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Predicting Fatigue in High-Intensity Turnaround Operations Using a Machine Learning Approach

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ABSTRACT

Workplace fatigue is a critical issue in high-risk industries such as construction, manufacturing, and mining, as it can reduce workers' readiness (fit to work), endanger their safety, and decrease productivity. This study developed a machine-learning-based model to predict work readiness by utilizing physiological data (Heart Rate (HR), Blood Pressure, VO_2 Max, Oxygen Saturation), subjective data (Multidimensional Fatigue Inventory (MFI-20)), and cognitive data (Psychomotor Vigilance Test (PVT-3)). The data was collected from participants performing intensive activities during the Turnaround (TA) period. The analysis results showed a significant increase in fatigue after 10 hours of work ($p = 0.000$; $R^2 = 91.65\%$), indicating a strong influence of work duration on fatigue. The Random Forest (RF) model demonstrated the best performance in predicting MFI scores ($R^2 = 0.9989$; Root Mean Square Error (RMSE) = 0.064616) and showed adequate accuracy for HR ($R^2 = 0.7996$; RMSE = 127.10849). Among the various physiological parameters analyzed, HR and the MFI-20 were the most representative in predicting work-related fatigue. Therefore, for field implementation, measurements can be focused on these two indicators to obtain efficient results without reducing the prediction accuracy. These findings demonstrate that machine learning is effective for predicting fatigue and supports strategic decision-making in occupational safety risk management.

1. INTRODUCTION

Fatigue is a multidimensional condition that reduces productivity, work performance, and quality of life due to accumulated physical, mental, and cognitive demands under prolonged high workloads [1, 2]. It is associated with reduced alertness, impaired response capability, and increased operational errors, particularly in high-precision tasks [3]. Fatigue also affects cognitive functions such as attention, information processing, and decision-making [4, 5]. High-intensity work characteristics, including repetitive tasks, extended working hours, and time pressure, accelerate fatigue development [6, 7]. In addition, physiological factors such as Heart Rate (HR) variability and recovery quality influence individual fatigue responses [8].

Turnaround (TA) operations in process industries involve highly demanding working conditions characterized by extended working hours, complete plant shutdowns, and accelerated task execution under strict time constraints [9]. These conditions impose substantial physical and cognitive workloads [9]. Due to the safety-critical and pre-scheduled nature of TA activities, this study focused on workers directly involved in technical tasks [10]. At the study site, TA operations were performed exclusively by male workers, resulting in a homogeneous sample of 15 participants. This limitation should be considered when interpreting the generalizability of the findings [11]. Expert assessments further indicate that fatigue during TA operations manifests as mental strain caused by sustained concentration and rapid decision-making in high-risk conditions [12, 13].

Fatigue levels are influenced by individual characteristics such as age, physical capacity, physiological condition, and prior workload exposure [14]. Variations in physiological indicators, including HR, aerobic capacity, and oxygenation status, further affect susceptibility to fatigue [14]. Fatigue commonly manifests as reduced muscle strength, delayed responses, sleepiness, and unstable physical performance [6, 15]. When fatigue is inadequately managed, operational errors and accident risk increase significantly in high-load and time-pressured environments [16]. This relationship has been widely reported in safety-critical sectors such as construction, aviation, and machine-based operations [17, 18].

Fatigue negatively affects physical output and cognitive efficiency, leading to slower reaction times and reduced task accuracy [19]. Because fatigue is inherently subjective, its assessment requires an integrated approach combining subjective, physiological, and behavioral indicators [20]. Subjective methods are widely used but remain vulnerable to perceptual bias [19]. Objective approaches, therefore, rely on real-time physiological monitoring, including HR measurement using wearable devices [21]. Additional indicators such as blood pressure, oxygen saturation, and VO_2 max are used to characterize baseline physiological conditions contributing to fatigue development [22, 23]. Cognitive performance assessments can further support fatigue detection, although sensitivity may decline with repeated task exposure [7]. Fatigue levels are also shaped by task characteristics, exposure duration, and psychological conditions [19].

Work-related fatigue is a major contributor to accident risk in high-intensity industrial environments [24, 25]. TA operations fall into this category due to critical maintenance activities, regulatory inspections, and strict completion timelines that elevate workload and hazard exposure [26]. Prolonged engagement in maintenance and inspection tasks during TA execution can further reduce cognitive stability and physiological resilience [27, 28]. Empirical evidence confirms that these conditions increase both physical and mental fatigue, thereby impairing decision-making accuracy and workplace safety [29]. Consequently, objective and data-driven fatigue monitoring systems are essential to support effective risk management during TA operations [27, 30].

The absence of universal fatigue measurement tools has encouraged the adoption of adaptive, technology-based approaches [30]. Machine learning enables predictive fatigue estimation by processing physiological and behavioral signals collected under real working conditions [31]. These methods integrate multimodal data such as HR, Heart Rate Variability (HRV), and attention-related indicators to improve detection accuracy [32]. In TA operations, machine learning is expected to support workforce assignment decisions and reduce accident risks.

In this study, machine learning is applied to support decision-making related to worker task assignment in high-risk TA operations. By adaptively analyzing multidimensional data, the proposed model improves fatigue pattern identification and enhances workplace safety [33]. This approach is supported by previous studies on physiological fatigue detection, mental fatigue prediction, adaptive monitoring systems, and AI-based analytical methods [13, 34]. Although focused on TA operations, the proposed framework is also applicable to other high-intensity industrial sectors with similar physical and cognitive demands.

2. METHODOLOGY

2.1 Research design

This study employed a descriptive observational design, in which the researchers did not administer any treatment or intervention to the participants but instead observed and recorded conditions that occurred naturally in the workplace [26]. The main focus of this study was to understand how fatigue levels among industrial workers change over the course of a 10-hour work period. To obtain a more accurate representation, this study used a repeated-measures approach, collecting data from the same individuals at multiple time points within a single workday. This approach was chosen because worker fatigue is dynamic and may vary according to the duration of work and the activities performed. Measurements were taken at three key time points: before work (baseline) to determine initial conditions, before the break (mid-shift) to assess changes after several hours of work, and after work (post-shift) to evaluate fatigue levels following completion of the full working hours [35].

2.2 Population and sampling

In this study, 15 male workers participating in high-intensity TA operations at a fertilizer industry facility were included. TA operations involve periods of intensive maintenance requiring sustained physical effort and high concentration during major plant shutdowns. Participant selection was preceded by health screening to ensure fitness for demanding tasks and was further constrained by operational availability, such that only workers scheduled for TA duties and willing to participate were included [36].

Purposive sampling was employed, targeting workers exposed to high physical and mental demands and extended working durations of approximately 10–14 hours per day [37]. The restriction to male participants reflected operational role assignments at the study site rather than sampling preference and should be considered when interpreting generalizability.

2.3 Research instrument

In this study, research instruments were used to obtain primary data that were organized as variables within the machine learning model [38, 39]. Dependent variables consisted of fatigue scores derived from the Multidimensional Fatigue Inventory (MFI-20) and HR, representing subjective and physiological fatigue responses. The MFI-20 assesses five fatigue dimensions: general fatigue, physical fatigue, reduced activity, decreased motivation, and mental fatigue [40].

Independent variables were obtained using multiple instruments. HR was monitored in real time using a Polar H10 sensor. Cognitive alertness was assessed using the Psychomotor Vigilance Test (PVT-3) through reaction time measurement. Additional physiological indicators, including blood pressure, oxygen saturation (SpO_2), and VO_2 Max, were recorded to establish baseline physical conditions and aerobic capacity [11, 35]. Supplementary information on sleep duration, calories burned, age, and HR Max was also collected.

All measurements were compiled into a dataset comprising HR values across multiple intervals (HR_0–HR_10), PVT reaction time, blood pressure, oxygen saturation, VO_2 Max, sleep duration, calories burned, age, HR Max, and MFI-20 scores recorded at pre-work, mid-shift, and post-work phases.

2.4 Data collection procedures

In this study, data collection was conducted in three main stages within a full work cycle during TA operations. The first stage was performed before work (baseline), during which participants completed the MFI-20 to assess their initial subjective fatigue level [41]. At this stage, physiological and cognitive measurements were also conducted, including HR, alertness assessment using the PVT-3, blood pressure, and oxygen saturation [42-44]. These measurements were intended to describe the workers' baseline physiological and cognitive conditions prior to exposure to prolonged work demands.

The PVT-3 assessment was administered under controlled and quiet conditions, away from operational noise and active work areas, to minimize external distractions and ensure consistency in cognitive performance measurement [26, 45]. In this study, PVT-3 was used as a supplementary instrument to support fit-to-work evaluation rather than as a primary input variable for machine learning modeling.

The second stage of data collection was conducted before the scheduled break (mid-shift). At this stage, participants completed the MFI-20 questionnaire again to monitor fatigue progression after several hours of continuous work without a full rest period. This mid-shift assessment was designed to capture intermediate fatigue development during TA operations.

The third stage was carried out after work, following approximately 10 hours of duty. During this post-shift stage, participants underwent a final series of measurements, including the MFI-20, HR, and PVT-3, to evaluate accumulated fatigue after completing the full duration of intensive work. The PVT-3 assessment at this stage focused on post-duty cognitive alertness. Because PVT-3 data were collected only at the end of the work shift and were not recorded in a time-series format, these data were not included as input variables in the machine learning dataset. In contrast, HR measurements were conducted every hour for a total duration of 10 hours to continuously monitor changes in physiological workload throughout the shift.

Due to the hazardous nature of TA operations and restricted access to active work zones, HR data were collected as spot measurements at the 60th minute of each working hour. The researcher entered the TA area only at these predefined time points, making continuous monitoring infeasible while ensuring worker safety and operational integrity. All data collection activities were conducted in compliance with company safety protocols to avoid interference with ongoing TA operations. Owing to time constraints and field conditions, the frequency of other measurements was limited, and data collection focused on the three primary time points considered most representative for capturing changes in physical and mental fatigue among industrial workers [46, 47].

