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Predicting the Impact of Cognitive Load and Psychological Well-Being Among Workers in Manufacturing Environments

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Abstract

The integration of Industry 4.0 technologies in manufacturing environments has significantly advanced production capabilities but has also introduced complex challenges for occupational health and safety. While previous studies have extensively explored the physical and technical impacts of these technologies, the psychological aspects, particularly cognitive load and psychological well-being, remain underexplored. This gap is significant because psychological factors play a critical role in influencing human performance and safety in complex, high-tech work environments. This study aims to address this gap by quantitatively investigating how cognitive load and psychological well-being affect safety incidents in smart manufacturing environments. Through a survey of 100 employees at a manufacturing company in Lagos, Nigeria, the relationship between cognitive load, psychological well-being, and reported safety incidents was analyzed. The findings reveal significant associations: higher cognitive load correlates with increased safety incidents, while better psychological well-being correlates with fewer incidents. This research underscores the critical need for interventions that manage cognitive load and enhance psychological well-being to improve safety outcomes in technologically advanced manufacturing settings.

Keywords: Cognitive load; psychological well-being; Occupational health and safety; Smart manufacturing; Industry 4.0.

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1. Introduction

The advent of Industry 4.0, also known as the Fourth Industrial Revolution, marks a significant transformation in the manufacturing sector, driven by the integration of cyber-physical systems, the Internet of Things (IoT), big data analytics, cloud computing, cognitive reasoning, and wireless sensors [1-3]. This technological integration has ushered in the era of smart manufacturing, where human operators engage with intelligent machines and robots, reshaping how products are produced and services are delivered, and promising enhanced efficiency, productivity, and economic growth [4-7]. The rapid adoption of Industry 4.0 technologies has driven innovation and opened new possibilities for sustainable growth and competitiveness in the manufacturing sector [8-10]. However, alongside these technological advancements, there is an increasing concern about their impact on the workforce, particularly in terms of occupational health and safety (OHS) [11-14].

Cognitive load represents the mental demand placed on an individual's cognitive system by a specific task [15]. Existing studies indicate that the digitization of manufacturing processes can lead to increased cognitive load and stress among workers [16]. For instance, Dombrowski and Wagner [17] found that the 4th Industrial Revolution requires significant human-machine collaboration and local process control, leading to new psychological demands. Thun et al. [18] discovered that in Norwegian manufacturing companies, managers had better access to and satisfaction with digital tools than operators. Zorzenon et al. [19] conducted a systematic literature review to examine the impact of Industry 4.0 technologies on OHS, finding both positive and negative effects. Positive impacts included safer work environments and healthier workers, while negative effects involved increased stress, fatigue, diseases, musculoskeletal problems, and psychosocial risks. Wollter Bergman et al. [20] explored the cognitive and mental workload experienced by assembly operators through interviews with 50 workers across three Swedish companies and found that cognitive performance and well-being were significantly influenced by various factors such as task design, timing, physical demands, and team dynamics. Arana-Landín et al. [21] found that Industry 4.0 technologies like AI, robotics, and IoT reduce physical and mechanical risks but introduce new psychosocial and mechanical risks. Timotius [22] also argued that workers in Industry 4.0 settings may experience heightened stress levels due to the complexity and demands of tasks when engaging with machines. Zacher and Rudolph [23] studied 1,661 German employees over 33 months and found that increased digitalization led to higher workload, and higher workload led to more digitalization, with this relationship growing stronger over time.

