# Mental fatigue analysis in an Industry 4.0 workstation using an intelligent R language-based model

Andrés Esquivias-Varela [1] Humberto García-Castellanos [2] Alberto Ochoa-Zezzatti[3]

[1] Tecnológico Nacional de México IT Ciudad Juárez, Chih. México
Student in Engineering Sciences PhD
aesquivias6@gmail.com
[2] Tecnológico Nacional de México IT Ciudad Juárez, Chih. México
Engineering Sciences PhD
humber.gc@cdjuarez.tecnm.mx
[3] Autonomous University of Ciudad Juarez, Chih. México
Research at Technology PhD
alberto.ochoa@uacj.mx

**Abstract.** Nowadays, it is common to present mental fatigue, which would decrease the physical and psychological capacity for developing a job. This effect leads us to the work stress presented by workers in Industry 4.0. It showed these two effects to a drop-in labor efficiency of workers and, in turn, impacting the productivity of the same, which represents production losses for the industry, considering the physical and psychological health of the users in their work environment. Mental fatigue implies the attention of the company's personnel to correct and prevent the problem.

The article represents analysis in a workgroup, which is processed information based on questionnaires to staff that seeks to find the effect of mental fatigue according to their work activities. In turn, it aims to find a faster analysis through digital virtualization and representation in virtual images to process the information captured in real-time. In this way, it will be possible to offer a better work environment to avoid the mental fatigue of workers and thus not affect their productivity and mental health.

**Keywords:** Psychosocial risk, Analysis, Fatigue, Productivity, Virtualization.

## 1 Introduction

Within the industry and under the new ways of working of Industry 4.0 imply that working methods refer to the path of work execution and the work environment surrounding the workers. Interaction plays a significant role in the climate of modern industries, where different and diverse types of work techniques help the idea of working in a fatigue-free environment. The physical environments of sectors are designed to simplify collaboration through a higher visual and psychosocial level. Scientific studies have analyzed the difficulties of performing mentally taxing tasks in the modern industrial environment. They are complying with Mexican Standards, especially NOM-035, implemented since 2018 at a national level, which is a regulation issued by the Ministry of Labor and Social Welfare. Which aims to identify, analyze and prevent psychosocial risk factors, workplace violence through separate agreements and regulations, both national and international, that Mexico has ratified in labor justice, competitiveness, and trade, to promote a favorable organizational environment in workplaces [1].

In 2016, the International Labor Organization OIT reported on Psychosocial Risk Factors (PRF) and determined that they are a global problem that causes conflict in the professions and all users in any work environment.

It is determining that Psychosocial Risk Factors (PRF) are present in the workplace and concluding that it is the best place to prevent and act on them, to ensure the health and welfare of workers.

We must understand the difference between PRF and RP. We can appreciate factors as causes/conditions and risks as consequences. Psychosocial risk factors (PRF) are the characteristics of working conditions, especially the characteristics of their organization, affect people's health through psychological and physiological mechanisms that we also call stressors, intertwined with each other:

- Environmental working conditions.
- The need to exceed capabilities.
- Degree of responsibility and psychological burden.
- Lack of work autonomy.
- Time, rhythm, and work schedule.
- The function and content of the task are not clearly defined.
- Conflict between family and work relationship.
- Method of command and communication.
- Harassment, discrimination, and violence.

Psychosocial risk (PSR) is the negative psychological, physical, and social consequences caused by deficiencies in the design, organization, and management of work. The most common are:

- Acute and chronic work stress.
- Absenteeism
- Survivor syndrome
- Burnout/boredom syndrome (job burnout syndrome)
- Work addiction
- Bullying (workplace harassment)
- Violence, harassment, and discrimination
- Pain, depression, somatization

## 2 Related Literature

In the workplace, most studies examine the behavior and performance of employees in the activities to be performed, considering the complexity of learning and executing these activities. The literature analyzes three groups of small, medium, and extensive activities with the same difficulty.

De Croon et al. conceptual model [2] Two sets of parameters are analyzed: office philosophy and working conditions, which affect workers' short-term physical and psychological responses and long-term health and performance.
The concept of efficiency affects working conditions, including job requirements (cognitive load, workload, and workday) and job resources (communication, job autonomy, privacy, interpersonal relationships) [2].

