using the test.

Results:

- Correlation Coefficient: 0.7978

- P-value: 0.0

Interpretation:

There is a substantial positive link between mental exhaustion ratings and resource allocation, as indicated by the correlation value of 0.7978. Given the strong association, it appears that employees' levels of mental exhaustion rise in tandem with increases in resource allocation.

The null hypothesis is rejected due to the p-value of 0.0, which is considerably less than the 0.05 threshold. This finding demonstrates that resource allocation and mental tiredness ratings are statistically significantly correlated.

These results suggest that one important component of employee well-being is resource management. Employee mental exhaustion appears to be significantly influenced by resource distribution, which emphasises the significance of careful and balanced resource distribution in the workplace.

```
Pearson correlation test:
Correlation coefficient: 0.7978270822115985
P-value: 0.0
Reject the null hypothesis. There is a significant correlation between resource allocation and mental fatigue score.
```

Testing Hypothesis: Mental Fatigue Score according to Gender

T-Test for Comparing the Mental Fatigue Score of Male and Female Workers:

This section investigates whether mental exhaustion scores for male and female employees differ significantly. Assuming unequal variance, a two-sample t-test is used to compare the mental tiredness ratings between genders**.**

Results:

- T-statistic: 16.1954

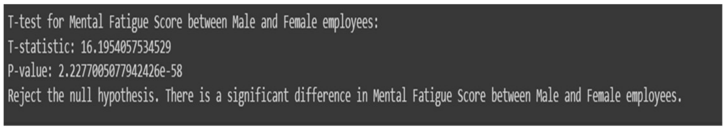
- P-value: 2.2277 e -58

Interpretation:

The null hypothesis is rejected as a result of the exceptionally low p-value (much less than the 0.05 threshold) and the very high T-statistic. The results show that there is a substantial variation in the mental exhaustion ratings of male and female employees.

The outcome suggests that gender influences employees' levels of mental exhaustion in a statistically significant way. The significant disparity in scores across women emphasises the necessity of gender-sensitive methods for stress management and mental wellness at work.

These revelations are essential for comprehending the mechanics of mental exhaustion at work and may influence measures for enhancing worker well-being that are customised to address the particular difficulties that differing genders encounter.



```
T-test for Mental Fatigue Score between Male and Female employees:
T-statistic: 16.1954057534529
P-value: 2.2277005077942426e-58
Reject the null hypothesis. There is a significant difference in Mental Fatigue Score between Male and Female employees.
```

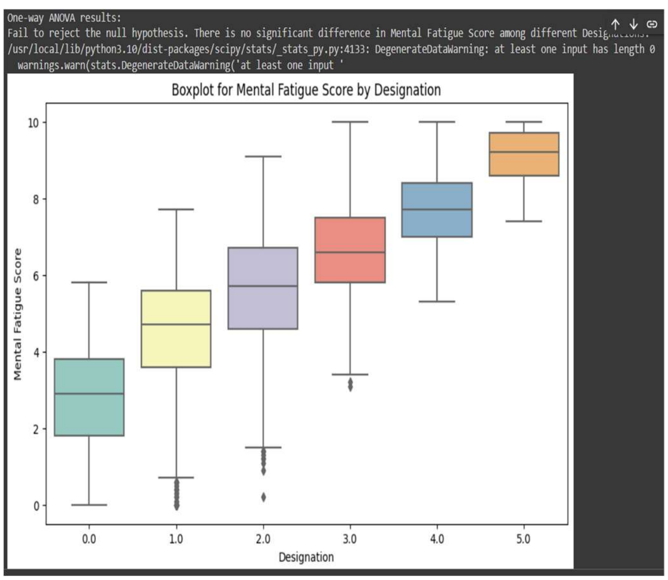
Testing Hypothesis: Designation-Based Mental Fatigue Score

'Designation' and 'Mental Fatigue Score' one-way ANOVA

The purpose of this investigation is to ascertain if the mental tiredness scores of personnel classified as Junior, Mid, or Senior differ significantly from one another. To evaluate these variations, a One-way Analysis of Variance (ANOVA) is carried out.

