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Exploring the Impact of Emotional States on Human Performance in Production Systems: A Simulation Approach

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Abstract

In modern industry, the focus is shifting towards Industry 5.0, which balances technology and humanity, putting workers' well-being at the forefront. This study explores the impact of emotional states on work performance through simulation, focusing on task execution times. A simulation model is developed that integrates emotional state data into production simulations. The case study analyzes a tuna processing manufacturing system, evaluating the effect of operators' emotional states on two key performance indicators. The results show a clear relationship between emotional states and performance, with positive emotions improving operational efficiency and negative emotions decreasing it. This innovative approach can transform human factors management in manufacturing settings, improving both efficiency and worker well-being.

Keywords: Human performance simulation; Emotional states; Operational efficiency

1. Introduction

The adoption of artificial intelligence (AI) technologies is growing rapidly, requiring regulations to ensure their safe and ethical use. The European Artificial Intelligence Regulation (AI Act), passed on 13 March 2024, represents a crucial step in this direction within the European Union. This piece of legislation protects fundamental rights, while addressing data protection, transparency and risk prevention. Emerging applications of AI include emotion recognition, which analyzes human emotions through various signals. The AI Act imposes transparency rules for these systems, ensuring that users are informed about the origin and use of emotional data. In the evolution of modern industries, we are witnessing a significant shift in the way we conceive production and work.

Industry 5.0 emerges as a response to this evolution, placing not only efficiency and automation at the forefront, but also human well-being and sustainability. In a world where advanced technologies are now an integral part of the fabric of production, it is becoming increasingly clear that considering worker well-being as a central element of the factories of the future is important. Industry 4.0 has brought us intelligent machines, advanced robotics, and unprecedented interconnectivity between devices and systems. However, as we venture into Industry 5.0, our focus is shifting to creating a balance between technology and humanity. This new approach recognizes that workers are not just cogs in a production machine, but human beings with needs, emotions, and aspirations. Worker well-being is not just a matter of social responsibility, but a real competitiveness factor. Research shows that happy and healthy workers are more productive, less error-prone, and more creative Bellet et al.(2023). Investing in their well-being means creating a work environment where they feel valued, motivated and safe. This translates into a reduction in absenteeism, an increase in loyalty and an overall improvement in company performance.

At this point, it becomes essential to connect the relevance of monitoring human factors and emotional states to ensure the health, safety and well-being of the workforce.

Historically, human factors have always influenced work performance. Studies such as Behrens et al. (2023) and Wang et al. (2022) show that stress, motivation and fatigue can negatively affect work performance, increasing the risk of errors and accidents.

The performance of operators in manufacturing systems is influenced by various human factors, including emotional states. In addition to physical aspects such as fatigue and ergonomic conditions, emotional well-being directly affects concentration, decision-making, and the ability to manage stress. When workers experience positive emotional states, they are more likely to be engaged, motivated, and productive. In contrast, negative emotional states can lead to decreased performance, higher error rates, and increased risk of accidents. Studies have shown that emotions such as stress and anxiety can impair cognitive functions, leading to poor judgments and errors (LeBlanc, 2009). On the other hand, positive emotions improve problem-solving skills and creativity (Isen, 2001). Therefore, maintaining a positive emotional climate in the workplace is not only beneficial for individual workers, but also for overall operational efficiency. Furthermore, monitoring emotional states can help identify early signs of burnout and mental fatigue, which are critical for implementing timely interventions. For example, programs that promote mental health awareness and provide stress management resources can significantly reduce absenteeism and improve job satisfaction (Goleman, 2020).

This paper investigates the impact of emotional states on operator performance, focusing on task execution times.

The aim of this study is to develop a prototype simulation model that integrates emotional state data into production simulations, providing a more complete understanding of human performance. The integration of this data will allow to evaluate the impact of emotional states on work performance, supporting companies in monitoring and managing human factors, thus improving productivity and overall well-being of workers.

The remainder of the paper is structured as follows. Section 2 presents the background theory, describing the literature on the topic. Section 3 describes the methodology, the model definition, and the case study. Section 4 presents the results and discussions, identifying the insights that indicate a significant correlation between emotional states and performance metrics. Finally, Section 5 concludes the study by demonstrating the feasibility and utility of integrating emotional state data into manufacturing simulations and suggests future directions for research and application of the model in different industrial sectors.

2. Theoretical background

In this section, we will review the underlying theory that underpins our research on the impact of emotional states on human performance in manufacturing systems. We will review the existing literature, identify gaps, and formulate specific research questions that our study aims to address.

2.1. Human factors and emotional states in production

Increasing employee productivity is crucial to the overall well-being of an organization. Productivity is linked not only to a company's profitability, but also to its operations and human resource management. Due to its importance in various fields, numerous studies have examined what affects employee productivity and how it can be optimized. Previous research has already shown that employee productivity is associated with various human factors.