2.5 Data analysis

In this study, data preparation began with preprocessing the reaction time variable (m_rt_end) obtained from the PVT assessment. The reaction time data were initially stored in text format and were converted into numerical float format using the pd.to_numeric() function to enable mathematical analysis and ensure compatibility with machine learning algorithms. Data type validation and initial exploration confirmed that no outliers were present, eliminating the need for additional data cleaning [48]. This procedure followed standard practices for processing reaction time–based cognitive performance data commonly applied in fatigue detection studies using sensors and machine learning approaches [7].

A missing data inspection was conducted prior to modeling, and no missing values were identified across physiological, psychological, or cognitive variables. Consequently, no imputation procedures were required.

The next stage involved encoding categorical variables, including PVT diagnosis and MFI-20 fatigue classifications. Categories such as “Good,” “Moderate,” and “Poor,” as well as “Low,” “Medium,” and “High,” were transformed into ordinal numerical values of 0, 1, and 2, respectively. This encoding approach enabled all variables to be processed numerically and is widely used in multimodal fatigue research to integrate subjective and objective indicators within a single predictive framework [41, 49].

The final dataset used for modeling consisted of a combination of physiological, psychological, and cognitive data. Physiological variables included maximum HR (HR Max), HR per minute, blood pressure, oxygen saturation, and calorie expenditure. Psychological variables were derived from MFI-20 scores collected at the pre-work, mid-shift, and post-work phases, while cognitive variables were obtained from PVT reaction time and PVT diagnosis. Blood pressure and oxygen saturation were included as machine learning inputs because they are mandatory physiological indicators routinely measured by the company and are physiologically relevant to fatigue-related cardiovascular responses.

All categorical variables were encoded, and numerical variables exhibited stable ranges; therefore, additional normalization was not applied. This multimodal dataset structure aligns with fatigue modeling approaches based on real-time physiological data commonly implemented in fatigue detection systems for industrial workers and operators [10, 20, 50].

To ensure clarity and reproducibility, the input features for each prediction task were explicitly defined based on the fatigue indicator being modeled. Two prediction objectives were considered: (1) prediction of subjective fatigue using MFI-20 scores and (2) prediction of physiological fatigue using HR. Different feature sets were intentionally employed for each task to reflect the distinct psychological, physiological, and temporal mechanisms underlying subjective and objective fatigue responses. The complete comparison of input features used in each prediction model is presented in Figure 1.

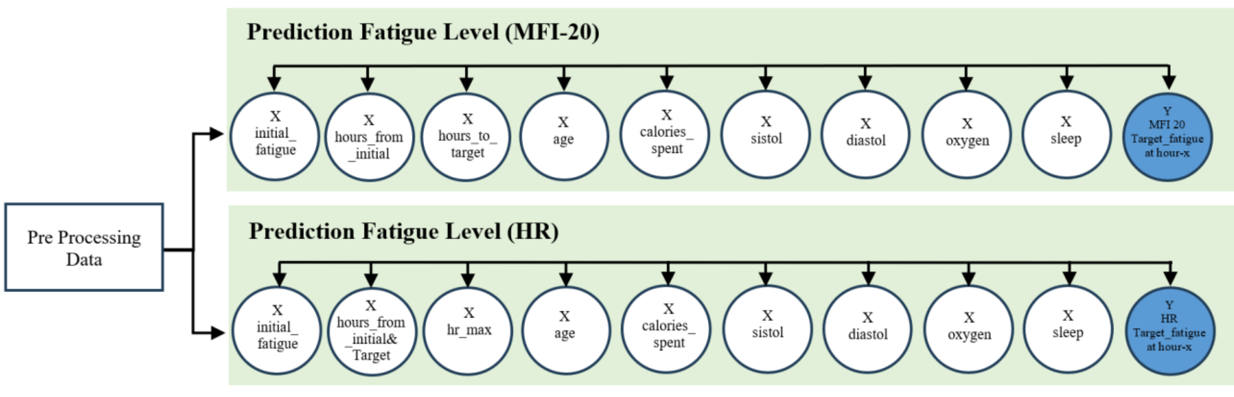

Figure 1. Comparison of the input feature prediction model

Outlier assessment was conducted using exploratory data inspection. No data points were removed, as increasing HR values approaching individual HR Max during prolonged work were interpreted as physiologically meaningful indicators of fatigue accumulation rather than statistical anomalies.

After data preparation, model development was performed using three machine learning algorithms: Linear Regression (LR), Support Vector Regression (SVR), and Random Forest (RF). LR was applied as a baseline model due to its ability to represent linear relationships and its common use as an initial reference in fatigue prediction studies [51, 52]. SVR was selected for its capability to capture non-linear patterns in physiological and cognitive data and its effectiveness in controlling error margins when modeling multidimensional fatigue dynamics [53]. RF was employed for its robustness to noise, ability to model complex feature interactions, and strong predictive performance in fatigue modeling based on physiological and work-performance indicators [53, 54].

Model performance was evaluated using the Root Mean Square Error (RMSE) and the coefficient of determination (R^2) [27, 52-54]. PVT results were analyzed qualitatively to support fit-to-work assessment and ergonomic recommendations. A leave-one-subject-out cross-validation strategy was implemented, in which one participant was excluded as the test set in each fold while the remaining participants were used for training, resulting in a total of 15 validation folds. The combination of these analytical steps provides a robust framework for identifying the most accurate predictive model for monitoring fatigue during intensive work activities [55, 56].

3. FINDINGS AND DISCUSSION

3.1 Respondent demographics

In this study, the respondents consisted of 15 male workers who participated in fatigue-related measurements during TA operations. The inclusion of male participants was not based on gender preference but reflected workforce composition and task allocation practices commonly applied in industrial TA settings [42, 57]. Personnel assigned to TA operations are typically selected based on their ability to perform physically demanding maintenance tasks over extended working hours, requiring high levels of physical endurance and psychological resilience [28, 58].

From an operational standpoint, male workers are more frequently assigned to tasks involving heavy component handling, intensive tool usage, and work in constrained or hazardous environments due to generally higher muscular strength and tolerance to sustained physiological load [59, 60]. This assignment pattern is consistent with findings from high-intensity occupations, where tasks with high metabolic and biomechanical demands require stable cardiorespiratory performance and physical robustness [61]. Field observations during TA operations confirmed that female personnel were not directly involved in physically intensive task execution, reflecting the biomechanical requirements of the work rather than organizational exclusion.

Similar workforce distributions have been reported in other physically demanding professions, such as firefighting and transportation-related operations, where high mechanical load, environmental pressure, and limited recovery capacity shape task allocation. Differences in physiological responses to strenuous work demands across industrial and transportation sectors further support this practice [62]. Consequently, the absence of female workers in the physical execution stages of TA operations is primarily driven by task-related physiological requirements and risk considerations.

Overall, all respondents were engaged in critical maintenance and repair activities essential for ensuring operational continuity during the TA period, which represents a key phase for restoring industrial production facilities [27, 58].

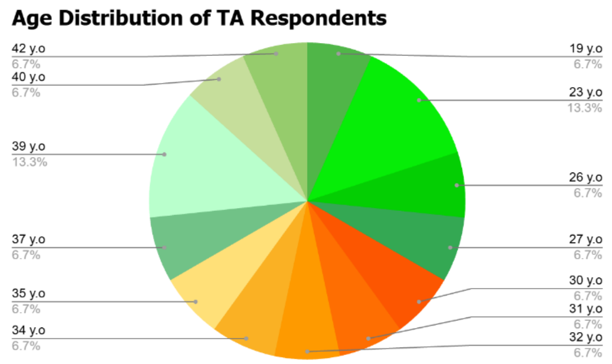

Figure 2. Age distribution of Turnaround (TA) respondents

The age distribution of the respondents ranged evenly from 19 to 42 years in Figure 2, with each age group representing approximately 6.7% of the sample. This variation reflects diverse team compositions, from younger individuals with high potential to more mature and experienced workers. Such diversity is important because HR max is strongly influenced by age, following the general formula HR max = 220 – age [15]. This means that the older a person is, the lower their HR Max. Therefore, the interpretation of HR data must account for age in order to produce a more accurate and physiologically relevant analysis of workload and fatigue [44, 53].

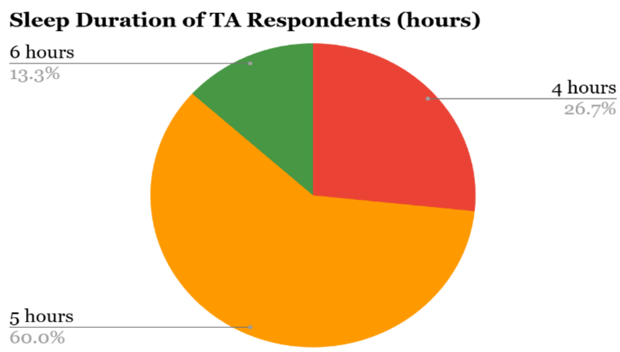

Figure 3. Sleep duration of Turnaround (TA) respondents

The majority of respondents slept in Figure 3 for 5 hours (60%), indicating that most workers obtained a moderate amount of rest, which may still be insufficient for optimal recovery from the intensive physical demands of the TA activities. Meanwhile, 26.7% of respondents slept for 4 hours, a duration considered low and potentially increasing the risk of fatigue or reduced concentration. Only 13.3% of participants slept for 6 hours, representing the group with relatively better sleep duration.

3.2 Objective measurement results

3.2.1 Calories burned

It can be observed in Figure 4 that the participants of Person_13 and Person_15 recorded the highest calories spent, at 4880 kcal and 4342 kcal, respectively, indicating that they experienced the heaviest workloads. Meanwhile, the participants from Person_10 to Person_12 showed the most extreme variation, ranging from 790 kcal to 3206 kcal, suggesting differences in work intensity despite being under the same subcontractor.