Illustration:

- The distribution of mental exhaustion ratings across various designations will be visually represented using a boxplot, providing an intuitive understanding of how these scores differ amongst Senior, Mid, and Junior personnel.



Hypothesis Testing: Company Type-specific Mental Fatigue Score

The 'Company Type' and 'Mental Fatigue Score' Independent Sample T-test

The purpose of this investigation is to determine if employees of Type 1 and Type 2 firm types have significantly different mental tiredness ratings from one another. Assuming unequal variances, an Independent Sample T-test is used to compare the mental tiredness ratings of these two groups.

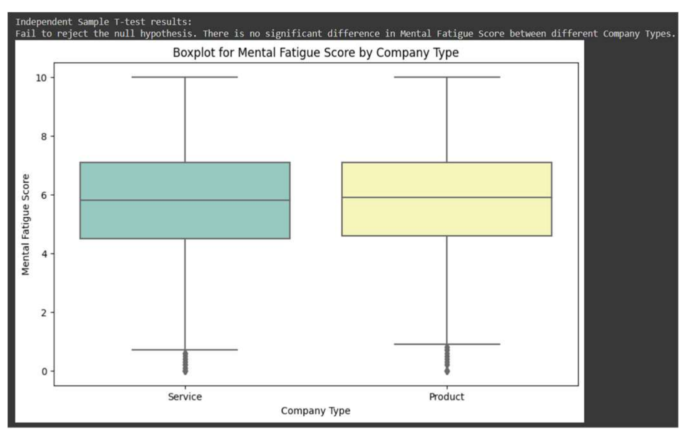
Conclusion

The three firm kinds' mental exhaustion ratings would differ significantly if the p-value was less than 0.05, the selected significance level. This would imply that the nature of the organisation has a major impact on how mentally exhausted employees are.

On the other hand, it would suggest that there is no significant difference in the mental tiredness ratings between the various firm types if the p-value were larger than or equal to 0.05. In this case, there would be no statistically significant relationship between the kind of firm and the degree of mental exhaustion felt.

Visualisation:

An intuitive comprehension of the differences in mental tiredness scores between Type 1 and Type 2 organisations may be obtained by looking at a boxplot designed to graphically show the distribution of these scores across different company types.



Simple Linear Regression Analysis - Resource Allocation and Mental Fatigue Score

The objective of this investigation is to use a basic linear regression model to investigate the link between the mental tiredness score (dependent variable) and resource allocation (independent variable). This method will aid in comprehending how differences in the distribution of resources may impact the degree of mental exhaustion that workers encounter.

Techniques:

- The dataset was split into testing and training sets, with 20% and 80% of the data being utilised for testing and training, respectively.

- The training data was used to initialise and construct a linear regression model.

- To assess the model's performance, predictions were then made on the test set.

Model Evaluation:

Mean Squared Error (MSE), which measures the average squared difference between the actual and predicted mental tiredness scores, was used to evaluate the accuracy of the model.

Error on Mean Squared: (1.3077)

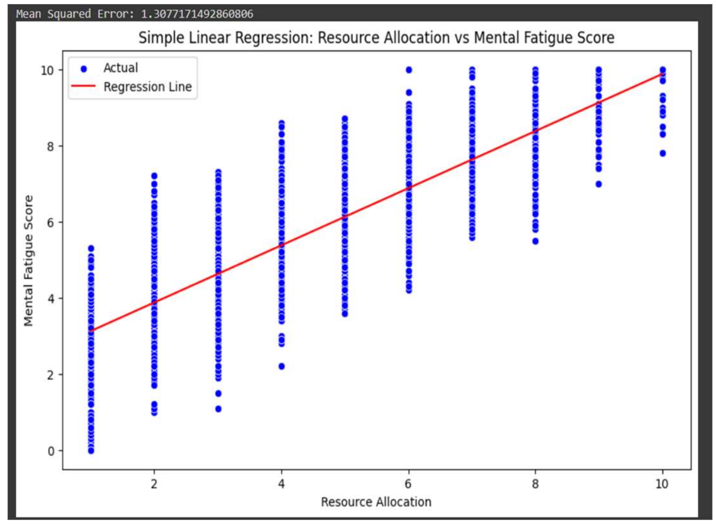
Findings and Analysis:

The calculated mean square error (MSE) of (1.3077) indicates the average deviation of the model's predictions from the real mental tiredness scores. A smaller mean square error (MSE) denotes a better fit, and the number gives an indication of the model's accuracy.