The continuous interaction with AI systems and robots requires constant attention and adaptability, which can be mentally exhausting [24-26]. Lagomarsino et al. [27] argued that the digitalization of the workplace has intensified work, created constant time pressures and required adaptation to rapid and frequent shifts in customer demands and requirements, whether for goods or services. Research has shown that workers in smart manufacturing environments often experience higher levels of anxiety and decreased job satisfaction due to the pressure to adapt to new technologies and workflows [28-31]. Moreover, the rapid pace of technological change in Industry 4.0 environments can lead to a sense of job insecurity and fear of obsolescence among workers. This fear can exacerbate stress levels and negatively impact mental health [32]. Furthermore, inadequate training and support for workers transitioning to these new roles can compound these psychological challenges, leading to a workforce that feels unprepared and overwhelmed by the demands of their evolving job functions [33]. Employees must independently and ergonomically monitor automated systems, make dispersed decisions, and engage in end-to-end engineering practices, which heightens OHS risks [34]. The need for skilled workers rises, as they must manage and intervene with advanced technologies, while older workers face unemployment risks due to the necessity of lifelong learning and the complexities of industrial automation [35]. Additionally, continuous digital surveillance of worker behavior, performance, and productivity can lead to privacy violations and psychological pressure. Advanced technologies may also weaken relationships between employees and management, creating an ambiguous work environment, increasing work-related stress, and potentially deteriorating long-term employee health [36].

Despite these challenges, some studies highlight the potential benefits of Industry 4.0 technologies in reducing physical strain and improving overall work conditions. For example, the use of collaborative robots (cobots) can help reduce the physical burden on workers, allowing them to focus on more cognitively demanding tasks [37]. These cobots can perform repetitive or strenuous tasks, thereby minimizing physical fatigue and injury risks. Additionally, smart wearable devices have been shown to monitor workers' health in real time, providing alerts and feedback that can prevent overexertion and enhance workplace safety [38]. However, while these technologies can mitigate physical strain, they also have potential psychological impacts of increased cognitive demands and constant system interactions [39].

While significant research has been conducted on the technical and operational benefits of Industry 4.0, the psychological impacts on workers remain underexplored. There is a notable gap in understanding how continuous interaction with intelligent systems affects cognitive load and stress levels in smart manufacturing environments. Studies have often focused on the physical and technical aspects of these advancements, overlooking the critical human factors that influence worker well-being and productivity [40]. Previous studies have predominantly employed qualitative methods, systematic reviews, and theoretical frameworks to explore these issues. For instance, Zorzenon et al. [19] and Timotius [22] used systematic literature reviews, while Kortmann et al. [16], Dombrowski and Wagner [17] and Wollter Bergman et al. [20] relied on observational studies and interviews. These methods provided valuable insights but lacked quantitative data to establish concrete relationships and measure the extent of psychological impacts.

This study aims to address these gaps by quantitatively investigating the impact of cognitive load and psychological well-being on occupational health and safety in smart manufacturing settings. By analyzing data collected from a representative sample of workers, this research seeks to identify the psychological risks associated with highly digitized and automated production environments. The quantitative approach will provide empirical evidence and measurable data to understand better and quantify the relationships between cognitive load, psychological well-being, and safety incidents.

2. Materials and Method

This study employed a quantitative approach to investigate the impact of cognitive load and psychological well-being on occupational health and safety in the smart manufacturing environment. The analysis was based on a dataset obtained from a manufacturing company in Lagos, Nigeria. The dataset included various employee characteristics and their self-reported scores on cognitive load and psychological well-being, as well as the number of reported safety incidents.

2.1. Questionnaire Development and Content

The questionnaire was developed to assess the impact of cognitive load and psychological well-being on safety outcomes in a smart manufacturing environment. The development process involved a thorough literature review to identify key variables influencing occupational health and safety in the context of Industry 4.0. Expert consultations with occupational psychologists and industry practitioners were conducted to ensure the relevance and comprehensiveness of the questionnaire. A pilot test with a smaller subset of the target population was performed to refine the questions based on feedback, ensuring clarity and reliability in the measurements.

The final questionnaire comprised several sections:

- Demographic Information: Collected basic demographic data to understand the background of the participants and control for variables such as age, gender, and job role.
- Cognitive Load: Utilized a modified version of the NASA-TLX scale to measure cognitive load, focusing on factors like mental demand, physical demand, and task complexity.
- Psychological Well-Being: Adopted scales such as the Short Form Health Survey (SF-12) to measure aspects of mental health and overall well-being.
- Technology Usage: Questions designed to gauge the frequency and proficiency of using advanced manufacturing technologies and smart devices.
- Incident Reporting: Included items on the frequency and type of safety incidents reported, aiming to correlate these with cognitive load and well-being scores.