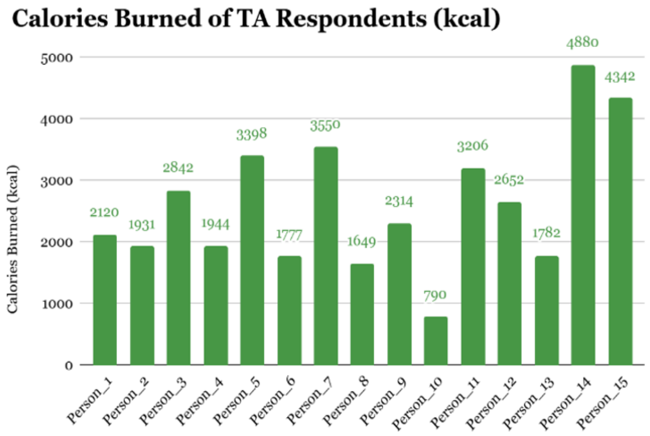

Figure 4. Calories burned by Turnaround (TA) respondents

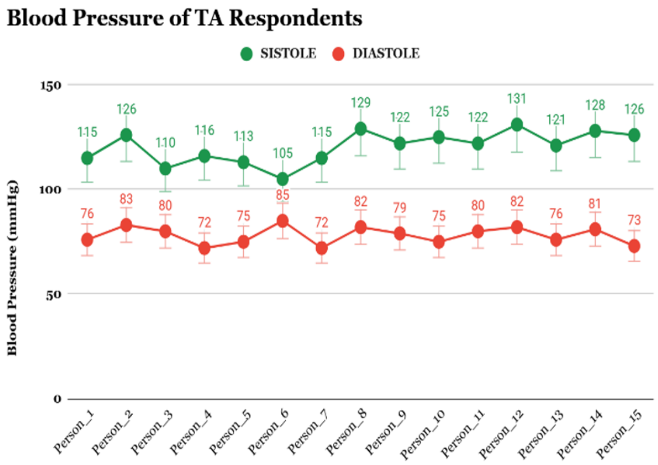

Figure 5. Blood pressure of Turnaround (TA) respondents

3.2.2 Respondent's blood pressure

Blood pressure measurements were taken before the participants began their work activities, meaning that the results reflected their initial physiological condition at rest [63, 64]. Overall, in Figure 5, the systolic blood pressure ranged from 105–131 mmHg, and the diastolic pressure ranged from 72–85 mmHg, indicating that most respondents were within the normal to mildly prehypertensive category. The participants in groups of Person_1 to Person_6 and Person_7 to Person_12 generally showed stable and relatively uniform blood pressure levels, whereas those of Person_13 to Person_15 recorded the highest values, particularly in systolic pressure, which may indicate higher physical activity levels or work-related stress prior to TA execution. No extreme values were found below 90/60 or above 140/90, suggesting that the overall physiological condition of the team was within safe limits and sufficiently optimal to undertake intensive activities [65].

3.2.3 Oxygen levels of participants

The oxygen saturation levels in Figure 6 ranged from 95% to 99%, all of which fall within the normal and healthy range for physical activity. The distribution graph shows that most participants had high and stable oxygen levels, with relatively small error bars, indicating minimal individual variation [23].

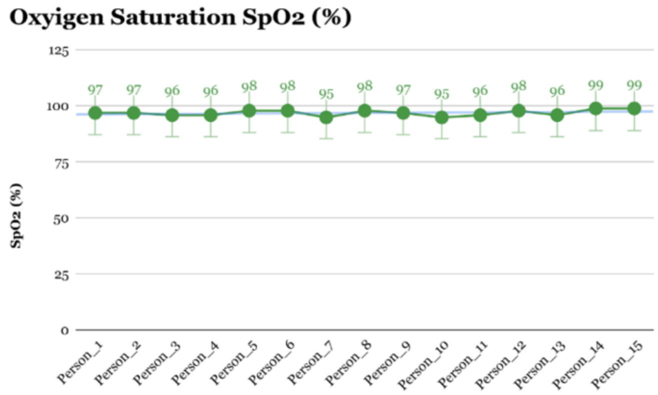

Figure 6. Oxygen saturation of Turnaround (TA) respondents

3.2.4 Respondent's Heart Rate

Fatigue assessment in this study was conducted objectively using the Polar H10 device with a continuous monitoring duration of 10 working hours. The monitoring took place from 07:30 to 18:00 and was divided into 11 measurement intervals recorded as HR 0 to HR 10. HR 0 served as the baseline before the work began, whereas HR 1 to HR 3 represented the early work phase when the physiological responses started to increase due to workload demands. The use of HR as a fatigue indicator aligns with the physiological monitoring principles that rely on biometric changes to identify early signs of fatigue [40]. Interval-based data collection supports the progressive analysis of fatigue dynamics as commonly applied in temporal-based detection systems that track physiological signal changes over prolonged work periods [49]. Continuous HR recording is also consistent with performance monitoring approaches that associate reductions in concentration and increases in fatigue with physiological changes occurring during specific work phases [44, 53]. HR 4 and HR 5 corresponded to the rest period, while HR 6 to HR 10 showed continued monitoring during the midday to afternoon work phase. The HR was recorded hourly to detect physiological responses to fatigue throughout the day. The collected HR data were used as an indicator of fatigue, where sequential increases in HR may reflect the accumulation of work-related strain. All results and related information are presented in Table 1.

The relationship between HR and blood pressure is an essential component in understanding the body's physiological response to physical activity and workload demands. In general, both are interrelated cardiovascular indicators that regulate the blood and oxygen supply throughout the body [15, 22, 23]. When an individual performs physical activity or experiences work-related stress, the sympathetic nervous system is activated, resulting in an increase in HR and vasoconstriction, which subsequently affects blood pressure. A progressive increase in HR during work hours may be accompanied by changes in blood pressure, particularly during intensive work phases or when the body begins to experience fatigue. Systolic pressure tends to rise along with HR because the heart pumps more forcefully to meet the oxygen demands of tissues, which is consistent with the physiological patterns described in fatigue prediction models based on mechanical and cardiovascular loads [34, 44]. The pattern of increasing HR followed by changes in blood pressure also aligns with fatigue detection indicators that use physiological responses as early markers of work strain and declining physical condition. Conversely, during periods of rest, both HR and blood pressure may decrease, indicating cardiovascular recovery.

Table 1. Heart Rate (HR) of Turnaround (TA) respondents

	HR 0	**HR 1**	**HR 2**	**HR 3**	**HR 4**	**HR 5**	**HR 6**	**HR 7**	**HR 8**	**HR 9**	**HR 10**
NAME	07:30	08:00-09:00	09:00-10:00	10:00-11:00	11:00-12:00	12:00-13:00	13:00-14:00	14:00-15:00	15:00-16:00	16:00-17:00	17:00-18:00
Person_1	96	123	134	128	92	82	127	129	141	137	139
Person_2	65	88	91	112	87	78	121	116	101	118	112
Person_3	91	127	138	130	117	102	123	131	136	132	127
Person_4	90	115	122	135	129	120	133	137	138	129	120
Person_5	108	118	125	144	135	128	139	132	140	143	137
Person_6	87	92	102	118	127	118	110	125	135	131	119
Person_7	120	155	136	161	132	126	112	142	170	179	181
Person_8	95	122	136	150	148	138	129	142	151	167	159
Person_9	88	114	124	153	154	138	148	168	151	141	130
Person_10	85	99	116	127	119	121	115	134	133	127	122
Person_12	109	120	126	135	134	120	129	141	146	150	147
Person_13	73	99	129	131	122	120	137	139	141	149	137
Person_14	68	81	93	109	90	74	119	111	103	120	118
Person_15	115	127	132	149	121	118	128	134	147	165	159
Person_16	100	123	139	140	136	122	131	149	164	188	178

3.3 Subjective measurement results

3.3.1 MFI-21 value

The fatigue assessment in this study was also conducted using a subjective method through the Indonesian version of the MFI-20 questionnaire. This instrument consists of 20 items grouped into five main dimensions, namely general fatigue, physical fatigue, reduced activity, reduced motivation, and mental fatigue. Each item uses a 1–5 Likert scale, where a score of 1 indicates *strongly disagree,* and a score of 5 indicates *strongly agree*. This approach provided a comprehensive overview of the multidimensional fatigue experienced by the participants. The use of a standardized measurement scale aligns with the instrument evaluation principles that emphasize consistency, reliability, and measurability, as described in the modern measurement methodology literature [41, 66].

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Based on the literature, the MFI-20 is designed to provide stable and reliable assessments, including when used in worker populations and environments that require high physical activity [49, 66]. These studies emphasize that self-report instruments such as the MFI-20 are effective when continuous objective fatigue monitoring is difficult to perform and that the instrument remains accurate even when administered manually. In this study, the fatigue measurements were conducted at three activity phases before work, before the break period, and after work to capture the dynamics of fatigue changes comprehensively.