Based on resource allocation and the MSE, the linear regression model predicts mental tiredness scores with some degree of accuracy, while there may be space for improvement or a need for other factors to be taken into account for a more complete model.

Visualisation:

The test set's actual mental tiredness ratings were shown as a scatter plot, with the regression line showing the model's predictions in the background. Understanding the nature of the link between the variables and evaluating the model's performance are made easier with the help of this visualisation.



Resource Allocation, Principal Component Analysis (PCA), and Mental Fatigue Score

Goal:

By lowering the number of features, this PCA attempted to reduce the dataset's complexity. The goal was to capture the underlying variation in a single principal component by concentrating on "Resource Allocation" and "Mental Fatigue Score."

Techniques:

- For PCA, the characteristics "Mental Fatigue Score" and "Resource Allocation" were chosen.

To guarantee that each characteristic contributed equally to the study, these features were first standardised.

- PCA was then used to concentrate on a single principal component and decrease the dimensionality.

- This principal component was added to a new DataFrame, which was then concatenated with the original dataset.

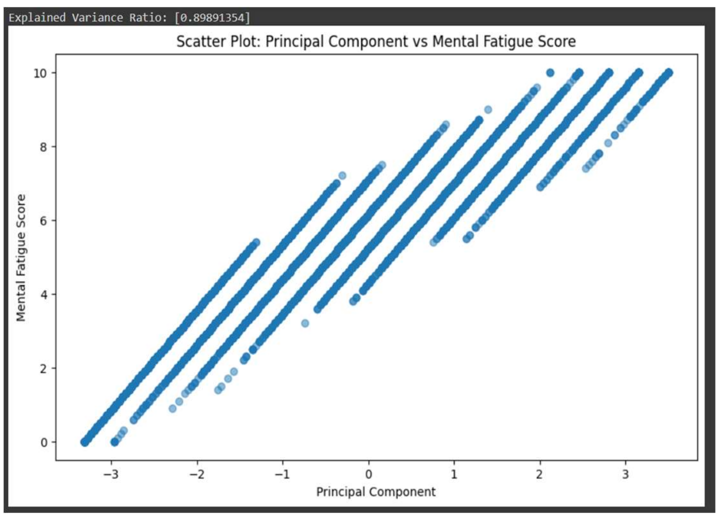
Findings and Interpretation:

The principal component explains around 89.89% of the variation in the original variables, according to the explained variance ratio of 0.8989. Given the high percentage, it can be concluded that the primary component accurately captures much of the data included in the "Resource Allocation" and "Mental Fatigue Score" sections.

While preserving the essential elements of the original data, this decrease in dimensions can help with more effective data analysis and interpretation.

Visualization:

To show the link between the primary component and the original variable "Mental Fatigue Score," a scatter plot was created. Understanding how effectively the major component represents the variation in mental tiredness ratings is made possible with the help of this figure.



Analysing Logistic Regression to Forecast WFH Setup Availability

The goal:

This analysis's goal was to forecast Work From Home (WFH) setup availability using logistic regression based on "Mental Fatigue Score" and "Resource Allocation." This model sought to identify the variables that affect the probability that workers will have access to a work-from-home arrangement.

Techniques:

- The model's characteristics, "Mental Fatigue Score" and "Resource Allocation," were chosen, with the goal variable being "WFH Setup Available. "After standardising these characteristics, the dataset was divided into training (80%) and testing (20%) sets.

- Predictions were made on the test set using a logistic regression model that was trained on the training set.