2.2. Sample Size Determination

The sample size was determined using a combination of statistical power analysis and practical constraints. A target power of 0.80 and an alpha level of 0.05 were set for detecting medium-sized effects (Cohen's d = 0.5) in the regression analysis. This calculation, based on guidelines from Cohen [41], suggested a minimum sample size of approximately 85 participants to ensure sufficient power. Considering potential non-responses and incomplete data, the sample size was increased to 120 to enhance the robustness and reliability of the study.

2.3. Questionnaire Administration

The questionnaire was administered electronically over a secure platform to ensure confidentiality and ease of data aggregation. Participants were informed about the study's purpose and assured of their responses' anonymity. Efforts to maximize the response rate included reminders and the provision of small incentives for completed responses.

2.4. Pre-testing and Validation

Before full deployment, the questionnaire underwent a pre-testing phase where feedback was solicited to adjust and improve the clarity and flow of questions. This phase helped identify ambiguities and adjust the technical language to fit the comprehension levels of all participants, ensuring the reliability and validity of the instrument in measuring the intended constructs.

2.5. Ethical Considerations

Ethical approval was obtained from the institutional review board, with all participants providing informed consent before participating. Special attention was given to ensuring data privacy and ethical handling of sensitive information.

2.6. Data Collection

Data were collected through self-reported surveys administered to employees. The surveys included questions designed to measure cognitive load and psychological well-being using standardized scales. The cognitive load scale comprised items related to task complexity, time pressure, and mental effort, while the psychological well-being scale covered aspects such as stress, job satisfaction, and mental health. Additionally, employees provided information on their demographic details, job roles, work hours, and the number of smart devices they used. The number of reported safety incidents and training hours were obtained from company records. A total of 120 questionnaires were distributed to ensure a broad and representative sample. Of these, 100 were returned, yielding a response rate of 83.3%, which is considered acceptable in survey research [42]. The dataset included the following variables: Serial Number (S/N), Age (A), Gender (G), Job Role (JR), Work Hours Per Week (WPHW), Years with the Company (YWC),

Table 1. Provides a Sample of Data Values.

S/N	*A*	*G*	*JR*	*WHPW*	*YWC*	*SDU*	*CLS*	*PWBS*	*RI*	*TH*
1	28	M	Operator	40	3	5	7	8	0	10
2	35	F	Engineer	45	5	8	6	7	1	12
3	30	M	Technician	38	2	6	5	6	2	8
4	42	F	Manager	50	10	10	8	9	0	15
5	25	M	Operator	42	1	4	7	5	3	7
...	…	…	…	…	…	…	…	…	…	…
100	31	M	Engineer	44	4	9	6	7	1	10

Number of Smart Devices Used (SDU), Cognitive Load Score (CLS), Psychological Well-Being Score (PWBS), number of Reported Safety Incidents (RI), and Training Hours (TH). See Table 1 for sample data values.

2.7. Data Preparation

The dataset was imported into Python for analysis. Data cleaning involved handling any missing values by either inputting or excluding incomplete records to ensure the integrity of the dataset. Variables were checked for correct formatting and consistency. Descriptive statistics were computed to provide an overview of the sample characteristics, including measures of central tendency (mean, median) and dispersion (standard deviation, range).

2.8. Explanatory Data Analysis

Exploratory Data Analysis (EDA) was conducted to visualize the distribution of cognitive load scores, psychological well-being scores, and reported incidents. Various visualization techniques, such as histograms, box plots, and scatter plots, were employed to examine the distributions and relationships between the variables. Correlation matrices were generated to explore the relationships between cognitive load, psychological well-being, and reported incidents, providing initial insights into potential associations.