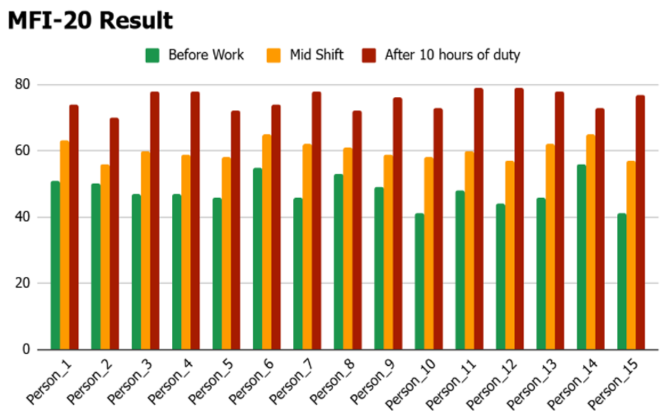

Figure 7. Multidimensional Fatigue Inventory (MFI-20) results of Turnaround (TA) respondents

The fatigue assessment was carried out through five main components to ensure that changes in the workers' conditions could be comprehensively captured. The objective aspects were obtained from physiological data such as HR, which was monitored in real time to evaluate the body's response to physical workload. The MFI-20 result can be shown in Figure 7. This approach is consistent with the findings of Zhang et al. [40], which showed that physiological indicators can provide an accurate depiction of the body's response to workload and changes in physical condition during intensive activities. The subjective aspects were captured in Figure 8 through the MFI-20, which measures physical, mental, and motivational fatigue based on individual perceptions. The results show that all five fatigue dimensions increase from before work to after work during TA operations, indicating cumulative strain across the shift. General and physical fatigue rise steadily, reflecting the demanding nature of the tasks. However, the largest increase occurs in mental fatigue, which shows the sharpest post-work escalation compared with other dimensions. This suggests that TA work imposes a strong cognitive load due to concentration demands, time pressure, task complexity, and continuous risk awareness. Meanwhile, reduced motivation temporarily improves during rest but rises again after work, and reduced activity indicates declining energy after the shift. Overall, although all dimensions contribute to worker fatigue, mental fatigue is the most influential and dominant aspect in TA operations and should be prioritized in fatigue-risk control strategies. The use of subjective instruments remains essential to complement the physiological data, as fatigue is not only reflected through bodily changes but also through individuals' perceptions of their energy levels and motivation. The relevance of this integrated approach is further supported by Ahmad et al. [31], who highlighted that combining self-report instruments such as MFI-20 with objective data enhances the accuracy of fatigue detection in work environments or activities requiring high performance [43].

3.3.2 ANOVA test of Multidimensional Fatigue Inventory

The ANOVA test was applied to evaluate the differences in fatigue levels across the three phases of work activity, namely pre-work, mid-shift (before rest), and post-work, using MFI-20 scores as a subjective indicator. This analysis aimed to determine whether statistically significant changes occurred in fatigue dynamics throughout the work cycle. The validity of using MFI-20 in this comparative analysis is supported by the findings of Jelsness-Jørgensen et al. [41], who demonstrated that MFI-20 possesses stable and reliable psychometric properties, making it suitable for quantitative studies involving between-group comparisons. Furthermore, the dimensional structure of the MFI-20 was confirmed by Bakalidou et al. [66], who emphasized that understanding the instrument's dimensionality is crucial to ensure that analyses across work phases, whether based on total scores or subscales, are conducted logically and methodologically sound. The data processing was performed using Minitab software, which supports a comprehensive range of analyses, from testing distributional assumptions to conducting ANOVA procedures, ensuring accurate interpretation of subjective fatigue variations during work activities, as shown in Table 2.

Table 2. Summary of one way ANOVA

	One Way ANOVA				
	Sum of Squares	**df**	**Mean Square**	**F**	**Sig.**
Factors	5655.2	2	2827.62	230.45	**.000**
Error	515.3	42	12.27		
Total	6170.6	44			

Based on the probability plots in Figure 9 for the MFI-20 results across the three measurement phases, namely pre-work, mid-shift (before break), and post-work, the Shapiro–Wilk normality test indicated that all data were normally distributed. This is evidenced by p-values which are greater than 0.100 for all conditions, suggesting that there is insufficient evidence to reject the null hypothesis of normal distribution.

The Ryan–Joiner (RJ) values, which were close to 1 across all measurement conditions, namely 0.992 before work, 0.989 before the break, and 0.974 after work, further indicated that the fatigue data obtained from the MFI-20 followed a pattern consistent with a normal distribution. The clustering of data points near the theoretical distribution line in each probability plot reinforces the interpretation that the data do not exhibit any extreme deviations. This characteristic aligns with the previous findings showing that fatigue measurement instruments such as the MFI-20 tend to produce stable and near-normal distributions when applied in work contexts with moderate response variability [9]. With the normality assumption satisfied, the MFI-20 data obtained from the three measurement phases were appropriate for further analysis using variance homogeneity tests and other parametric statistical methods [41, 49].

3.4 Machine learning

3.4.1 Random Forest algorithm

The RF algorithm was employed in this study as one of the predictive approaches due to its strong capability to handle variables with high noise levels and to generate ensemble-based decisions derived from multiple decision trees. This method aggregates predictions from numerous trees to enhance the model accuracy and stability while reducing the risk of overfitting. RF also supports both numerical and categorical data processing, making it well-suited for complex datasets involving physical and mental fatigue indicators [27, 54].

In its implementation, an RF model was developed for two scenarios: predictions based on subjective fatigue scores (MFI-20) and predictions based on physiological data (HR). Each model was designed to map the relationships between the input variables and fatigue targets at different time phases, with the goal of projecting fatigue conditions based on historical patterns. The model evaluation was conducted by examining the RMSE and R^2 values to measure the prediction error and accuracy levels showed in Table 3.

Table 3. Summary of Random Forest (RF) model accuracy

	Train		Test	
	RMSE	**R^2**	**RMSE**	**R^2**
MFI-20	0.02269	0.99965	0.064616	0.9989
HR	14.82701	0.9574	127.10849	0.7996

Note: RMSE = Root Mean Square Error; MFI-20 = Multidimensional Fatigue Inventory; HR = Heart Rate.

The RF model Table 3 demonstrated excellent predictive performance in quantitatively mapping worker fatigue levels. For predicting MFI scores, the model achieved R^2 values of 0.99965 and 0.9989 in the training and testing datasets, respectively, accompanied by very low RMSE values of 0.0227 and 0.0646, respectively. These results indicate that the model can explain nearly all the variability in fatigue scores with exceptionally high precision, both during training and when applied to unseen data.

For HR prediction, the model's performance was slightly lower but remained robust. The R^2 values of 0.9574 during training and 0.7996 during testing suggest that the model can still capture HR patterns reasonably well, although a decline in accuracy is observed when evaluating new data. The RMSE for HR increased substantially from 14.827 to 127.108, indicating that the physiological fluctuations inherent in HR measurements are more challenging to the model than the fatigue patterns represented by MFI scores [41, 66].

Overall, RF performed exceptionally well for MFI prediction and provided acceptable performance for HR prediction. This evaluation confirmed that the model can serve as a reliable predictive tool within fatigue monitoring systems, offering high dependability for subjective fatigue estimation and adequate adaptability for physiological analysis.

RF for MFI-20 prediction. The use of RF is well supported for physiological and temporal data processing. For example, Lestari et al. [27] developed an RF model to predict microsleep events based on driver data by incorporating physiological and behavioral variables, demonstrating that RF can effectively recognize drowsiness-related fatigue patterns [31, 64]. Opris et al. [68] utilized real wearable-derived HRV data to classify cognitive fatigue using an RF model, showing the reliability of RF in real-time fatigue monitoring contexts and in predicting fatigue relative to each participant's actual data.

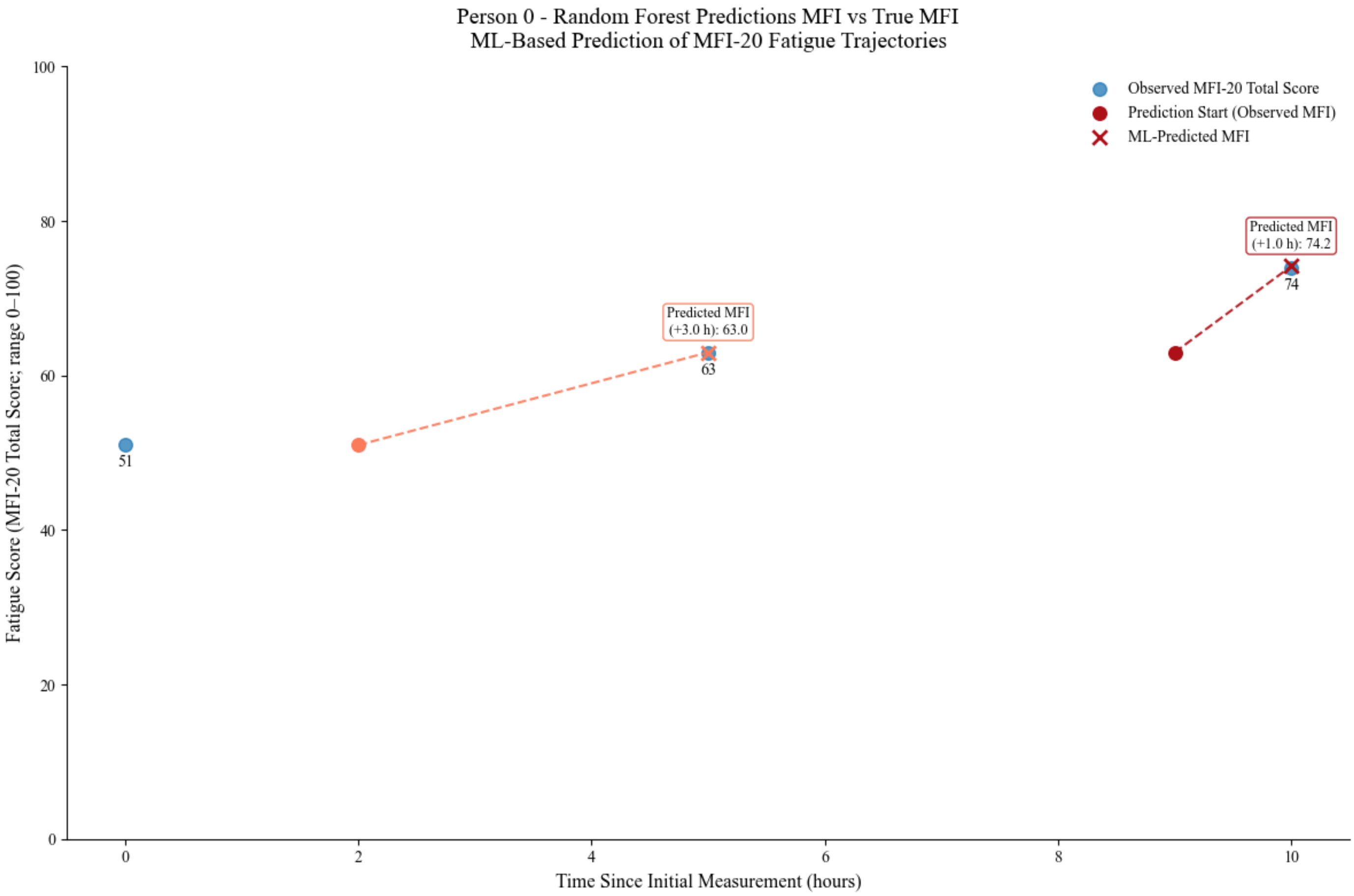

Figure 8. Random Forest (RF) visualization for Multidimensional Fatigue Inventory (MFI-20) of worker 1