Wilson (2000) states that Human Factors is “the basic and theoretical understanding of human behavior and performance in interactive socio-technical systems and the application of this understanding to the design of interactions within real environments”. Human factors are a significant component that significantly influences productivity, both in terms of time and quality, especially in industrial settings that involve a variety of manual activities with different degrees of experience and knowledge. In recent years, there has been a growing interest from experts in understanding how human factors can influence overall performance, in order to improve productivity and ensure better ergonomic conditions in the workplace. Otto and Battaïa (2017) state that ergonomics at work is based on three fundamental aspects: physical, cognitive and organizational.

Physical aspects concern the interaction of the human body with the physical components of the work environment, such as the use of equipment and working posture, which can influence fatigue and operational efficiency. Cognitive aspects, on the other hand, include mental processes such as attention, memory and decision-making, all of which are essential for the correct performance of tasks. Finally, organizational aspects include the structure of work, human resource management and company policies that can influence employee motivation and satisfaction.

Recent research has shown that mental health and its associated risks significantly influence employees' work effectiveness (Rasool et al., 2019; Bubonya et al., 2017; Holden et al., 2011). Positive attitudes and a sense of calm can increase productivity. Studies have shown that happy and satisfied workers tend to perform better at their jobs (DiMaria et al., 2019; Frey, 2018; Tenney et al., 2016). Good physical health also plays a crucial role: healthy employees are more productive, as found by Neumann and Dul (2010), as well as Ødegaard and Roos (2014). Furthermore, wellness programs in companies have increased productivity, according to Gubler et al. (2018). Companies are therefore investing more in health and wellness programs.

Employee emotions, including feelings and physical reactions, are crucial in modern work environments where people interact frequently with machines. Being enthusiastic makes tasks easier to complete, while feeling listless makes them more difficult. Yang and Hung (2017) found that happy people tend to work better.

While there have been numerous studies linking productivity to employee emotions, there is a lack of specific research examining how a worker's emotional state while at work correlates with, or directly influences, performance.

Few mathematical models have been developed to predict the influence of emotional states on performance. For example, Jaber and Neumann (2010) proposed a mixed integer linear programming model that considers productivity and fatigue, demonstrating that partial recovery after each task improves system performance. Furthermore, models that incorporate fatigue and recovery cycles with task performance metrics, such as the exponential models introduced by Jaber et al. (2013), offer a perspective to predict the accumulation and recovery of emotional and physical fatigue over time.

Therefore, the specific impact of emotional states requires further investigation. Developing a more detailed and integrated understanding of how emotional states influence performance can lead to more targeted and effective interventions, thus improving the health, safety and well-being of the workforce in the era of Industry 5.0.

2.2. Human performance simulation

Assessing human performance in manufacturing environments is critical to designing and optimizing production systems.

Simulation models are essential tools for predicting and improving human performance in manufacturing. In the literature, two types of human performance models can generally be identified: models that deal with low-level factors and those that deal with high-level factors.

Low-level models represent basic physiological mechanisms. For example, dehydration models estimate changes in performance mediated by environmental conditions (James et al., 2019). These models are relatively simple and can be applied to any individual and are therefore particularly suitable for simulation. Based on this type of model, Baines et al. (2004) conducted a study using two low-level human performance models. The first model addresses changes in performance due to aging, showing that cognitive and physical abilities decline by 1% per year after the age of 20, but can be attenuated by factors such as training and experience. The second model considers the effects of circadian rhythms on performance, influenced by time of day and time since last sleep, building on the work of Smith and Brown (2022) to simulate daily fluctuations in performance.

Thus, Baines et al. (2004) demonstrate the integration of these models into a discrete event simulation (DES) of an automotive assembly line. The simulation includes pre-calculated data on changes in performance as a function of age and circadian rhythms, allowing for realistic representation of variations in worker performance throughout the day and over the course of their working lives. Experimental results show that the inclusion of these models can significantly influence system performance predictions, highlighting the importance of considering human factors in manufacturing simulations.

In contrast to low-level models, high-level models address complex interactions of psychological mechanisms. For example, job satisfaction is known to influence job performance (Katebi, 2022), but this effect is mediated by psychological and environmental factors (Zhang et al., 2022). Such models are inherently complex, context-specific, and dependent on individual differences between people. The combination of low contextual validity and complexity makes such models difficult to integrate into manufacturing simulations. Therefore, a more indepth study of simulation models based on human factors, such as the impact of emotional state on performance, is needed given the scarcity of literature on this topic, and this is precisely what our study is based on. This approach can provide a more comprehensive understanding of human performance and further improve the accuracy and effectiveness of manufacturing simulations.

The research questions that this study intends to address are the following:

1. How do workers' emotional states affect organizational performance?

2. What mathematical models can be developed to predict the influence of emotional states on human performance?

3. Methodology, Model Definition and Case study

This section provides details on the materials (data, resources, software), methodologies, experiments and analyses used to support the conclusions of the study. The concept of the emotional state model, the data and materials used, the mathematical model developed, the specific case study of the tuna processing manufacturing system, the development of the simulation model and the integration of the emotional state model will be described. The objective of each analysis will be clarified and the main results obtained will be presented.