2.9. Regression Analysis

A multiple regression analysis was conducted to investigate the relationship between cognitive load, psychological well-being, and reported safety incidents. The dependent variable is the number of reported safety incidents, and the independent variables are cognitive load score and psychological well-being score. The regression model used is specified as:

$$\boldsymbol{RI} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1} \times \mathbf{CLS} + \boldsymbol{\beta_2} \times \boldsymbol{PWBS} + \boldsymbol{\epsilon} \qquad (\mathbf{1})$$

where β_0 is the intercept, β_1 is the coefficient for cognitive load score, β_2 is the coefficient for psychological well-being score, and ϵ is the error term. The regression model was fitted using the Ordinary Least Squares (OLS) method, see Figure 1. The analysis was conducted using the Statsmodels library in Python. The goodness-of-fit of the model was evaluated using the R-squared and adjusted R-squared values. The significance of the regression coefficients was assessed using t-tests, with a significance level set at $p < 0.05$. The F-statistic was used to test the overall significance of the model. Model assumptions, including linearity, homoscedasticity, independence, and normality of residuals, were evaluated to ensure the validity of the regression model. Residual plots were examined to check for any deviations from these assumptions.

3. Results

The fitted regression model was used to predict the number of reported incidents for each employee in the dataset. Predicted values were compared with the actual values to assess the model's predictive accuracy. Cross-validation techniques, such as k-fold cross-validation, were performed to ensure the robustness of the model.

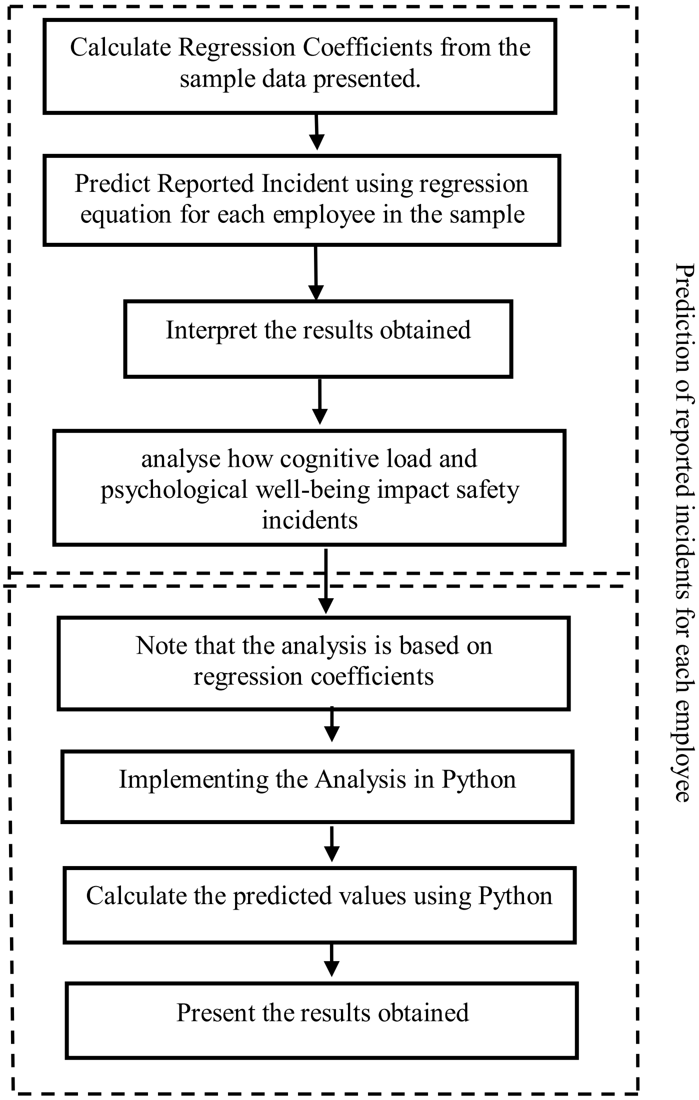

Fig. 1. Flowchart showing step by step method to approach regression model

The summary of the model and predictions is presented in Table 2 and 3. Cognitive Load Impact: The coefficient for cognitive load score (β_1) is positive but not statistically significant (P>|t| = 0.657). This indicates that while there is a positive relationship between cognitive load and reported incidents, it is not strong enough to be considered significant based on this small sample.