To fully understand the impact of the work environment, other aspects that affect employee satisfaction, like the importance of furniture, quality of IT facilities, lighting, air quality, etc., must be considered. These factors affect the health and performance of employees, color, and material [2]. Saidi et al. [3]. Participants completed the test under normal working and quiet (off-work) conditions. The researchers found that although the memory performance of the smaller open area compares to the larger open space, cognitive performance: the number of interruptions (human and virtual) has a more significant impact on cognitive performance than the number of employees and virtual interruptions.

Psychological causes such as antipathy, discouragement, anguish, and job displacement appear to be related to physical health, especially heart disease. [4,5]. The unfavorable hazard status in psychological aspects seems categorized as a general social disadvantage. [6,7] Accordingly, the " psychosocial assumption" suggests that psychosocial stressors are an essential contributor to health disparity [8]. Those contributors involve numerous states of mind, psychological features, or aspects of health inequality. With a derogatory meaning. This article considers "psychosocial factors" for any physical health outcome that may affect physical health through psychological mechanisms—revisiting critically the emerging proof that a causal association causes the relationship between psychosocial stressors and physical well-being.

If this is not causal, it is unlikely that targeted psychosocial exposure interventions will benefit population health. An agreement reached that the results of the tests are sufficient to form the basis for health policy should come from health policy and should come from controlled trials of interventions that can change the relevant exposure and assess the impact of that exposure. Manipulate to guide health outcomes [6]. In some cases, this method is so. In some cases, this method is impractical or unlikely to be adopted for other reasons [5].

## 3 Methods

Recruit 33 workers aged 24 ± 5 years (3 classes, 28 men) and 24 ± 5 years (5 women). Recruit only workers without cognitive impairment or recent physical injury. Each participant completed a psychological assessment questionnaire, which included production lines in the automotive industry and workstations:

- Company selection
- Design pattern implementation

- Prototyping - Cutting Accuracy
- Time to design a prototype
- Difficult to follow design rules of design
- Difficult to generate the creativity required
- Difficult to organize the prototype
- Final course rating

All participants also reported normal or corrected vision and described themselves as being able to answer the questionnaire. The research was in a company specializing in seat fabrics for the automotive industry in Ciudad Juarez, Chihuahua, Mexico.

### 3.1 Measurements

Considering a set of work performance variables including different nominative categories, such as gender, age, and shift of workers, we used three classifiers (Bayesian network, random forest, and neural network-perceptron). We analyzed the performance algorithm of each classifier; it was used to establish a set of suitable indicators that will produce promising results in the main aspects related to mental fatigue.

Each algorithm can correctly classify more than two-thirds of the data set (dataset), which is the decisive element in finding the group and factors related to overwork. Due to the pressure to increase the number of parts, the male group continues to perform activities but considers that quality declines. In contrast, in the female group, quality is prioritized, where production is raised and minimizes delays, especially when using laser cutting plans. This tool is not as bold as a drill but has greater precision and adaptability in the cutting method and its accuracy in producing parts. However, among the vehicle objects, the female group is more detailed than the male sample, and the female group is only interested in mass production. Factors such as age, gender, and shifts also show significant differences in work performance, hence in the mental fatigue of each worker. The article is based on the analysis of a working group, which seeks the effect of mental fatigue according to their work activities in which will be measured: Selection of the company, implementation of the design pattern, prototyping - cutting, accuracy in cutting, the average time to design a prototype, difficulty in following the rules of design, difficulty in generating the required creativity, difficulty in organizing the prototype, average rating, end of the course, where the sum of the factors of each of the measures will have to give us a rating of 10 at its highest point, with these ratings and subdivisions. We will be able to understand better the areas in which the improvement issues will have evaluated to achieve optimal product production without having a difference in gender, age, and shift schedules. Figure 1 shows the data captured for the analysis in this study.