3.1. Emotional state model concept definition

The emotional state model presented in this study is designed to model how workers' emotions influence their operational performance. The basic idea is that emotional states, whether positive or negative, can have a significant impact on work efficiency and overall company performance. The components of this model include 6 emotional variables (2 positive, 2 neutral and 2 negative) which are joy, relaxation, calm, contemplation, grief and frustration. These were randomly chosen with the aim of verifying whether, regardless of the type of emotion selected, the three categories (positive, neutral and negative) can specifically influence operational performance. The influence mechanism of the presented model is based on the fact that each emotional state is hypothesized to have a specific effect on operators' efficiency. The final goal is to understand this influence.

3.2. Data and material

The development of the model, which relates emotional state to performance, was based on the findings of Hersey (1932). For a year, he studied the emotions and behaviors of 17 skilled workers in two departments of a railroad car and locomotive repair plant. Each worker was interviewed four times a day for alternating periods of 13 weeks with intervals of eight and four weeks without measurements. The interviews included a mood checklist with 22 items such as "happy", "hopeful", "tense", "angry", etc. Hersey found a definite relationship between emotional state and work productivity. The results showed that the negative effects of a negative mood were much more pronounced than the positive effects of a positive mood as can be seen in Figure 1.

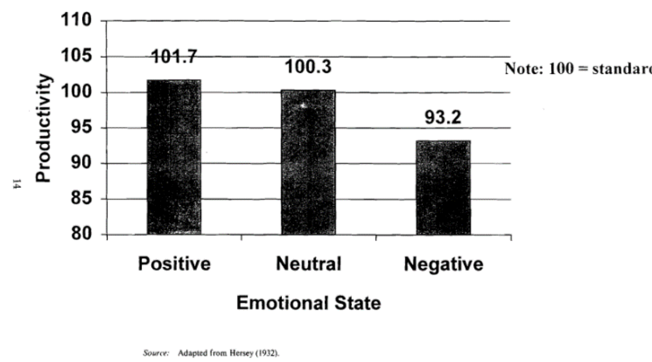


Figure 1. Relationship between Productivity and Emotional State (adapted from Hersey, 1932)

Assuming this conclusion is valid, it then continued with the analysis of Circumplex Model of Affect (Meska et al. 2020) for the development of the model. According to this model in Figure 2, on the basis of two elements - Valence and Intensity, it is possible to classify emotions as positive (on the left side of the circumference), neutral (central part) and negative (on the right side).

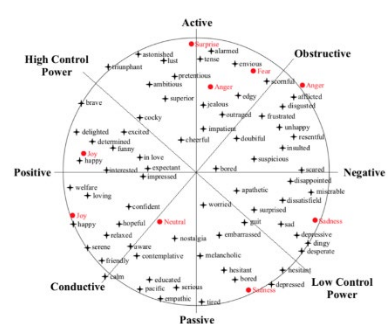


Figure 2. Circumplex Model of Affect

Each axis of the model was assigned numerical values: the x-axis represents Valence and the y-axis Intensity. The x-axis was quantified with extremes 1 and -1, decreasing from right to left, while the y-axis has extremes 1 and -1, decreasing from top to bottom. The intersection of the two axes corresponds to the value zero.

For the numerical calculation of the valence and intensity values, a graphical approach was followed. Each axis was initially divided into portions of 0.1, then further divided into portions of 0.05 and finally into divisions of 0.025 using a system of vertical and horizontal lines, as illustrated in Figure 3.

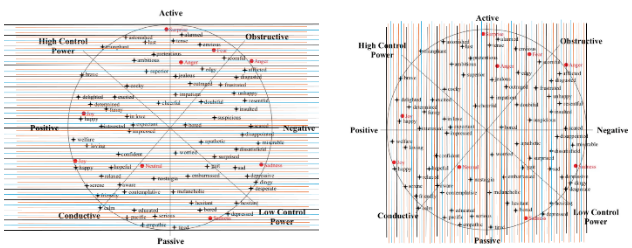


Figure 3. Graphic calculation of valence and intensity of emotions in the Circumplex Model

Based on this procedure, the following valence and intensity values were obtained for the different emotions as reported in the Table 1.

Table 1. Valence and Intensity values for the emotions of interest

Emotional State	Valence	Intensity
Joy	0,93	0,15
Calm	0,68	-0,75
Afflicted	-0,74	0,56
Relaxed	0,68	0,48
Frustrated	-0,50	0,43
Contemplative	-0,175	0,025

3.3. Mathematical model for emotional states

To develop a mathematical model that relates emotional state to performance, a global impact coefficient was calculated to determine how each emotion affects the efficiency of operators, based on valence and intensity. The formula used is the following:

$$\text{Emotion Impact} = \text{Global Coefficient} \times \text{Valence} \times (1 + \text{Intensity}) \tag{1}$$

The value "1" added to the intensity was considered to take into account at least the valence when the intensity is close to zero or null.

To determine the global coefficient C, the results of a study conducted by Bellet et al. (2023) were used, which demonstrated a significant link between happiness and productivity, concluding that an emotional state of happiness can increase productivity by 13%. In this context, the concept of productivity includes various aspects related to the efficiency of the operator.