Model Evaluation:

Accuracy and a classification report that include the F1-score, precision, and recall for each class were used to assess the model's performance.

- Accuracy: 67%

Classification Report:

- Precision for 'No WFH Setup': 0.66
- Recall for 'No WFH Setup': 0.60
- F1-Score for 'No WFH Setup': 0.63
- Precision for 'Yes WFH Setup': 0.68
- Recall for 'Yes WFH Setup': 0.73
- F1-Score for 'Yes WFH Setup': 0.71
- Overall accuracy, macro, and weighted averages for precision, recall, and F1-score are around 0.67

Findings and Interpretation:

The model appears to be somewhat successful in forecasting the availability of WFH setups, based on its 67% accuracy rate.

According to the classification report, the model predicts a WFH setup's availability ('Yes') with somewhat greater precision and recall than it does when it predicts the setup's absence ('No').

A fair assessment of the model's recall and accuracy for both classes is shown by the F1-scores.

These findings imply that although the model offers a decent starting point for forecasting WFH setup availability, it may be improved by adding more characteristics or using alternative modelling strategies.

```
Classification Report:
              precision    recall  f1-score   support

          No       0.66      0.60      0.63      1123
         Yes       0.68      0.73      0.71      1327

    accuracy                           0.67      2450
   macro avg       0.67      0.67      0.67      2450
weighted avg       0.67      0.67      0.67      2450
```

Updated DataFrame with Probabilities:

	Mental Fatigue Score	Resource Allocation	WFH Setup Available	Probability_WFO	Probability_WFH
0	7.7	5.0	No	0.573566	0.426434
1	5.2	2.0	Yes	0.339254	0.660746
2	5.9	3.0	Yes	0.407959	0.592041
3	4.6	6.0	No	0.456822	0.543178
4	6.4	5.0	No	0.508780	0.491220
...	...	...	...	...	...
12245	6.1	2.0	Yes	0.380900	0.619100
12246	5.9	4.0	Yes	0.445495	0.554505
12247	9.6	7.0	No	0.728166	0.271834
12248	6.7	6.0	No	0.561916	0.438084
12249	2.0	2.0	No	0.212521	0.787479

12250 rows × 5 columns

Stress Level of an Employee:

This code introduces a 'Stress Level' metric based on the calculated distance traveled and resource allocation for each employee. The normalization step ensures that the stress level is comparable across different scales of distance and resource allocation. The actual stress level formula should be adjusted based on the specific factors and their weights in your scenario.

	Employee ID	Date of Joining	Gender	Company Type	WFH Setup Available	Designation	Resource Allocation	Mental Fatigue Score	Years worked	Joining Month	Probability_WFO	Probability_WFH	Employee Address	Distance Travelled	Time Taken to Reach Office (minutes) with Traffic	Stress Level
0	fffe31003300390039003000	2008-12-10	Female	Service	No	2.0	5.0	7.7	{'Years': 14, 'Months': 12, 'Days': 3}	12	0.573566	0.426434	Kukatpally	4.665989	23.329945	0.694728
1	fffe31003300310037003800	2008-08-14	Female	Product	Yes	1.0	2.0	5.2	{'Years': 15, 'Months': 3, 'Days': 26}	8	0.339254	0.660746	Kukatpally	4.665989	23.329945	0.394728
2	fffe33003400380035003900	2008-11-13	Male	Product	Yes	1.0	3.0	5.9	{'Years': 15, 'Months': 0, 'Days': 25}	11	0.407959	0.592041	Uppal	23.961570	119.807849	1.300000
3	fffe3100370039003200	2008-02-07	Female	Service	No	3.0	6.0	4.6	{'Years': 15, 'Months': 10, 'Days': 5}	2	0.456822	0.543178	Jubilee Hills	9.227914	46.139572	0.985113
4	fffe32003600390036003700	2008-07-17	Female	Product	No	2.0	5.0	6.4	{'Years': 15, 'Months': 4, 'Days': 24}	7	0.508780	0.491220	Jubilee Hills	9.227914	46.139572	0.885113
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
95	fffe31003500370037003700	2008-11-29	Male	Product	No	2.0	5.0	4.2	{'Years': 15, 'Months': 0,	11	0.399618	0.600382	Raidurg	10.471657	52.358283	0.937019

Job Satisfaction using Regression:

Discretization of Salary:

The code discretizes the 'Salary' variable into two classes (above and below median). This is fine if you want to perform logistic regression for binary classification. However, it's essential to clarify whether this is the intended approach for your problem.