| | Company selection | Design pattern implementation | Prototyping - Cutting Accuracy | Precision in Cutting | Average | Time to design a prototype | Difficult to follow design rules of design | Difficult to generate the creativity required | Difficult to organize the prototype | Average | Final course rating |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **First working shift** | | | | | | | | | | | |
| 141021 RUÍZ GALLEGOS ÁNGEL | 5.9 | 2.1 | 3.7 | 3.6 | 3.8 | 1.8 | 2 | 1.6 | 5.4 | 2.7 | 9.3 |
| 153148 HERNANDEZ SANCHEZ DANIELA VALERIA | 4 | 5.4 | 5.7 | 3.4 | 4.6 | 1.5 | 4 | 1.9 | 6.8 | 3.5 | 8.1 |
| 154665 HERNÁNDEZ ANTILLÓN JEAN OLIVER | 5.7 | 4.1 | 3.4 | 6.5 | 4.9 | 6.2 | 5.3 | 4.4 | 1.5 | 4.3 | 9.4 |
| 154780 NORIEGA ANGULO RUBÉN | 3.8 | 2.1 | 4.1 | 2.5 | 3.1 | 4.5 | 3.9 | 6.3 | 3.4 | 4.5 | 7.9 |
| 158790 GALLEGOS BORUNDA FERNANDO HUMBERTO | 6.2 | 2.5 | 6.5 | 4 | 4.8 | 3.9 | 2.6 | 6.7 | 1 | 3.5 | 8.1 |
| 162988 MADRID DIAZ DE LEON JULIAN ANDRES | 5.2 | 5.5 | 6.4 | 6.2 | 5.8 | 3 | 5.7 | 4.2 | 4.5 | 4.3 | 8.5 |
| 163010 HOLGUIN HERNANDEZ ROBERTO | 3.1 | 3.3 | 6 | 6.8 | 4.8 | 6.5 | 2.7 | 6.6 | 3.8 | 4.9 | 8 |
| 163023 SOTO QUIROZ PEDRO | 4.6 | 3.2 | 4.5 | 3.8 | 4 | 4.2 | 3.7 | 2.9 | 5.3 | 4 | 9.6 |
| 163037 RODRIGUEZ CABRALES ANGEL DE JESUS | 2.4 | 2.4 | 1.5 | 2.8 | 2.3 | 3.1 | 5.8 | 7 | 2.1 | 4.5 | 8 |
| 168792 DÍAZ DOMÍNGUEZ CARLOS OMAR | 1.6 | 2.2 | 2.8 | 4.7 | 2.8 | 6.9 | 3.6 | 2.1 | 7 | 4.9 | 9.2 |
| **Second working shift** | | | | | | | | | | | |
| 155986 CORRAL MELÉNDEZ ERIC ARIEL | 5 | 1.6 | 5.5 | 5.7 | 4.4 | 1.9 | 3.5 | 5.3 | 6.2 | 4.2 | 8.4 |
| 162974 FRAIRE MEJIA JOSE ANGEL | 3.5 | 4.4 | 5.3 | 5.3 | 4.6 | 2 | 5.1 | 5.4 | 3.7 | 4 | 9.4 |
| 168768 ESPINOSA PERALES JORGE ANIBAL | 1 | 4.7 | 6.6 | 4 | 4.1 | 2.9 | 6 | 4 | 5 | 4.4 | 8.3 |
| 168836 HERRERA GONZÁLEZ HÉCTOR ARMANDO | 5.2 | 4.8 | 4.7 | 4.9 | 4.9 | 6.7 | 6.2 | 4 | 5 | 5.5 | 8.2 |
| 169038 GOMEZ ALVARADO BALTAZAR ANTONIO | 2.4 | 3.2 | 3.7 | 6 | 3.8 | 2.6 | 5.6 | 2.1 | 2.7 | 3.2 | 9.1 |
| 172126 REYES PENAGOS ISIS ARIADNA | 1.8 | 1.2 | 5.3 | 6.2 | 3.6 | 4.1 | 5.5 | 4.9 | 3.4 | 4.5 | 9.5 |
| 179709 QUEZADA MEDINA PEDRO ARMANDO | 5.3 | 1.4 | 6.4 | 6.2 | 4.8 | 1.2 | 1.9 | 3.5 | 5.4 | 3 | 8.8 |
| 179748 QUIROZ MEDRANO THOMAS ANTONIO | 2.5 | 5.4 | 5.1 | 4.2 | 4.3 | 6.9 | 1.9 | 6.1 | 6.1 | 5.3 | 9.1 |
| 179810 AGUILAR AVILA ERICK EDMUNDO | 5.1 | 1.4 | 2.9 | 2 | 2.9 | 4.2 | 4.4 | 3.9 | 6.3 | 4.7 | 9.3 |
| 179846 BERTHELY GONZÁLEZ EVELYN | 4.7 | 6.9 | 6.3 | 5 | 5.7 | 1.1 | 6.7 | 6.1 | 2.6 | 4.1 | 8.3 |
| 182080 SOLEDAD ZEPEDA RAUL ISAAC | 6.7 | 1.8 | 5.8 | 3 | 4.3 | 4.7 | 3 | 1.3 | 3.1 | 3 | 9.3 |
| **Third working shift** | | | | | | | | | | | |
| 145429 MUÑOZ PEREZ JONATHAN | 2.2 | 6.5 | 2.2 | 6.3 | 4.3 | 2.8 | 1.9 | 2.1 | 1.6 | 2.1 | 8.5 |
| 154684 MONTOYA JAQUEZ LUIS OMAR | 3.9 | 4.8 | 5.8 | 2.8 | 4.3 | 5.3 | 1.6 | 3.2 | 5.7 | 4 | 8.4 |
| 168701 LOPEZ MONTOYA FABIAN | 4.3 | 1.5 | 5.2 | 5 | 4 | 6.4 | 5.7 | 5.1 | 4.9 | 5.5 | 9.6 |
| 172087 RIVERA HERNANDEZ ALEXIS MICHELLE | 6.1 | 3.4 | 1.3 | 4.4 | 3.8 | 6.6 | 3.7 | 6.2 | 4.8 | 5.3 | 8.2 |
| 172095 APODACA JUÁREZ JESÚS ADRIÁN | 3.3 | 4.7 | 3.3 | 5.5 | 4.2 | 2.7 | 2.9 | 5.6 | 5.7 | 4.2 | 8.7 |
| 172127 MOTA MEDINA MISAEL IGNACIO | 3.6 | 2.4 | 2.3 | 4.6 | 3.2 | 6.7 | 3.7 | 3.2 | 5.3 | 4.7 | 9.6 |
| 172156 RUVALCABA DE LA FUENTE CÉSAR | 1.3 | 2.8 | 2.3 | 4.3 | 2.7 | 3 | 1.8 | 5.5 | 6.2 | 4.1 | 8.9 |
| 179758 MENDOZA SOSA NAOMI GUADALUPE | 5.2 | 1.5 | 4.5 | 1.4 | 3.1 | 5.4 | 5.1 | 6 | 3.3 | 5 | 8.2 |
| 179798 SILVA AGUIRRE SAMUEL | 4.9 | 5.7 | 5.1 | 1.7 | 4.4 | 6.8 | 6.6 | 6.3 | 5.7 | 6.3 | 9.7 |
| 179813 CARMONA MARTINEZ CARLOS DANIEL | 4.2 | 1.9 | 2.2 | 4.4 | 3.2 | 5.7 | 4.7 | 3.4 | 5 | 4.7 | 7.9 |
| 182568 CHAVEZ VELAZQUEZ ALAN GERARDO | 1.4 | 2.5 | 6.8 | 4.1 | 3.7 | 2.8 | 4 | 4.9 | 4 | 3.9 | 8.2 |
| 185442 MONROY AGUIRRE DIEGO ALEJANDRO | 2.3 | 4.5 | 4 | 3.7 | 3.6 | 6.8 | 4 | 2.3 | 1.7 | 3.7 | 9.4 |