Having the impact of happiness and the values of valence and intensity of this emotion, respectively 0.875 and 0.1, the following inverse calculation was used to determine the global coefficient:

$$C = \frac{\text{Emotion Impact}}{100 \times \text{Valence} \times (1 + \text{Intensity})} \tag{2}$$

Using the calculated coefficient of 0.135 and the previously mentioned formula, the impacts of each emotion were determined, as reported in the Table 2.

Table 2. Values Valence, Intensity and Impact for the emotions of interest

Emotional State	Valence	Intensity	Impact
Joy	0,93	0,15	0,14
Calm	0,68	-0,75	0,02
Afflicted	-0,74	0,56	-0,15
Relaxed	0,68	0,48	0,13
Frustrated	-0,50	0,43	-0,10
Bored	-0,175	0,025	-0,02

These will then be integrated into the plant simulation model for performance evaluation.

3.4. Case study

The case study on which the following work is based concerns a manufacturing system for tuna processing (Figure 4), analyzed over a reference period of 40 days. In this plant two types of products are produced: glass tuna (a premium product) and canned tuna (a standard product intended for a different market).

Every day, 28 tuna are delivered and stored in a cold room waiting to be processed. Then, through a conveyor belt, the raw material (tuna) is transferred to the cutting machine. At this stage, a tuna enters the machine and a scrap and a clean tuna come out, which is then transported to the oven for the cooking process. After cooking, the tuna is divided into different slices: 16 premium slices and 20 standard slices.

After cutting, the cans and glass jars are filled. The product is then subjected to a sterilization phase, carried out by two separate machines since the process varies for the two types of product. At the end of sterilization, the glass product (Jar) is subjected to quality control, while the can product (Can) must first undergo a closing operation before reaching quality control. The last operation for the glass product is the labeling phase.

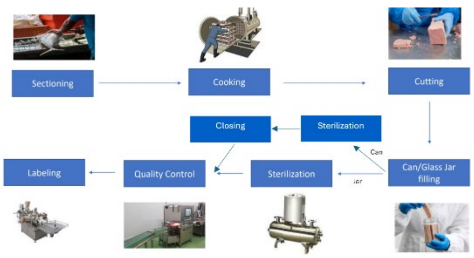


Figure 4. Tuna processing processes

The entire manufacturing plant employs five workers, each assigned to a specific step in the process: sectioning, cutting, can filling, can filling, and can sealing. Work schedules include shifts from 7:00 a.m. to 2:00 p.m. and 2:00 p.m. to 6:00 p.m., with a lunch break from 12:00 p.m. to 2:00 p.m. and other breaks during the shift. The work week is Monday through Friday, excluding Saturday and Sunday.

The aim of this study is to evaluate the introduction of wellness programs for staff, trying to understand, through a simulation model, if and how the emotional state of operators affects collective performance. In particular, the analysis focuses on two key performance indicators (KPIs): the average production time for glass jars (Jar) and for cans (Can).

3.5. Simulation model development

To simulate the tuna processing manufacturing system,PlantSim (Retrieved from Siemens Digital Industries Software: siemens.com) was used, a simulation software developed by Siemens for discrete simulation and optimization of manufacturing processes. This software allows to represent the workflow in detail, using various interconnected objects.

The model involves the use of various stations and components, including workstations (station), assembly stations (assembly station), dismantle stations (dismantle station), conveyors and buffers for storing goods. The main stations in the process include:

- Work stations: Cooking, sterilization, closing, quality control and labeling.
- Disassembly stations: Sectioning and cooking.
- Assembly stations: Filling Jar and filling Can.

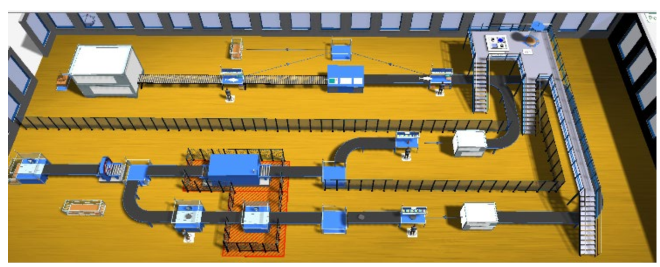
The times for each station were set based on the information provided in the Table 3.

Table 3. Station parameter setting

Process	Distribution	Lower Bound	Upper Bound	Process Type
Sectioning	Uniform	03:00	05:00	Semi Automatic
Cooking	Uniform	09:00	10:00	Automatic
Cutting	Uniform	05:00	08:00	Semi Automatic
Jar Filling	Uniform	00:30	01:00	Semi Automatic
Can Filling	Uniform	00:20	00:40	Semi Automatic
Sterilization	Constant	00:30	-	Automatic
Closing	Constant	00:10	-	Automatic
Quality Control	Constant	00:10	-	Automatic
Labeling	Constant	00:10	-	Automatic

The workflow, as can be seen from the Figure 5, starts with the source object, which has been configured to generate 28 tunas every morning at 7:00 a.m. via a trigger. These tunas are then processed through the different phases of the system. The outputs of the process are managed via three separate drains: one for waste, one for the canned product (Can) and one for the glass product (Jar).