Psychological Well-Being Impact: The coefficient for psychological well-being score (β_2) is negative and nearly significant (P>|t| = 0.089). This suggests a potential inverse relationship between psychological well-being and reported incidents, indicating that higher psychological well-being might lead to fewer reported incidents.

Table 2. Model parameters

Dependent Variables	Reported Incidents	R-Squared	0.914
Model	OLS	Adj. R-Squared	0.857
Method	Least Squares	F-statistic	16.20
Date	Resumption date	Prob (F-Statistic)	0,0123
Time	00:00:00	Log-Likelihood	-3.6208
No. Observations	6	AIC	13.24
DF Residuals	3	BIC	12.63
DF Model	2		

Table 3. Model predictions

	COEF	STD ERR	T	P>|T|	[0.025	0.975]
Const.	11.2604	3.287	3.428	0.042	0.731	21.790
Cognitive Load Score	0.0360	0.073	0.491	0.657	-0.172	0.244
Psychological Well-Being Score		-0.5365	0.215	-2.497	0.089	-1.228

4. Discussion

The production environment has changed dramatically because of the quick adoption of Industry 4.0 technology, creating new difficulties for occupational health and safety. This study looked at the relationship between psychological health and cognitive load and occupational safety and health in smart manufacturing settings quantitatively. The dataset contained reports of safety occurrences, job roles, work hours, smart device usage, demographic information, and scores for psychological well-being and cognitive load. The sample characteristics were compiled and the correlations between the variables were visualized using descriptive statistics and exploratory data analysis. The associations between reported safety occurrences, psychological well-being, and cognitive stress were investigated using multiple regression analysis. Even though the relationship between cognitive load and incidents was not statistically significant in this small sample used in this paper, it is important to monitor cognitive load regularly. High cognitive load can lead to increased stress and mistakes, so strategies such as workload management, regular breaks, and task rotation should be implemented.

The observed negative relationship between psychological well-being and reported incidents, though not statistically significant, suggests that improving employees' psychological well-being may help reduce the number of safety incidents. Companies should invest in mental health support, provide a positive work environment, and offer resources such as counseling and stress management programs. Regular training focused on safety and well-being may improve employees' ability to manage cognitive load and stress, potentially reducing the incidence of workplace accidents. It is essential for organizations to provide comprehensive training on the effective use of smart devices and other technologies to avoid cognitive overload. Our analysis suggests that developing personalized interventions for employees who report higher levels of cognitive load and lower psychological well-being could be beneficial. Implementing such targeted strategies could proactively mitigate risks and enhance occupational health and safety outcomes.

5. Conclusion

In this study associations between reported safety occurrences, psychological well-being, and cognitive stress were investigated using multiple regression analysis using a dataset from a manufacturing company in Lagos, Nigeria. The dataset focused on occupational health and safety, specifically targeting psychological well-being and cognitive load among workers in the organization. The results showed that while improved psychological well-being was linked to a drop in occurrences, increased cognitive load was linked to an increase in safety events that were recorded. Through cross-validation, the predictive accuracy of the model was verified. To control cognitive load and improve psychological well-being in smart industrial settings, this study emphasizes the necessity of focused interventions.

The study on the impact of cognitive load and psychological well-being on safety incidents in smart manufacturing environments can be useful in several areas generically: occupational health and safety management, workplace design and ergonomics, risk management, healthcare and employee assistance programs, educational institutions and research etc. By applying the findings of this study in these areas, organizations can create safer, healthier, and more productive work environments, ultimately leading to improved employee well-being and operational efficiency.

Ethical considerations: This study adhered to ethical guidelines for research involving human participants. Informed consent was obtained from all employees participating in the survey, and data confidentiality and anonymity were maintained throughout the study. The study was approved by the relevant institutional review board.

Competing interests: The authors declare that they have no competing interests, financial or non-financial, that could be perceived as influencing the content or conclusions of this paper.

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