**Fig. 1.** Data capture of workers in different work shifts

### 3.2 Description of used algorithms

In the next part of the survey, the three algorithms used will be described, and the numbers related to the performance of each algorithm will be shown in terms of their main characteristics and correctly characterized by this survey:

**Naive Bayes** Supposes that the occurrence or lack of a given feature is not linked to the event or lack of any other component. Its classifications are based on probability. In general, the Naive Bayes model is a machine learning algorithm for data classification. This algorithm is based on a statistical classification technique called "Bayes' Theorem." This algorithm is one of the simplest algorithms and has a great capacity to perform classification on large data sets. A Bayesian classifier works to assume that a feature taken from a class is independent of the different components extracted. Taking as an example the application for a bank loan by a specific person, it will be granted depending on other factors such as his loan history, monthly or biweekly income, location, age, and even his occupation where although the conclusion depends on all these characteristics, the Bayesian classifier deals with it independently, that is why it is called naïve.

This classifier has excellent advantages such as its ease of implementation and the speed with which it predicts a class or label within a dataset likewise; by having some independence in its characteristics, it works with a success rate and requires a smaller amount of data for training. However, it also has several disadvantages; the first is known as zero probability. If the training data set does not have a category found within the test data set. It cannot make any prediction, and he ends up developing a probability of 0. The second significant advantage is the limited application to real-world problems. The benefit is almost impossible to obtain a set of fully independent predictors. To execute the Naive Bayes classifier within this research, Naïve Bayes Classifier was implemented as part of the Text Blob library, which is used for textual data processing within the Python environment. This library has several applications such as spelling corrections, word frequency, or in this particular case, sentiment analysis.