Since the goal is to evaluate the time performance, two global variables of type datetime were created: AVGFTJar (average production time for glass jars) and AVGFTCan (average production time for cans). To track the flow time during the transition between the phases, Python-based methods were developed shown in the equations (3) and (4). These methods record the start and end times of the operations, ensuring accurate monitoring of the process.



@.FTStart := eventController.abssimTime (3)

dateMachine:=@.Ftstart (4)

Figure 5. Tuna manufacturing plant illustration on PlantSimulation

3.6. Emotional state model integration

It was then integrated a model that simulates the operators' performance, adapting to emotional states characterized by valence and intensity. To track emotional states a single worker was selected instead of all five, in order to lighten the computational load.

The operator under analysis is worker number 2 (**W2**) who works in the cutting station and his task is to divide the tuna coming out of the cooking station into 16 premium pieces and 20 standard pieces intended for the subsequent filling phases (Figure 4).

For this operator, a global variable, **Emotional_State_W2** (of type string) has been created. The value of this variable changes based on the six emotions identified previously: joy, calm, frustration, relaxation, contemplation and grief.

The variable is set using the information contained in the Table 1 that, based on the values of valence and intensity of the emotions, quantifies their impact. At this point, an other global variable was created, **Impact_On_W2**, which represents the increase or decrease in the efficiency of the W2 caused by each emotion.

Using the special *init* method of PlantSimulation, a code was programmed that, based on the emotion type of the Emotional_State_W2 variable, assigns the respective numerical impact value to the Impact_On_W2 variable at the beginning of each simulation.

Subsequently, another code links this variable to the efficiency of the W2 **(5).** In practice, the percentage of impact is added to the standard efficiency of an operator, quantified as 100%, thus quantifying how the operator's efficiency varies as a function of his emotional state.

```
.Resources.Worker:2.Efficiency := 100 + (100*Impact_On_W2)
```
(5)

To evaluate the results, a study was conducted based on the **Emotional_State_W2** factor, which includes six levels corresponding to the 6 emotions. These levels were generated using the *Calc > Make Patterned Data > Text Values* function on the Minitab 17 statistical software. (Figure 6)

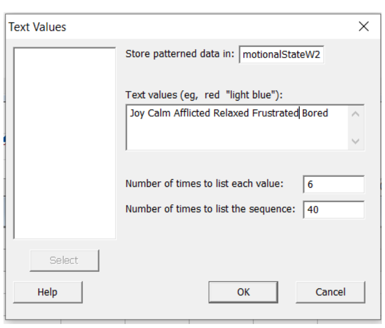


Figure 6. Setting parameters for generating experiments

In the study, simulations were carried out to examine how performance varies in a single day based on six different emotional states. Each day was simulated six times, each with a different emotion, thus forming a "block" of six lines representing a single day under these different emotional conditions. Considering a month composed of four working weeks (28 days in total), and taking into account that weekends are excluded, 20 working days remain. For this case have been simulated two months, or 40 working days. Therefore, for each simulation day (40 days in total), were carried out 6 simulations, each corresponding to a different emotional state. This led to 40 blocks of 6 lines each, where each block represents a specific day with performance recorded under each of the six emotions. In total, were carried out 240 simulation experiments (40 days × 6 emotions). This allowed to observe and analyze how different emotional states influence performance day by day, with a detailed comparison between different emotional conditions applied to the same daily context. Thus, the experimental design allowed to analyze the impact of emotions on performance through a systematic and repetitive structure, ensuring that each day was evaluated under all six emotional conditions, for a complete and comparative analysis.

These experiments were fed as input to the PlantSimulation model. At each simulation, the value of the emotional state variable varied, providing a series of results showing how the two performance measures changed in response to the emotional states.

4. Results and Discussion

After running 240 experiments using the PlantSimulation simulator, the results were recorded in an Excel spreadsheet. The Excel software automatically converted the performance units from hours to seconds, so the conclusions will be based on this unit.

Subsequently, the data were analyzed in relation to the two KPIs of the study. For the data analysis, the statistical software Minitab17 was used. In particular, a one way analysis of variance (ANOVA) was performed to examine the differences between the groups and to evaluate the influence of emotional states on production times.

For ANOVA results to be valid, it is important that some fundamental assumptions are satisfied:

1. The response variable is normally distributed.
2. The variance of the response variable must be constant.
3. The observations must be independent of each other.

To verify these assumptions, the residual graphs for the 2 performance measures were generated, see Figure 7 and Figure 8.