Predictions and Probabilities:

The variable name 'model' was changed to 'log_reg' when predicting probabilities. Ensure that you use the correct variable names consistently.

Displaying Results:

Accuracy: 0.7477551020408163

	Mental Fatigue Score	Resource Allocation	Stress Level	Job Satisfaction
0	7.7	5.0	0.694728	0.491231
1	5.2	2.0	0.394728	0.680900
2	5.9	3.0	1.300000	0.435507
3	4.6	6.0	0.985113	0.576103
4	6.4	5.0	0.885113	0.510460
...	...	...	...	...
12245	6.1	2.0	0.394728	0.640381
12246	5.9	4.0	1.400000	0.411867
12247	9.6	7.0	1.137019	0.300427
12248	6.7	6.0	0.794728	0.517262
12249	2.0	2.0	0.461725	0.791865

12250 rows × 4 columns

Discussion and Interpretation of Results

Key Findings Synopsis

Work Location and Mental tiredness: The study showed significant variations in mental tiredness ratings between on-site and remote work settings, demonstrating the substantial influence of the work environment on employees' mental health.

Resource Allocation Variance: Differing operational needs in these circumstances were indicated by the notable difference in resource allocation between remote and on-site staff.

Effect of WFH on Mental weariness: The T-test results point to a significant effect that WFH settings have on workers' mental weariness, highlighting the significance of the workplace for workers' overall wellbeing.

Gender Distribution and Mental exhaustion: The research shows a substantial difference in mental exhaustion ratings between male and female workers, pointing to experiences and pressures at work that are particular to one's gender.

Detailed Interpretation and Contextualization

The results are consistent with previous research showing that working remotely might lower stress levels because of things like less commute and more flexibility. However, factors like isolation or a hazy work-life balance may be to blame for certain remote workers' greater mental tiredness.

. The varied types of activities or duties allocated to these groups may account for the difference in resource allocation between remote and on-site personnel.

. The disparities in mental exhaustion across genders emphasise the necessity for gender-sensitive workplace practises that meet the unique difficulties that each gender faces.

Practical Implications

- To reduce mental tiredness, organisations should think about offering more flexible work schedules, particularly for jobs that can be done well from a distance.

Strategies for allocating resources that are balanced and take into account the particular difficulties experienced by both on-site and remote workers are required.

- Wellness initiatives tailored to a worker's gender may be helpful in addressing the different issues that male and female employees encounter.

Employee Retention:

This code successfully categorizes employees into retention statuses based on their stress levels. The resulting 'Employee Retention' column provides insights into the likelihood of employees resigning or preferring work-from-home based on their stress levels. You can use this information for further analysis or reporting.