The series of sentences declared within the Python script was used. The sentences that are used as training sets are obtained from a JSON file, although in some other circumstances, they can also be obtained from an Excel file. In this file extracted from Python are the various phrases, along with the label of the emotion given by the same human analysis during the pre-processing stage of the data. After performing the execution, labeling is consistent with the various emotions initially established. The implementation of the Naive Bayes algorithm is less extensive in terms of code, unlike the rest of the algorithms implemented in this research. However, it requires a well-selected bag of phrases for the JSON file because this makes the difference between a good classification or one with low success.

**Neural Networks** The primary goal of this model is to learn by modifying itself automatically to perform complex tasks that could not be carried by classical rule-based programming. The network receives a set of incoming data, and each of these feeds arrives at a node named neuron. The neurons in the network are arranged into layers that make up the neural network. Each neuron in the network has a value, a weight and uses it to change the incoming value. The new value gained leaves the neuron and continues through the web. The algorithm outputs a rating instead of a probability. It seeks to "learn" from examples of what can be adjudicated by a label (class) but not what is not (this sorter does not try to determine the definition of a sentence but to rank it).

It is possible to determine that classes with large training sets are present; this can create distorted classification scores, which forces the algorithm. To adjust the scores relative to the size of the class (not ideal as its equivalent in an actual situation would be when a person is forced to decide in an ipso facto manner). The researcher uses a natural language toolkit to develop this method. Because it was required to find a way to convert the phrases into words accurately and reliably derive them, it is then necessary to input the data into a training array, making sure to input the corresponding sentences along with their associated emotion.

Once you have all the data, you now need to organize the training data to identify sentences, classes, and the words that you can find within the sentences to determine a word bank and derive unique expressions. The derivation helps the network to match words such as "power" (force) and "power" (permission) to exclude the context where they are used. Since each sentence in training is reduced to a matrix of 0's and 1's, it can identify the unique words in the corpus.

It also allows to determine or associate this matrix within a class. Still, consider that a sentence can have several types or none at all. (this usually happens when there is a sentence whose reaction is unique and could not be interpreted previously in training or when it has no meaning at all, as if we were trying to make the network try to understand "asdfghjkl"). The function to standardize the values and their derivative was used to estimate the error rate. Repeat and adjust up to an acceptable low error rate. A problem also arose when implementing the bag of words since its unique character was required. For training, ten neurons were used within the hidden layers and put through 10000 epochs. It is considering that this allows better to classify the sentences with a reasonable error rate. It is configured inside a JSON file to store the synaptic weights (those that define the connection strength between two neurons). Once you have the model, it is possible to "predict" a new sentence that has not been described before and generate the probability of belonging to one of the classes. During the realization of this project, in the feature selection to improve the model. The test requires verifying the predictions in each case since, for an extensive dataset, it could take a considerable amount of time to check if there is some parameter that allows establishing some confidence with the user. Some prediction situations demand more reliability than others, and not all text categorization scenarios are equivalent to others.

**Random Forest** A Random Forest is a set of decision trees combined with bagging. When bagging is used, what happens is that different trees look to varying portions of the data; no single tree sees all the training data, so each tree is trained with varying samples of data for the same problem. Thus, by combining their results, some errors are compensated with others, and we have a generalized prediction with a better result. The characteristics selected after each training, the set of trees chosen can vary, having better or worse accuracy than the last time, for the exercise of this system.
The texts require pre-processing before training the system. The texts begin with creating a bag of unique words from the texts, words that will be used to establish the criteria the design of bag words a transformation of texts to numerical values made. These texts count the number of times that each phrase is repeated, thus creating a training matrix. With the data already pre-prospected, the training is performed. After data processing, the Random Forest algorithm had an accuracy of 84% used to predict future texts.

Once the analyzed algorithms are clarified, we can graphically (Figure 2) the selection processes of the individuals. We can appreciate more greatly the comprehension of the article detailed here. From which we can say that to process the information, it is necessary to have a database of the information capture of the study.

It will help us to be able to determine the mental fatigue of the individuals and thus to be able to look for improvements in the production to help the workers in this subject.