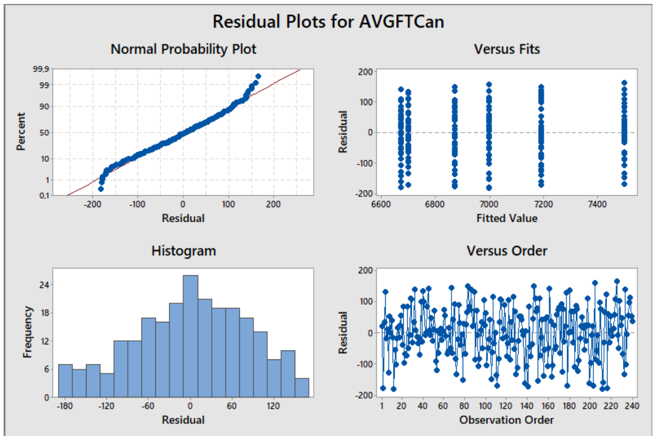


Figure 7. Residual Plots for AVGFTCan

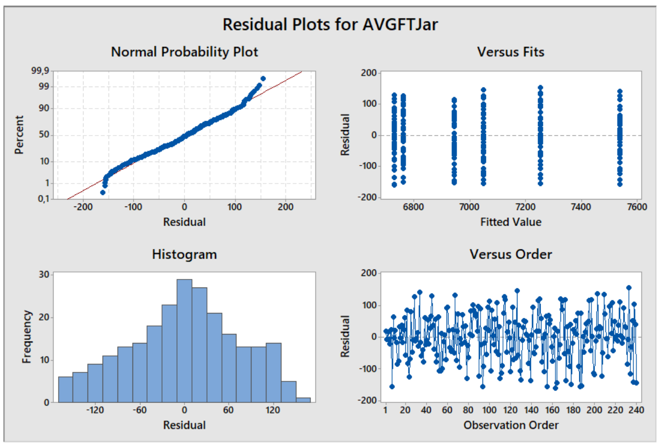


Figure 8. Residual Plots for AVGFTJar

The representations in Figure 7 and in Figure 8 confirm what was requested and this provides confidence in the interpretation of the results, knowing that our inferences are statistically valid and reliable. The next step was to analyze the main effects plots as you can see in Figure 9 and in Figure 10. These plots are very important as they help directly understand the impact of emotional states on our performance measures.

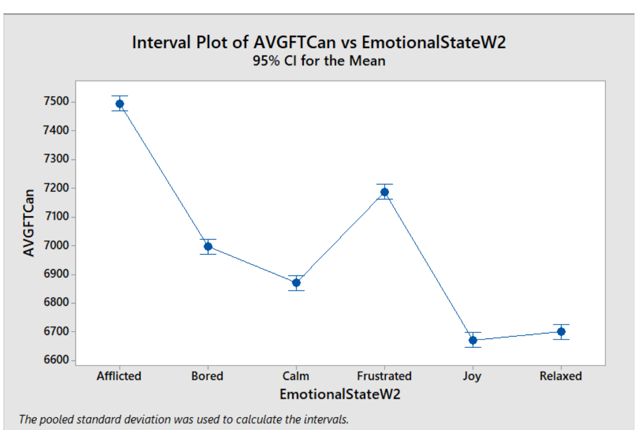


Figure 9. Main Effects Plot for AVGFTCan

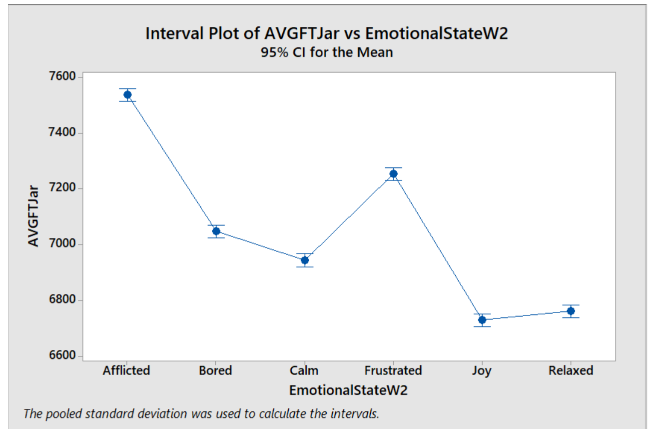


Figure 10. Main Effects Plot for AVGFTJar

As highlighted by the graphs in Figure 9 and in Figure 10, there is a clear influence of emotional states on production times. In particular, it can be observed that positive emotional states (such as joy and relaxation) correspond to better performance, with shorter production times. On the contrary, negative emotional states (such as affliction and frustration) are associated with worse performance, with longer production times. Neutral emotional states (such as calm and bored) are placed in an intermediate position, moderately influencing production times.

These findings are consistent with experiments conducted by Hersey, who demonstrated the relationship between emotional states and business performance as we can see in Figure 1. Although the results are graphically represented differently, please see Figure 11, the basic principle is the same.