	Employee ID	Date of Joining	Gender	Company Type	WFH Setup Available	Designation	Resource Allocation	Mental Fatigue Score	Years worked	Joining Month	Probability_WFO	Probability_WFH	Employee Address	Distance Travelled	Time Taken to Reach Office (minutes) with Traffic	Stress Level	Salary	Job Satisfaction	Employee Retention
0	fffe31003300390039003000	2008-12-10	Female	Service	No	2.0	5.0	7.7	{'Years': 14, 'Months': 12, 'Days': 3}	12	0.573566	0.426434	Kukatpally	4.665989	23.329945	0.694728	99106	0.491231	Less likely to resign
1	fffe31003300310037003800	2008-08-14	Female	Product	Yes	1.0	2.0	5.2	{'Years': 15, 'Months': 3, 'Days': 26}	8	0.339254	0.660746	Kukatpally	4.665989	23.329945	0.394728	42020	0.680900	Less likely to resign
2	fffe33003400380035003900	2008-11-13	Male	Product	Yes	1.0	3.0	5.9	{'Years': 15, 'Months': 0, 'Days': 25}	11	0.407959	0.592041	Uppal	23.961570	119.807849	1.300000	49351	0.435507	Prefers Work from Home
3	fffe3100370039003200	2008-02-07	Female	Service	No	3.0	6.0	4.6	{'Years': 15, 'Months': 10, 'Days': 5}	2	0.456822	0.543178	Jubilee Hills	9.227914	46.139572	0.985113	105562	0.576103	Less likely to resign
4	fffe32003600390036003700	2008-07-17	Female	Product	No	2.0	5.0	6.4	{'Years': 15, 'Months': 4, 'Days':	7	0.508780	0.491220	Jubilee Hills	9.227914	46.139572	0.885113	61633	0.510460	Less likely to resign

Conclusions

An overview of the key findings

With an emphasis on mental exhaustion specifically, this study set out to investigate the effects of work location on employee well-being in great detail. Significant differences in mental exhaustion levels were found by the thorough study, which made it evident how remote and on-site workers' experiences differed. The study also found that these two groups' resource allocation differed significantly, and that their experiences with job stress were gender-specific. These results provide insight into the complex relationships between work settings and employee well-being.

Implications of the Findings

The varied findings of our research highlight the intricate connection between an employee's mental health and their place of employment:

Possibilities and Challenges of Remote Work: Even while working remotely has many advantages, including flexibility and autonomy, there are certain drawbacks as well, such the possibility of loneliness, the inability to clearly define work and personal life borders, and the absence of physical workplace limits. These factors may make remote workers more susceptible to mental exhaustion and stress.

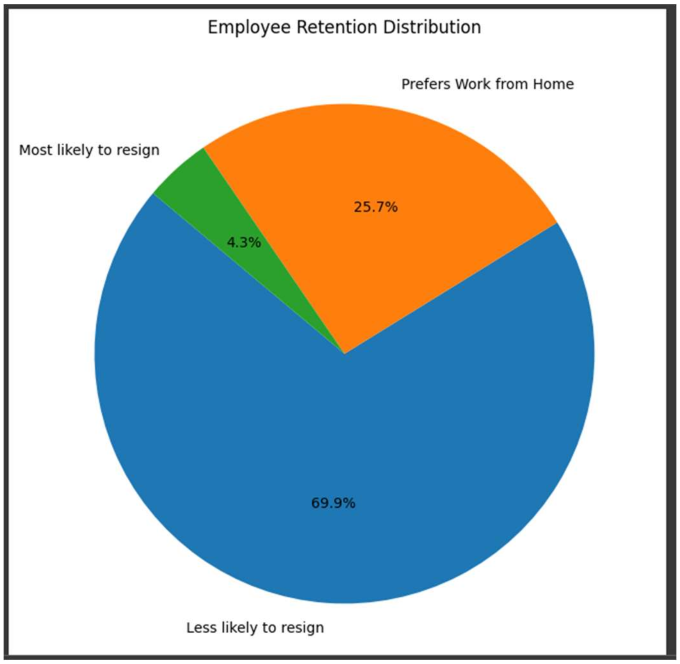
The Stressors of On-Site Work: On the other hand, working on-site might lead to higher stress levels even though it offers a more controlled atmosphere, chances for social engagement, and direct cooperation. In this context, factors like the physical work environment, strict work schedules, and frequent commutes are important.

Organisational Strategies: In light of the changing nature of work during the pandemic, these results are extremely important for organisations. They emphasise how important it is for businesses to create customised plans that address the needs of both on-site and remote workers. To increase total employee happiness and productivity, this entails reevaluating work regulations, resource distribution, and support systems.