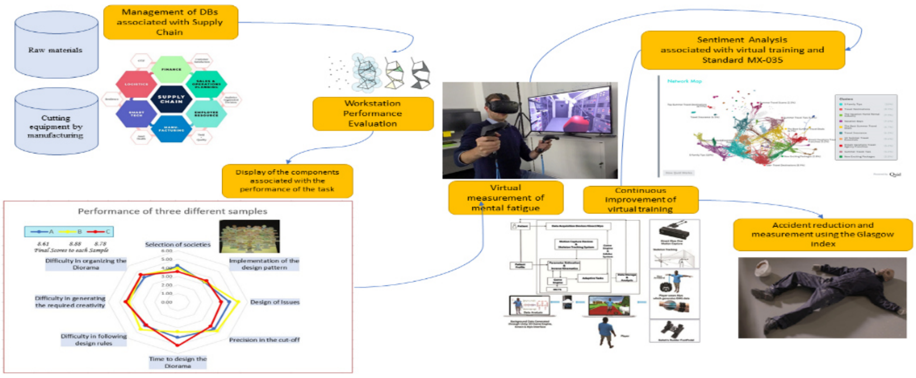


**Fig. 2.** Mental fatigue analysis scenario

## 4 Results

The Bayesian algorithm gave us a result in favor of the men. Due to the pressure to increase the number of parts, the male group continued to perform activities, making it more productive. Still, compared to the results presented in the female group, the quality is lower, and the concept of quality is prioritized, i.e., increasing production and minimizing delays. However, among the analysis subjects, the female group is more detailed than the male sample. The female group is only interested in mass production. Factors such as age, gender, and shifts also show more significant differences in job performance and mental fatigue.

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**NAÏVE BAYES**

We have the results obtained by the Weka program from the analysis of the Naïve Bayes algorithm, which can be seen in figure 3.

Scheme: weka.classifiers.misc.InputMappedClassifier -I -trim -W weka.classifiers.bayes.NaiveBayes

Relation: mentalfatigue-weka.filters.unsupervised.attribute.StringToWordVector-R1-W1000-prune-rate-1.0-N0-stemmerweka.core.stemmers.NullStemmer-stopwords-handlerweka.core.stopwords.Null-M1-tokenizerweka.core.tokenizers.WordTokenizer -delimiters " \r\n\t.,;:\'\"()?!"

Instances: 33
Attributes: 47

| | | |
|---|---|---|
| Correctly Classified Instances | 28 | 84.85% |
| Incorrectly Classified Instances | 5 | 15.15% |
| Kappa statistic | 0 | |
| Mean absolute error | 0.271 | |
| Root mean squared error | 0.3591 | |
| Relative absolute error | 100% | |
| Root relative squared error | 100% | |
| Total Number of Instances | 33 | |

=== Detailed Accuracy By Class ===

| TP Rate | FP Rate | Precision | Recall | F-Measure | MCC | ROC Area | PRC Area | Class |
|---|---|---|---|---|---|---|---|---|
| 0 | 0 | ? | 0 | ? | ? | 0.5 | 0.152 | f |
| 1 | 1 | 0.848 | 1 | 0.918 | ? | 0.5 | 0.848 | m |
| 0.848 | 0.848 | ? | 0.848 | ? | ? | 0.5 | 0.743 | |

=== Confusion Matrix ===

| a b <-- classified as | |
|---|---|
| 0, 5 \| | a = f |
| 0, 28 \| | b = m |

**Figure 3.** Results of Naïve Bayes algorithm

## MULTILAYER PERCEPTRON

The analysis of the multilayer perceptron shows us the result in the classes of the three work shifts, taking as the highest productivity in the first shift that this algorithm categorizes the values in production, leaving aside the other types analyzed in the article.

We can see the breakdown of the data inputs on the left side of Figure 4. There are three hidden layers of 5,10,20 neurons in the central part, and on the right side, we find the data output nodes. At the same time, we have the results obtained by the Weka program from the analysis of the multilayer perceptron, which is shown in figure 5.

Run information:
Scheme: weka.classifiers.misc.InputMappedClassifier -I -trim -W weka.classifiers.functions.MultilayerPerceptron -- -L 0.3 -M 0.2 -N 500 -V 0 -S 0 -E 20 -H a
Relation: mentalfatigue-weka.filters.unsupervised.attribute.StringToWordVector-R1-W1000-prune-rate-1.0-N0-stemmerweka.core.stemmers.NullStemmer-stopwords-handlerweka.core.stopwords.Null-M1-tokenizerweka.core.tokenizers.WordTokenizer -delimiters " \r\n\t.,;:\'\"()?!"
Instances: 33
Attributes: 47
=== Summary ===

| | | |
|---|---|---|
| Correctly Classified Instances | 24 | 72.73% |
| Incorrectly Classified Instances | 9 | 27.27% |
| Kappa statistic | 0.5909 | |
| Mean absolute error | 0.1969 | |
| Root mean squared error | 0.3278 | |
| Relative absolute error | 44.30% | |
| Root relative squared error | 69.54% | |
| Total Number of Instances | 33 | |