Figure 8 illustrates the relationship between work duration (in hours) and fatigue level based on the MFI scores predicted using the RF model. The initial measurement point began at hour 0 with an MFI value of 51. After two hours of work (hour 2), the fatigue level increased to 63 based on the actual measurement, and the model successfully predicted this value with high accuracy (63.0). At hour 10, which marked the end of the work period, the actual fatigue score reached 74, while the model predicted a value of 74.16, demonstrating that the predicted outcome closely matched the observed data.

The graph shows that the model is able to consistently replicate the progressive increase in fatigue as work hours accumulate, particularly in the interval between hours 2 and 10 after the initial measurement. The predictive trend closely following the actual data suggests that worker fatigue increases progressively and monotonically, making it suitable for time-dependent projections with stable accuracy. The visualization in Figure 8 of the differences between the actual and predicted values, highlighted using distinct colors and symbols, further reinforces the model's capability to capture temporal fatigue dynamics.

These findings are consistent with Sharif et al. [54], who reported that RF can effectively learn long-term physiological patterns from non-invasive sensors and maintain prediction consistency under continuous activity conditions. This approach is especially crucial in high-intensity work environments such as TA operations.

RF for HR prediction. The RF-HR model was developed to project physiological fatigue by analyzing changes in HR across different phases of work activity. The input variables included the current HR, personal information, work duration, and rest-phase status. This approach is aligned with the findings of Gu and Wang [56], who demonstrated that physiological signals such as HR and HRV can reflect real-time changes in bodily conditions when processed using machine learning algorithms, including RF. Further validation was provided by Shilov et al. [42], who showed that combining HR data with machine learning models enables accurate fatigue prediction, particularly in work activities with highly dynamic load patterns. These findings reinforce the premise that HR fluctuations can serve as an objective representation of fatigue dynamics in intensive work environments.

The model training was conducted using a supervised learning approach with the RF Regressor. The prediction results focused on identifying extreme HR points and physiological trends relevant to work-related fatigue. Visualization using the HR prediction function supports individualized interpretation for each participant, enabling a detailed assessment of physiological fatigue responses across the work duration.

The graph presented in Figure 9 illustrates the comparison between the actual HR values and those predicted using the RF model for a single individual (Person 0) over a time span of 0 to 10 hours. The light blue line represents the actual HR trend recorded over time, whereas the pink dashed line and red cross markers indicate the model's predicted values at specific time points.

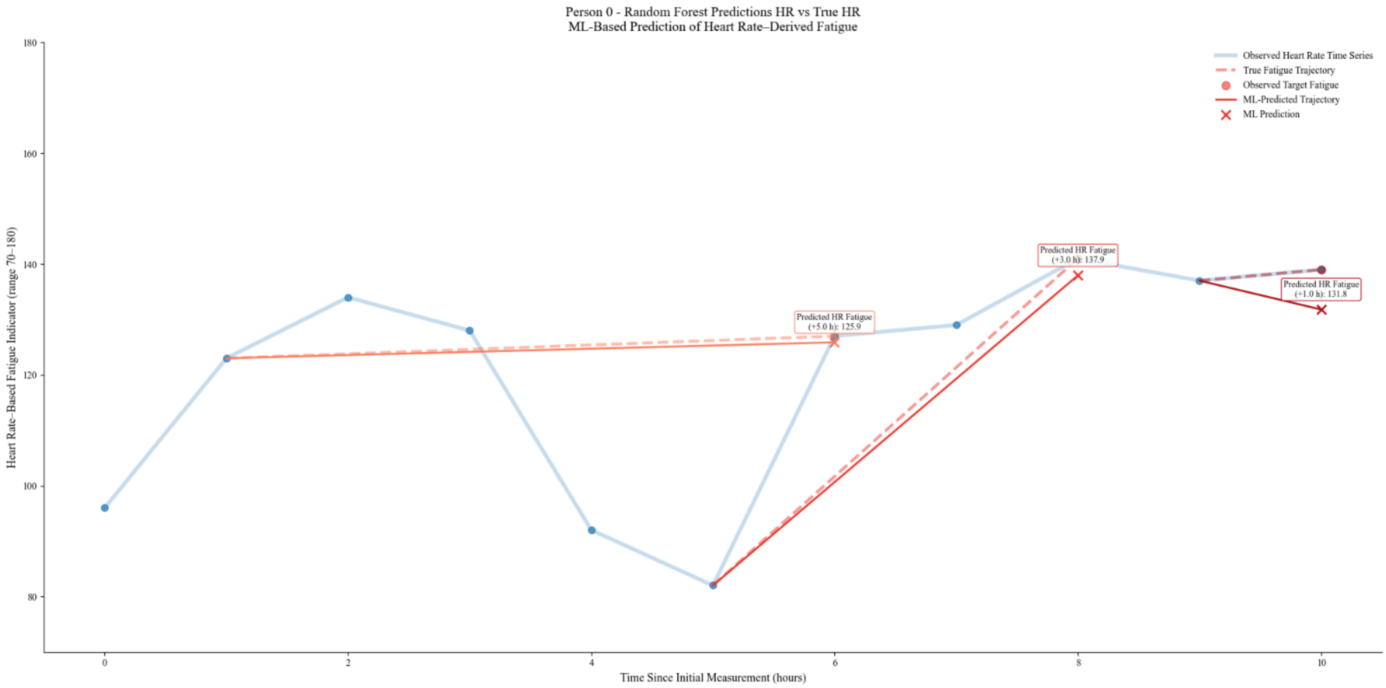

Figure 9. Random Forest (RF) visualization for the Heart Rate (HR) of worker 1

From the graph, it can be observed that the RF model is able to predict HR values with considerable accuracy. At hour 6, the predicted value of 126 bpm matched the actual HR, indicating that the model successfully captured the physiological pattern during that period. Similarly, at hour 8, the predicted value of 138 bpm aligned with the actual measurement, demonstrating strong model performance. At hour 10, the predicted HR of 132 bpm was slightly lower than the actual value of 137 bpm; however, the difference was relatively small and remained within an acceptable tolerance range.

Overall, the model showed strong capability to recognize HR variation patterns and generate predictions that closely followed the actual data. This indicates that the features used during model training were sufficiently representative and relevant to the physiological fatigue conditions experienced by the worker.

3.4.2 Support Vector Regression algorithm

The SVR algorithm Table 4 was employed due to its ability to efficiently capture nonlinear relationships through the use of kernel functions, its robustness against outliers, and its suitability for datasets of relatively small size. This approach enables the model to learn complex fatigue patterns without requiring deep architectures or large amounts of data [52]. The implementation was carried out in two scenarios: fatigue prediction based on MFI scores and prediction based on HR, with each scenario utilizing input configurations relevant to the participants' physiological and psychological conditions. The model training process was followed by an evaluation using the RMSE and the coefficient of determination (R^2) to assess the accuracy and model fit. All results and related information are presented in Table 4. The capability of SVR to map nonlinear patterns related to cognitive performance and fatigue dynamics aligns with the findings of Matuz et al. [12], who demonstrated that changes in mental state and performance can be effectively modeled using SVM-based machine learning approaches in the context of fatigue and vigilance assessment [53].

Table 4. Summary of Support Vector Regression (SVR) model accuracy

	Train		Test	
	RMSE	**R²**	**RMSE**	**R²**
MFI-20	25.09225	0.62304	31.93260	0.9989
HR	214.0133	0.38587	406.721	0.50296

Note: RMSE = Root Mean Square Error; MFI-20 = Multidimensional Fatigue Inventory; HR = Heart Rate.

<u>SVR for MFI-20 prediction.</u> The SVR–MFI model was developed to predict MFI-20 fatigue scores based on baseline measurements and personal characteristics such as age, HR Max, blood pressure, calories, sleep duration, and other physiological parameters relevant to work conditions. The pre-modeling process included feature standardization using StandardScaler to ensure that all variables were on a comparable scale, given that SVM is highly sensitive to differences in feature magnitudes. This approach aligns with the findings of Ni et al. [15], who emphasized that SVM-based fatigue modeling requires normalization and signal preprocessing to maintain the model sensitivity to subtle fatigue patterns, particularly when the input variables exhibit high physiological variability [53]. Implementing

standardization in the SVM-MFI model ensures more stable learning and enhances the model's ability to recognize fatigue trends derived from participants' temporal and physiological information.

The prediction visualization was carried out through graphs comparing the actual fatigue values with the model's predicted values for each participant. This analysis aimed to assess the extent to which the model can reconstruct mental fatigue trends based on the provided input data.