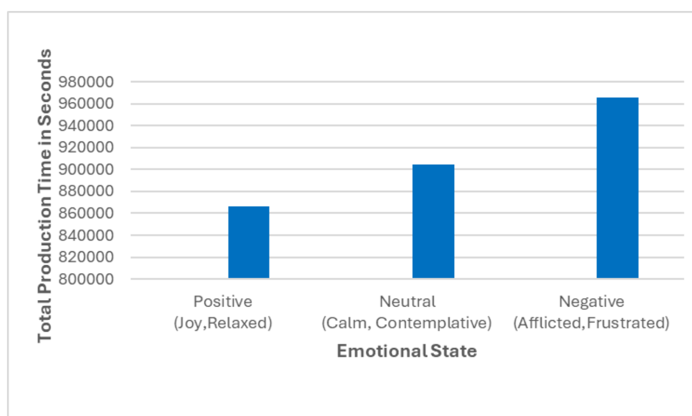


Figure 11. The results of this study

Despite the different graphical representation, both studies emphasize the same principle: emotional states have a significant impact on work performance. In our case, a shorter production time is indicative of better performance, while Hersey measures the percentage improvement in productivity. Both data sets converge on the fact that positive emotions improve performance, while negative emotions worsen it.

In addition the ANOVA analysis revealed a significant effect of emotional state on the variable AVGFTCan, as indicated by the low **p-value** (< 0.001)The R^2 value of **92.36%** suggests that the model is a good fit for the data, explaining a high proportion of the variability in AVGFTCan. The means, standard deviations, and 95% confidence intervals for each emotional state provide additional context for understanding the differences between groups. (Table 4)

Table 4. Descriptive Statistics for AVGFTCan

Emotional State	Mean	Standard Deviation	95 % Confidence Interval
Afflicted	7538,5	70,5	(7514.9, 7562.0)
Bored	7048,0	78,2	(7024.4, 7071.5)
Calm	6945,3	75,2	(6921.7, 6968.8)
Frustrated	7084,5	80,3	(7230.7, 7277.7)
Joy	6729,4	74,6	(6705.9, 6753.0)
Relaxed	6746,3	74,1	(6737.8, 6784.9)

In the same way, the ANOVA analysis revealed a significant effect of emotional state on the variable AVGFTJar, as indicated by the **p-value** being less than 0.001 The R^2 value of **93.46%** suggests that the model explains a large proportion of the variability in AVGFTJar, indicating an excellent fit. The means, standard deviations, and 95% confidence intervals for each emotional state provide additional context for understanding the differences between groups (Table 5).

Table 5. Descriptive Statistics for AVGFTJar

Emotional State	Mean	Standard Deviation	95 % Confidence Interval
Afflicted	7496,3	78,3	(7470.2, 7522.4)
Bored	6996,5	87,4	(6970.4, 7022.6)
Calm	6870,4	91,6	(6844.3, 6896.5)
Frustrated	7188,7	90,1	(7162.6, 7214.8)
Joy	6671,3	76,8	(6645.2, 6697.4)
Relaxed	6699,5	76,9	(6673.4, 6725.6)

Therefore, the results obtained offer valuable insights to optimize working conditions and improve production performance. Understanding how emotional states influence operator performance can help develop more effective management and training strategies.

5. Conclusions and Future Research

This study demonstrates the feasibility and utility of integrating emotional state data into manufacturing simulations. By better understanding how emotional states influence performance, we can develop more effective strategies to manage human factors in manufacturing environments. This innovative approach can transform the way companies monitor and optimize their employees' performance, improving not only production efficiency but also operator well-being.

The results obtained clearly show that emotional states have a significant impact on production times.

Future studies could further investigate if the impact changes as the work carried out changes and try to understand if there are other factors that affect in combination with the emotional state. For example, the nature and complexity of the task could influence how much emotional states impact performance. Simpler and more repetitive tasks could be less sensitive to emotional variations than complex and delicate tasks. Gender differences could influence the emotional reaction and the management of stress in work contexts. The social and cultural background of the operators could influence their emotional response and work performance. Other aspects such as work experience, age, individual skills, and even personality could play a role in determining the impact of emotional states on performance.

Therefore, further research and future analyses could explore how these factors interact with emotional states to influence firm performance.

In addition, one could also think of innovative approaches for data collection and analysis that allow real-time monitoring of workers' emotional states.

Understanding how workers feel and react to different work situations allows companies to intervene promptly to prevent more serious problems. For example, through the use of advanced technologies such as biometric sensors and behavior analysis software, it is possible to collect real-time data on the state of stress or fatigue of workers. This data, once analyzed, can provide valuable information to adopt corrective measures, such as scheduled breaks, job rotation or psychological support interventions. Furthermore, monitoring emotional states allows you to create a more empathetic and responsive work environment to the needs of employees. Detecting signs of burnout or dissatisfaction allows you to intervene with personalized support programs, improving morale and motivation. Companies that adopt these approaches could not only improve the well-being of their workers, but would also benefit from increased productivity and a more positive company culture.

This real-time data collection method would provide detailed and immediate insight into employees' emotional conditions, allowing for timely and targeted interventions to improve well-being and operational efficiency. Companies that adopt these approaches could transform human factors management, optimizing performance and creating a safer and more productive work environment.

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References

Baines, T., Mason, S., Siebers, P. O., & Ladbrook, J. (2004). Humans: the missing link in manufacturing simulation?. *Simulation Modelling Practice and Theory*, 12(7-8), 515-526.