=== Detailed Accuracy By Class ===

| | TP Rate | FP Rate | Precision | Recall | F-Measure | MCC | ROC Area | PRC Area | Class |
|---|---|---|---|---|---|---|---|---|---|
| | 0.818 | 0.136 | 0.75 | 0.818 | 0.783 | 0.668 | 0.942 | 0.928 | first |
| | 0.636 | 0.091 | 0.778 | 0.636 | 0.7 | 0.577 | 0.868 | 0.845 | second |
| | 0.727 | 0.182 | 0.667 | 0.727 | 0.696 | 0.535 | 0.921 | 0.856 | third |
| **Weighted Avg.** | 0.727 | 0.136 | 0.731 | 0.727 | 0.726 | 0.593 | 0.91 | 0.876 | |

=== Confusion Matrix ===

| a b c <-- classified as |
|---|
| 9, 0, 2 \| a = first |
| 2, 7, 2 \| b = second |
| 1, 2, 8 \| c = third |

**Figure 4.** Results of Perceptron algorithm

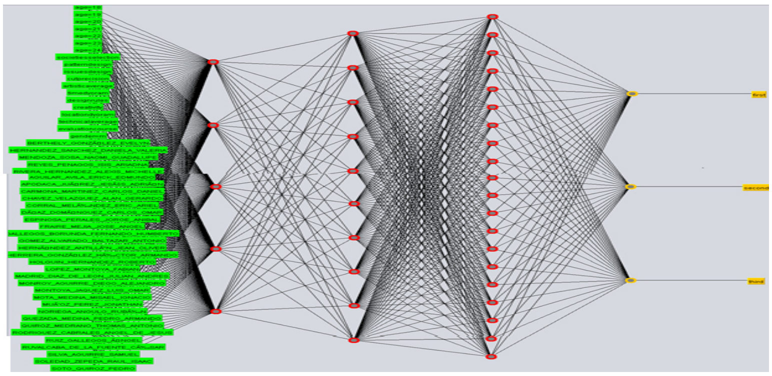

**Figure 5.** Neuronal network of mental fatigue

**Random Forest**

The Random Forest shows us 47 trees executed in the algorithm. We can obtain a result of instances classified in 93.94% evaluating the age class of the three different groups, showing significant differences in work performance in the mental fatigue of each worker. Mental fatigue is the highest efficiency found in the ages between 21 and 22 years old.

We can see in Figure 6 the run of the data produced by the Weka program using the Random forest algorithm.

=== Run information ===

Scheme:weka.classifiers.misc.InputMappedClassifier-I-trimWweka.classifiers.trees.RandomTree -- K 0 -M 1.0 -V 0.001 -S 1

Relation: mentalfatigue-weka.filters.unsupervised.attribute.StringToWordVector-R1-W1000-prune-rate-1.0-N0-stemmerweka.core.stemmers.NullStemmer-stopwords-handlerweka.core.stopwords.Null-M1-tokenizerweka.core.tokenizers.WordTokenizer -delimiters " \r\n\t.,;:\'\"()?!"

Instances: 33
Attributes: 47
Size of the tree : 47
=== Evaluation on test set ===
Time taken to test model on supplied test set: 0.01 seconds

= Stratified cross-validation =
= Summary =

| | | |
|---|---|---|
| Correctly Classified Instances | 31 | 93.94% |
| Incorrectly Classified Instances | 2 | 6.06% |
| Kappa statistic | 0.9285 | |
| Mean absolute error | 0.0202 | |
| Root mean squared error | 0.1058 | |
| Relative absolute error | 8.31% | |
| Root relative squared error | 30.37% | |
| Total Number of Instances | 33 | |