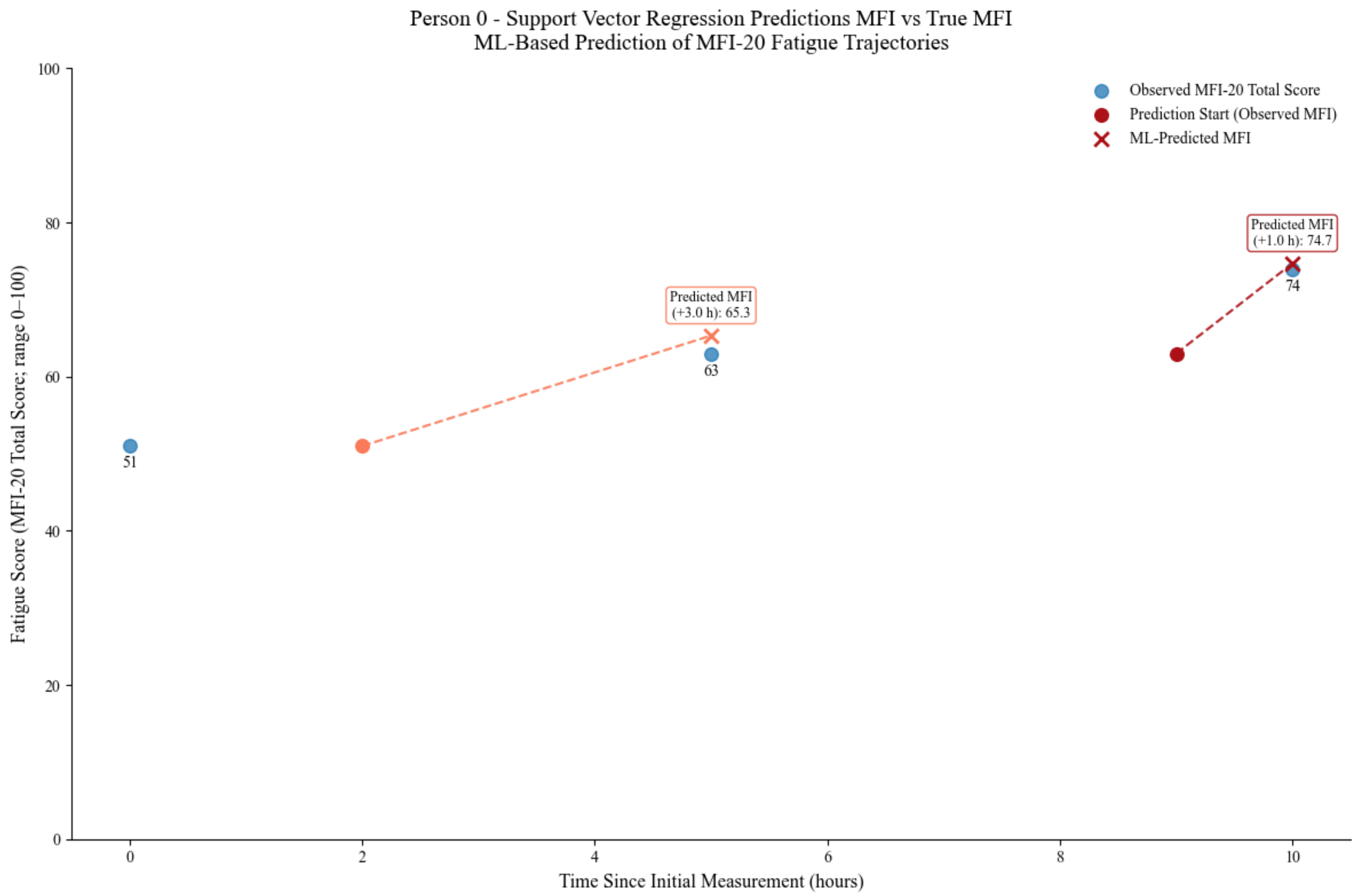

Figure 10. Support Vector Regression (SVR) visualization for Multidimensional Fatigue Inventory (MFI-20) of worker 1

Figure 10 illustrates the application of the SVR algorithm to predict the MFI-20 scores based on work duration. The blue points represent the actual MFI data, with the values of 51, 63, and 74 at the hour 0, 3, and 10, respectively. Meanwhile, the orange and red points indicate the SVR predictions at the hour 2 and 9, with the values of 65.33 and 74.70, respectively. Although the SVR model successfully captured the nonlinear upward trend of fatigue, a larger deviation was observed at the 2-hour prediction compared to the actual data. This indicates that the predictive accuracy of SVR is not as strong as that of the RF algorithm, which previously demonstrated highly precise predictions at all time points.

RF tends to outperform SVR when dealing with data exhibiting complex variations due to its ensemble nature, whereas SVR requires more precise tuning of parameters and kernel functions. Prediction accuracy is critical in the context of workplace fatigue monitoring, particularly in high-intensity scenarios such as TA operations. Therefore, selecting a more stable algorithm such as RF becomes a more advantageous choice for practical implementation and data-driven intervention strategies [27, 30].

SVR for HR prediction. The SVR-HR model was developed to predict changes in physiological fatigue, represented by the HR value at the next working hour. The model inputs included current HR, personal metadata such as age, blood pressure, and HR Max, as well as temporal variables such as work duration and rest status. All features were normalized using StandardScaler to ensure uniform data scaling, consistent with the characteristics of SVR algorithms, which are sensitive to the differences in feature magnitudes. The model was trained using an SVR approach, leveraging kernel functions to capture nonlinear relationships within complex physiological patterns. This approach is consistent with the findings of Frade et al. [38], who demonstrated that combining physiological signals with machine learning algorithms, including SVM, can improve the prediction accuracy for physical condition and fatigue when the data are structured as time series [52, 53].

The generated predictions focused on estimating future HR values in the context of the participants' workload. The evaluation was performed by comparing the predicted HR with the actual HR through individual visualizations and calculating the RMSE and R^2 metrics. This model aims to capture HR fluctuations predictively to support real-time fatigue mapping.

Figure 11 illustrates the performance of the SVR algorithm in predicting an individual's HR over a 10-hour work period. The blue line represents the actual HR time-series data, whereas the red cross markers and dashed line depict the SVR predictions at specific time intervals. Three key point pairs are shown: in the interval from hour 1 to hour 6, the model predicts an HR of 127 bpm, which is considerably lower than the actual value of 141 bpm; in the interval from hour 5 to hour 8, the predicted value of 131 bpm is slightly higher than the actual 127 bpm; and in the interval from hour 9 to hour 10, the predicted value of 137 bpm is very close to the actual measurement of 139 bpm.

These results indicate that although SVR is capable of capturing the general physiological trend, there are notable fluctuations in the prediction accuracy, particularly during the early stages of work activity. Compared with the RF algorithm, the performance of SVR appears less consistent and exhibits larger deviations in several time segments. This suggests that applying SVR for physiological fatigue monitoring requires further parameter tuning to achieve more precise predictions. Therefore, in high-intensity work scenarios such as TA operations, the RF model remains the more recommended approach due to its reliability in producing stable and accurate estimates of workers' HR dynamics [15, 22].

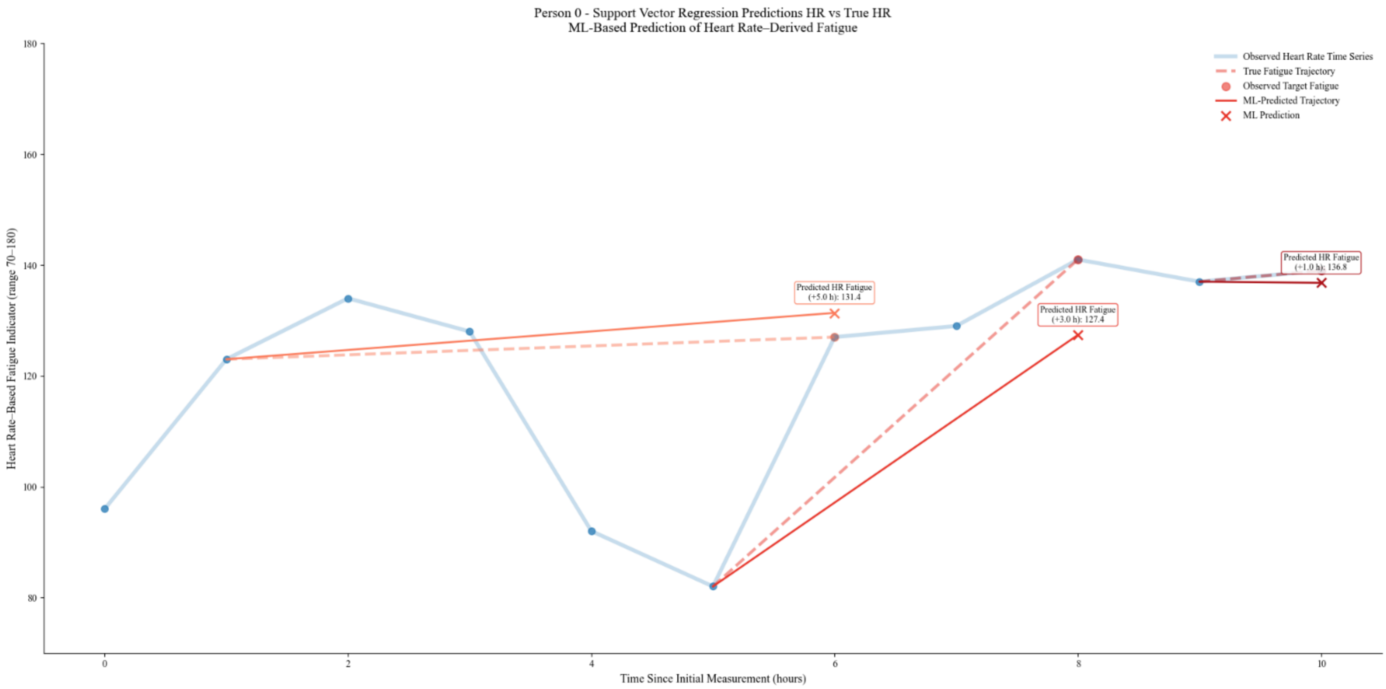

Figure 11. Support Vector Regression (SVR) visualization for the Heart Rate (HR) of worker 1

3.4.3 Linear Regression algorithm

LR was used as a baseline approach in fatigue modeling to map the relationship between input features and the target variable. This algorithm operates by forming a regression line that minimizes the error between the predicted and actual values, making it suitable for capturing the linear relationships between variables. The use of regression for physiological data has been shown to be effective in various studies, such as in the development of predictive equations for HRV using multiple LR, demonstrating that physiological variables, such as age and HR, can be modeled linearly to produce stable estimations [56]. Regression-based approaches are also relevant in fatigue detection contexts, as evidenced by EEG-based regression studies that predict fatigue levels across datasets using linear relationships among physiological signal features [57].