Behrens, M., Gube, M., Chaabene, H., Prieske, O., Zenon, A., Broscheid, K.-C., Schega, L., Husmann, F., & Weippert, M. (2023). Fatigue and Human Performance: An Updated Framework. *Sports Medicine, 53*, 7-31.

Bellet, C. S., De Neve, J. E., & Ward, G. (2024). Does employee happiness have an impact on productivity?. *Management Science*, 70(3), 1656-1679.

Bubonya, M., Cobb-Clark, D. A., & Wooden, M. (2017). Mental health and productivity at work: Does what you do matter?. *Labour Economics*, 46, 150-165.

Cao, X., Zhang, H., Li, P., & Huang, X. (2022). The Influence of Mental Health on Job Satisfaction: Mediating Effect of Psychological Capital and Social Capital. *Frontiers in Public Health,* 10, Article 797274, 1-12.

Chen, B., Wang, L., Li, B., & Liu, W. (2022). Work stress, mental health, and employee performance. *Frontiers in Psychology*, 13, Article 1006580, 1-10.

DiMaria, C. H., Peroni, C., & Sarracino, F. (2020). Happiness matters: Productivity gains from subjective well-being. *Journal of Happiness Studies*, 21(1), 139-160.

Frey, B. S., (2018). Consequences of happiness. SpringerBriefs in Economics, in: *Economics of Happiness*, Chapter 0, pages 21-23, Springer.

Goleman, D. (2020). *Emotional Intelligence: Why it can matter more than IQ*. Bloomsbury Publishing.

Gubler, T., Larkin, I., & Pierce, L. (2018). Doing well by making well: The impact of corporate wellness programs on employee productivity. *Management Science*, 64(11), 4967-4987.

Hersey, R. B. (1932). *Workers' Emotions in Shop and Home: A Study of Individual Workers from the Psychological and Physiological Stand-point*. University of Pennsylvania Press.

Holden, L., Scuffham, P. A., Hilton, M. F., Ware, R. S., Vecchio, N., & Whiteford, H. A. (2011). Which health conditions impact on productivity in working Australians?. *Journal of Occupational and Environmental Medicine*, 53(3), 253-257.

Isen, A. M. (2001). An influence of positive affect on decision making in complex situations: Theoretical issues with practical implications. *Journal of Consumer Psychology*, 11(2), 75-85.

Jaber, M. Y., & Neumann, W. P. (2010). Modelling worker fatigue and recovery in dual-resource constrained systems. *Computers & Industrial Engineering*, 59(1), 75-84.

Jaber, M. Y., Givi, Z. S., & Neumann, W. P. (2013). Incorporating human fatigue and recovery into the learning–forgetting process. *Applied Mathematical Modelling*, 37(12-13), 7287-7299.

James, L. J., Funnell, M. P., James, R. M., & Mears, S. A. (2019). Does Hypohydration Really Impair Endurance Performance? Methodological Considerations for Interpreting Hydration Research. *Sports Medicine*, 49(Suppl 2), S103-S114.

Katebi, A., HajiZadeh, M. H., Bordbar, A., & Salehi, A. M. (2022). The Relationship Between "Job Satisfaction" and "Job Performance": A Meta-analysis. *Global Journal of Flexible Systems Management, 23*(1), 21-42.

LeBlanc, V. R. (2009). The effects of acute stress on performance: implications for health professions education. *Academic Medicine*, 84(10), S25-S33.

Neumann, P.W., & Dul, J. (2010). Human factors: spanning the gap between OM and HRM. *International Journal of Operations & Production Management*, 30(9), 923-950.

Ødegaard, F., & Roos, P. (2014). Measuring the contribution of workers' health and psychosocial work-environment on production efficiency. *Production and Operations Management*, 23(12), 2191-2208.

Otto, A., & Battaïa, O. (2017). Reducing physical ergonomic risks at assembly lines by line balancing and job rotation: A survey. *Computers & Industrial Engineering*, 111, 467-480.

Rasool, S. F., Maqbool, R., Samma, M., Zhao, Y., & Anjum, A. (2019). Positioning depression as a critical factor in creating a toxic workplace environment for diminishing worker productivity. *Sustainability*, 11(9), 2589.

Meska, M. H. G., Mano, L. Y., Silva, J. P., Pereira Junior, G. A., & Mazzo, A. (2020). Emotional recognition for simulated clinical environment using unpleasant odors: quasi-experimental study. *Revista Latino-*

Americana de Enfermagem, 28, 3248.

Smith, J. A., & Brown, R. K. (2022). Circadian Rhythms and Performance: A Review of Recent Advances. *Journal of Biological Rhythms*, 37(3), 223-235).

Tenney, E. R., Poole, J. M., & Diener, E. (2016). Does positivity enhance work performance?: Why, when, and what we don't know. *Research in Organizational Behavior*, 36, 27-46.

Wilson, J. R. (2000). Fundamentals of ergonomics in theory and practice. *Applied Ergonomics*, 31(6), 557-567.

Yang, J. S., & Hung, H. V. (2017). Happy workers value effort, sad workers value reward. *The International Journal of Human Resource Management*, 28(11), 1591-1624.