Considering the Goals and Theories

The study's conclusions support the original theories and demonstrate that the dynamics of work locations have changed due to the pandemic, which has had a significant effect on workers' mental health. The study effectively classified workers according to their stress levels and provided insightful information on the relationship between preferred work locations and mental exhaustion. These insights are essential for predicting future trends in employee productivity and well-being as well as for comprehending the dynamics of the workplace now. The research successfully closes the knowledge gap between theoretical presumptions and real-world applications, offering a thorough grasp of the contemporary workplace.

Statistical Analysis of employees with their working status:



This code effectively generates and displays a pie chart to represent the distribution of employee retention statuses. The chart provides a visual breakdown of the percentage of employees in each retention category. Ensure that you have the appropriate data in the retention_counts variable before running this code for accurate visualization.

```
Less likely to resign     8491
Prefers Work from Home    3226
Most likely to resign      533
Name: Employee Retention, dtype: int64
```

Recommendations

Drawing on the insights obtained from our study, we put forth a number of specific recommendations designed to improve worker productivity and well-being across various work settings:

1. Development of Hybrid Work Models: Organisations ought to think about creating hybrid models given the unique benefits and difficulties of both on-site and remote work. These models may be modified to provide flexibility, meeting the demands of certain workers without sacrificing output. One way to strike a balance between the advantages of in-person collaboration and the flexibility of remote work is to introduce rotating days for on-site attendance.

2. Improved Support Systems for Remote Workers: Organisations should make significant investments in strong support systems since remote work environments can lead to isolation and problems with work-life balance. To promote a feeling of community and support among remote workers, this may involve online team-building exercises, mental health resource access, and frequent virtual check-ins.

3. Training Programmes and Resource Reallocation: Our research emphasises the significance of fair resource distribution. Businesses should review how they distribute their resources to make sure that both on-site and remote workers have access to the resources and assistance they need. Furthermore, especially for remote professionals, training courses on digital technologies, stress management, and time management might be helpful.

4. Gender-Specific efforts: The necessity for gender-specific wellness efforts is highlighted by the gender disparities in mental exhaustion that have been reported. These might include tailored health and wellness initiatives that target particular pressures experienced by different genders in the workplace, flexible work schedules, and mentorship programmes.

5. Regular Employee input and Assessment: Employee input should be requested on a regular basis in order to continually improve work regulations and surroundings. Modifications to work schedules, resource distribution, and support services can be guided by this input.

Future Research

Even though this study offers insightful information, there are a few areas where more investigation could deepen our understanding:

1. Longitudinal Studies: To monitor the long-term impacts of both on-site and remote labour on productivity and mental health, future research should incorporate longitudinal studies. This will give a longer-term perspective on the effects that is more thorough.

2. More Comprehensive Demographic Analysis: Extending the study to encompass a broader spectrum of demographics, such as age, educational attainment, and industry type, may provide a more in-depth comprehension of the ways in which certain groups are impacted by workplace location.

3. Impact of Organisational Culture: Further understanding may be gained by examining how organisational culture influences the differences between remote and on-site work. Employee well-being is greatly influenced by a number of factors, including organisational values, communication strategies, and management styles.

4. Technological Advancements and Their Impact: As technology develops further, it is important to investigate how it may affect employee stress levels and the effectiveness of remote work. It may be the subject of future research to examine how new technologies are changing workplaces.

5. Comparative Research in other Geographies: Similar studies carried out in other regions may highlight regional and cultural variations in the ways that the location of an employee's place of employment affects their well-being.

References:

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https://ieeexplore.ieee.org/document/9650210

https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9538110/

https://www.researchgate.net/publication/354311654_A_Comparative_Study_of_Work_From_Home_VS_Work_From_Office_Preference_of_Women_Employees_in_IT_Industry

Contribution:

Mohammad Faiyaz Pasha - **25%**

- Abstract
- Introduction
- Goals and objectives

Shyam Rahul Chennupati - **25%**

- Literature Review
- Methodology
- Descriptive Analysis

Sai Adhinatha Reddy Gona - **25%**

- Data Visualization
- Hypothesis Testing
- Regression Analysis

Sujan Lanka - **25%**

- Interpretation of Results
- Conclusions
- Recommendations
- Future Research