In this study, two testing scenarios were conducted: fatigue prediction based on MFI scores and prediction based on HR, each of which used relevant input configurations. After the model training was completed, the performance evaluation was carried out using the RMSE and the coefficient of determination (R^2).

Based on Table 5, the evaluation results of the LR model for predicting MFI fatigue scores and HR values, the model demonstrated relatively stable performance for MFI but remained limited in capturing HR dynamics. For the prediction of MFI scores, the model showed good performance, yielding an RMSE of 9.12 and an R^2 of 0.863 for the training dataset, indicating that the model was able to explain approximately 86% of the variance in MFI scores. Although the error increased in the testing dataset, with an RMSE of 17.09, the R^2 remained fairly high at 0.7339, suggesting that the model retained a reasonable level of generalizability for the unseen data. These findings indicate that LR is reasonably reliable for capturing the relationship between physiological factors and subjective fatigue scores measured using the MFI.

In contrast, the model's performance in predicting HR was substantially lower. On the training data, the model achieved an R^2 of only 0.450 with an RMSE of 191.48, whereas on the testing data, the R^2 slightly improved to 0.496 but was accompanied by a larger RMSE of 319.56. These values show that the model was able to explain less than 50% of the variability in HR and was not sufficiently precise in predicting HR across the work cycle. This is likely due to the highly dynamic nature of HR responses, which do not follow simple linear patterns.

Table 5. Summary of Linear Regression (LR) model accuracy

	Train		Test	
	RMSE	**R^2**	**RMSE**	**R^2**
MFI-20	9.1180374	0.86302	17.09153	0.7339
HR	191.48423	0.45052	319.5594	0.49620

Note: RMSE = Root Mean Square Error; MFI-20 = Multidimensional Fatigue Inventory; HR = Heart Rate.

Overall, LR is suitable for predicting progressive and relatively linear fatigue indicators such as MFI but is not appropriate for HR, which exhibits more complex and fluctuating behavior. For variables like HR, models capable of capturing nonlinear patterns, such as RF or Support Vector Machines, are recommended.

LR for MFI-20 prediction. The LR–MFI model was selected as a baseline approach to predict future MFI fatigue scores due to its ability to map linear relationships between input variables such as age, HR Max, blood pressure, sleep duration, and baseline MFI score and the subsequent MFI values. The model is highly interpretable because the contribution of each variable to the prediction can be directly observed from the regression coefficients. Prior to training, all features were standardized to ensure uniform scaling and prevent bias toward variables with larger numerical ranges. The model performance was evaluated using metrics such as RMSE and the coefficient of determination (R^2) to assess how closely the predictions aligned with the actual data. This approach aligns with the findings of Bazazan, who used LR to model physio-psychological relationships in fatigue assessment [58].

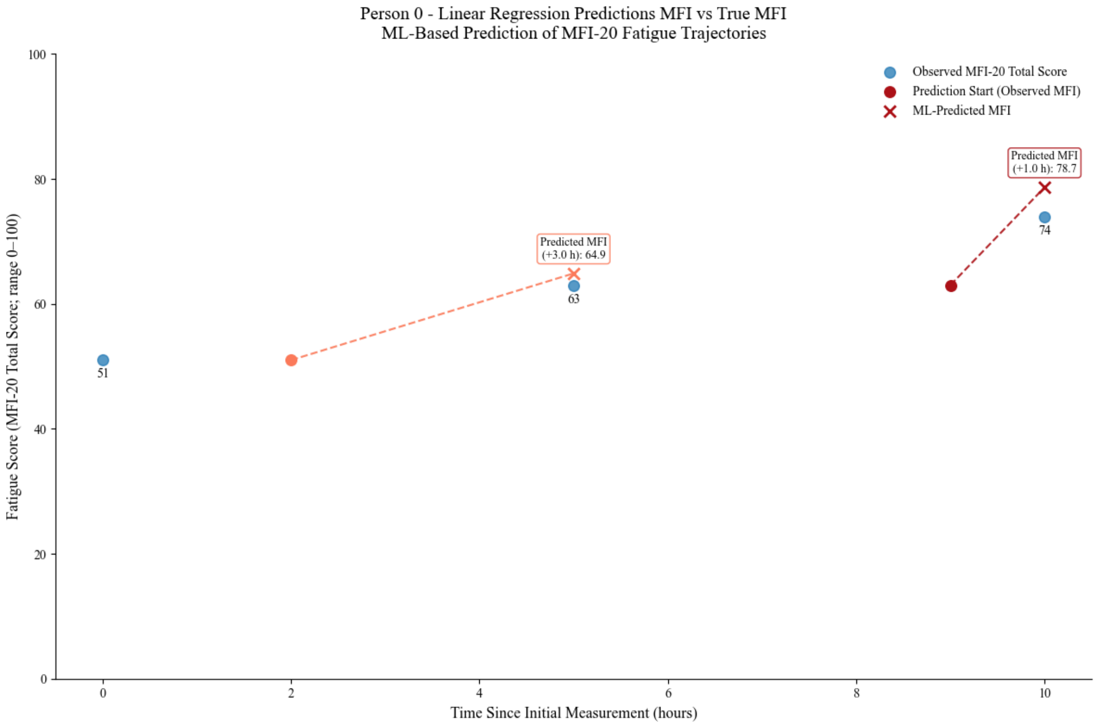

Figure 12. Linear Regression (LR) visualization for Multidimensional Fatigue Inventory (MFI-20) of worker 1

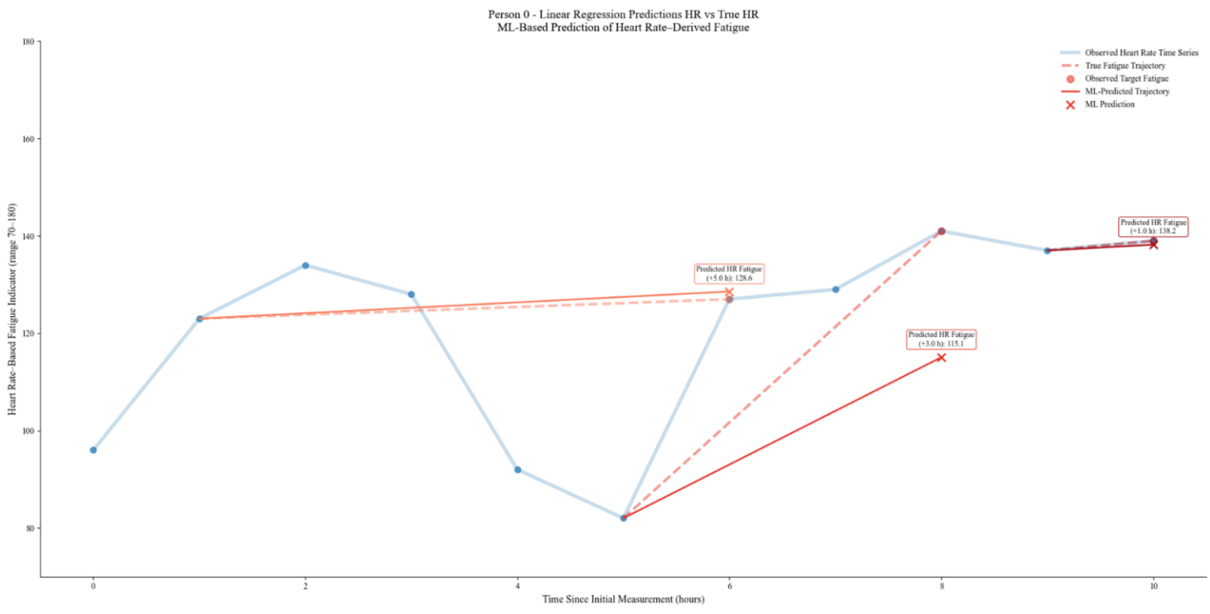

Figure 13. Linear Regression (LR) visualization for the Heart Rate (HR) of worker 1

Figure 12 illustrates the performance of the LR algorithm in predicting fatigue scores (MFI-20/MFI) based on an individual's work duration over a 10-hour period. The blue points at hours 0, 5, and 10 represent the actual MFI values of 51, 63, and 74, respectively. The prediction points are shown at hours 2 and 10, where the model estimates the MFI values of 64.88 and 78.66, respectively. The dashed lines connect each actual measurement with the corresponding predicted value, highlighting the discrepancies produced by the model [58].

LR for HR prediction. The LR–HR model was developed to predict the next working HR based on the current HR, personal data such as age and resting HR, and work-related variables including working hours and rest status. All input features were standardized to ensure model stability and prevent scale-related bias. The training was conducted by forming time-paired data so that the linear relationship between the current physiological conditions and subsequent HR values could be learned effectively. The findings of Tao and Galperin indicate that LR is effective for modeling HR and fatigue dynamics, allowing the prediction outputs to be visualized for assessing model precision [44, 53].