=== Detailed Accuracy By Class ===

| | TP Rate | FP Rate | Precision | Recall | F-Measure | MCC | ROC Area | PRC Area | Class |
|---|---|---|---|---|---|---|---|---|---|
| | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 18 |
| | 0.8 | 0 | 1 | 0.8 | 0.889 | 0.879 | 0.993 | 0.943 | 19 |
| | 1 | 0.037 | 0.857 | 1 | 0.923 | 0.909 | 0.994 | 0.952 | 20 |
| | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 21 |
| | 1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 22 |
| | 0.8 | 0 | 1 | 0.8 | 0.889 | 0.879 | 0.996 | 0.967 | 23 |
| | 1 | 0.036 | 0.833 | 1 | 0.909 | 0.896 | 0.996 | 0.967 | 24 |
| Weighted Avg. | 0.939 | 0.012 | 0.949 | 0.939 | 0.939 | 0.931 | 0.997 | 0.973 | |

=== Confusion Matrix ===

| a b c d e f g | <-- classified as |
|---|---|
| 3 0 0 0 0 0 0 | a = 18 |
| 0 4 1 0 0 0 0 | b = 19 |
| 0 0 6 0 0 0 0 | c = 20 |
| 0 0 0 3 0 0 0 | d = 21 |
| 0 0 0 0 6 0 0 | e = 22 |
| 0 0 0 0 0 4 1 | f = 23 |
| 0 0 0 0 0 0 5 | g = 24 |

**Figure 6.** Results of Random Forest

## 5 Discussion

This study used a qualitative design to examine psychosocial factors, work stress, and mental stress as applied to the automotive industry, focusing on a company engaged in the production of fabric cutting for car seats. Although this paper aims not to evaluate gender differentials, we emphasize a few critical gender issues that are relevant and valuable for mention. Compared to men, there were fewer female study participants involved in the work shifts analyzed. In the tailoring management value chain, women have the highest role, which shows that women tend to do more beautiful and efficient work. Some reasons, such as cultural and socio-cultural value systems, consider cleanliness and precision cutting as traditional female roles, which can improve production and thus realize the cutting function.

The occupational hazards with workers ' activities are minimized through the systematic use of personal protective equipment (PPE). Previous cutting and sewing training courses can also minimize them to understand the process pattern to be followed. However, the committee members stated that their working conditions are terrible and the work pressure to finish the product on time is far from seeking better production quality. Hence, there are quality failures related to the pressure to achieve the target. The company has established daily production but has not received sufficient training in abatement measures and work-related practices and methods for reducing health hazards. These situations seem to indicate that they have limited skills to identify the psycho-social risks related to their work surroundings and implement safety and health precautions.

**Conclusions**

Risk management is one of the main activities of modern supply chain management. One of the main risks is operational risk, which is linked to the level of mental fatigue that operators can tolerate, as well as their wandering mind [9,10]. These risks are inherent to the daily activities of the company, perhaps operational risks do not have the degree of destructive risk, but without their consideration and management, they will significantly affect business results [10]. The flexibility of employee participation is relevant, because they are indispensable when performing activities to overcome changes in the demand and production of items, they are what makes them suitable for the production process to adjust to them [11].

The automotive workers who participated in the study faced risks related to mental health and reported unsafe behaviors related to the company's measures to ensure a good working environment. Workers are also aware of the implementation of standard production control procedures related to the management of fabric manufacturing. Still, the company does not comply with occupational health and safety standards regarding production quality.

The study presents three different results: the evaluations are age, gender, and work shift, wherein part of the gender clarifies that the most efficient was the male group. The concepts were evaluated with the Bayesian algorithm. Most of the data collected in the three assessed groups were of male origin since the female group was only 15% of the population analyzed. Although the result was given for the male group, it is necessary to understand the data analyzed where the female group presented better results in production quality.

On the side of the work shifts, it was found that the algorithm of neural networks or multilayer perceptron gave us favorable results. The first shift is more efficient than the other two analyzed. It is necessary to understand cultural impact since we had the same amount of personnel studied between the other two groups. When analyzing the three groups by their ages with the random forest algorithm, we found that the most effective ages for production were between 21 and 22 years of age, mixing genders and work shifts. The variation of ages is similar in the three groups analyzed.

Poor interpersonal relations between workers and their managers and the lack of social protection and job security are other problems that harm workers' social and mental health needs. Negative attitudes, perceptions, and stigmatization of workers by the community and lack of production standards lead to low job pressure and satisfaction. A tailored workplace policy is needed to provide counseling and psychosocial support in a social psychology company canteen and help employees improve work stress management. In addition, the company policy should comply with the standard Mexican NOM-035 on psychosocial risk factors, solve problems and solutions to avoid this impact in the workplace, especially among low-wage workers, which will seek to improve job satisfaction observed in this study.

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