Figure 13 presents the performance of the LR algorithm in predicting an individual's HR over a 10-hour work period. The blue line in the graph represents the actual HR time series, including points such as 100 bpm at hour 0, approximately 130 bpm at hour 2, a decrease to 90 bpm at hour 4, an increase to 130 bpm at hour 6, a peak of 140 bpm at hour 8, and then a slight decrease to 130 bpm at hour 10. The predicted HR values are shown using red cross markers and dashed lines at hours 6, 8, and 10.

At hour 6, the predicted HR was 115 bpm, which was noticeably lower than the actual value of 130 bpm. At hour 8, the prediction was 118 bpm, substantially below the actual 140 bpm. Similarly, at hour 10, the prediction of 119 bpm remained below the actual 130 bpm. This pattern demonstrates that LR fails to capture the dynamic fluctuations of HR during work activity. The model tends to produce overly smoothed estimates and is insufficiently responsive to actual spikes in the physiological data.

Compared with algorithms such as RF or SVR, the performance of LR appears weaker in modeling HR changes that are complex and context-dependent. This limitation stems from the model's assumption of linear relationships, which is inadequate for representing physiological dynamics influenced by multiple interacting factors during high-intensity work scenarios such as TA operations. Therefore, while LR may serve as a baseline model, more adaptive and robust approaches are recommended for HR prediction in the context of occupational fatigue evaluation [15, 22].

3.5 Leave-One-Participant-Out cross-validation models

The Leave-One-Participant-Out (LOPO) evaluation highlights a clear contrast between subjective and physiological representations of fatigue [69]. The RF model achieved consistent cross-participant performance in predicting MFI-20 scores (mean $R^2 = 0.75 \pm 0.33$, RMSE = 2.95 ± 1.17). In contrast, performance for HR-based fatigue prediction was poor, with predominantly negative scores (mean $R^2 = -3.76 \pm 6.05$, RMSE = 20.08 ± 9.96). These findings indicate that fatigue expressed through absolute physiological measures (HR) does not generalize well across individuals due to substantial inter-individual variability. Conversely, MFI-20 represents fatigue as a relative index, enabling more robust cross-subject learning. This suggests that model generalization is driven primarily by the representation of fatigue rather than by model complexity. A summary of the LOPO cross-validation results is presented in Table 6.

Table 6. Summary of Leave-One-Participant-Out (LOPO) cross validation

Fatigue Indicator	Validation Strategy	Mean R^2	Std R^2	Mean RMSE	Std RMSE	Generalization Interpretation
MFI-20	LOPO (15 folds)	0.75	0.33	2.95	1.17	Good cross-participant generalization
HR	LOPO (15 folds)	−3.76	06.05	20.08	9.96	Poor cross-participant generalization

Note: RMSE = Root Mean Square Error; MFI-20 = Multidimensional Fatigue Inventory; HR = Heart Rate.

Table 7. MFI-20 cross validation

Fold	Left_Out_Group	RF MFI		SVR MFI		LR MFI	
		R^2	RMSE	R^2	RMSE	R^2	RMSE
0	Person_1	0.92	2.58	0.72	4.72	0.97	1.52
1	Person_2	0.88	2.40	0.68	3.98	0.60	4.41
2	Person_3	0.96	1.89	0.72	5.04	0.95	2.03
3	Person_4	0.98	1.40	0.76	4.69	0.95	2.08
4	Person_5	0.93	2.70	0.32	8.22	0.93	2.62
5	Person_6	0.59	4.48	0.87	2.57	0.78	3.32
6	Person_7	-0.35	4.65	0.75	2.01	-0.21	4.40
7	Person_8	0.80	3.59	0.89	2.66	0.90	2.50
8	Person_9	0.85	4.28	0.63	6.72	0.67	6.33
9	Person_10	0.65	4.41	0.41	5.76	0.79	3.40
10	Person_11	0.87	2.84	0.80	3.62	0.97	1.39
11	Person_12	0.73	2.33	0.19	4.04	-3.80	9.86
12	Person_13	0.77	2.62	0.94	1.34	0.92	1.60
13	Person_14	0.99	0.71	0.91	2.50	0.97	1.50
14	Person_15	0.62	3.39	0.83	2.24	0.80	2.45

Note: MFI-20 = Multidimensional Fatigue Inventory; RF = Random Forest; SVR = Support Vector Regression; LR = Linear Regression; RMSE = Root Mean Square Error.

3.5.1 Multidimensional Fatigue Inventory Leave-One-Participant-Out cross-validation

The LOPO cross-validation results indicate that the models are generally able to predict MFI-20 fatigue scores across participants, with RF and LR achieving high accuracy in most folds (several R^2 values > 0.90 and RMSE < 3.0), as shown in Table 7. However, a few participants show markedly lower or negative R^2 values, reflecting inter-individual variability that is more difficult to generalize under subject-independent evaluation. SVR yields more stable but slightly lower accuracy overall. These findings suggest that MFI-20 fatigue patterns can be learned across workers, although prediction performance remains influenced by individual fatigue response differences.

3.5.2 Heart Rate Leave-One-Participant-Out cross validation

The LOPO cross-validation results for HR indicate that the models generally exhibit poor cross-participant generalization, as reflected by predominantly negative R^2 values and large RMSE scores across most folds. Only a small number of participants (e.g., Person-4, Person-5, Person-7, and Person-15) show positive R^2 values, and even in these cases, the prediction errors remain relatively high. Compared with MFI-20, the instability of HR-based prediction suggests that HR functions as a highly individualized and variable physiological signal, making it challenging to model as a single population-level fatigue target under subject-independent validation. The HR cross-validation results are presented in Table 8.

Table 8. Heart Rate (HR) cross validation

Fold	Left_Out_Group	RF HR		SVR HR		LR HR	
		R^2	RMSE	R^2	RMSE	R^2	RMSE
0	Person_1	-1.33	14.18	-1.01	13.18	-0.25	10.40
1	Person_2	-7.23	37.67	-3.59	28.13	-1.70	21.57
2	Person_3	-4.14	15.84	-1.08	10.07	-2.09	12.28
3	Person_4	0.69	5.33	0.14	8.80	-1.23	14.17
4	Person_5	0.58	14.59	-0.78	30.05	-0.04	22.99
5	Person_6	-22.65	24.01	-0.02	4.98	-6.39	13.43
6	Person_7	0.40	12.67	0.10	15.50	-0.52	20.10
7	Person_8	-1.43	21.65	-2.23	25.00	-1.03	19.79
8	Person_9	-0.97	11.95	0.15	7.83	0.06	8.27
9	Person_10	-3.76	13.82	-0.95	8.84	-1.18	9.35
10	Person_11	-0.40	29.41	-0.80	33.37	-1.34	38.05
11	Person_12	-1.44	13.11	-1.65	13.64	-16.05	34.62
12	Person_13	-9.61	38.92	-1.50	18.87	-5.21	29.76
13	Person_14	-5.24	30.29	-1.47	19.07	-1.63	19.65
14	Person_15	0.07	17.74	0.04	18.08	0.02	18.24

Note: RF = Random Forest; SVR = Support Vector Regression; LR = Linear Regression; RMSE = Root Mean Square Error.

4. CONCLUSIONS AND RECOMMENDATIONS

The results of this study consistently demonstrate that fatigue is a multidimensional phenomenon that develops progressively throughout the intensive work cycle of TA activities. The subjective findings (MFI-20), objective indicators (HR), and cognitive measures (PVT) confirm that the high physical and mental workload during TA has a direct impact on workers' physiological responses and perceived fatigue levels. ANOVA analysis shows that work duration is a highly dominant and statistically significant factor influencing fatigue fluctuations, with a p-value of 0.000 and variance contribution of $R^2 = 91.65\%$. This indicates that changes in working time are the primary driver of fatigue accumulation, occurring both linearly and nonlinearly throughout the workday.

The increasing fatigue is clearly reflected in the MFI-20 scores, which rise significantly from the pre-work phase to the pre-break phase and peak after 10 hours of continuous activity. This trend supports the existing literature showing that long working hours, time pressure, and physically demanding tasks are the key determinants of fatigue accumulation in high-risk industrial sectors. Meanwhile, hourly HR measurements provide objective evidence that cardiovascular responses also progressively increase, indicating heavy physiological strain. This is further supported by the combination of rising HR, fluctuating blood pressure, and high calorie expenditure among several participants, reinforcing the conclusion that workers are subjected to sustained physical workloads requiring continuous physiological adaptation.

A major contribution of this study lies in the implementation of three machine learning algorithms (RF, SVR, and LR) to model fatigue using multimodal data. The results show that RF is the most superior algorithm, especially for predicting subjective fatigue based on MFI-20, achieving extremely high performance with training $R^2 = 0.99965$, testing $R^2 = 0.9989$, and very small RMSE values. This indicates that the progressive and relatively stable pattern of fatigue can be optimally captured by the ensemble characteristics of RF, which effectively handles complex interactions between physiological features and temporal data. For HR prediction, RF maintained strong performance, although it was lower than that of the MFI prediction. A testing R^2 of 0.7996 suggests that the model can capture most of the HR pattern, despite the heavy influence of contextual factors such as task intensity, environmental conditions, and individual aerobic capacity on HR. The relatively high RMSE on the test data (127.109 bpm) reflects the more extreme nonlinear dynamics of HR, which cannot be fully represented by simpler regression-based models or SVR. Nevertheless, the RF's ability to predict HR at several critical time points demonstrates its potential relevance for real-time monitoring, especially for detecting physiological fatigue patterns or high-risk activity spikes.

In contrast, SVR and LR showed lower performance, particularly in HR prediction. SVR struggled to maintain stable predictions for data with sharp fluctuations, while LR is inherently limited by its linearity assumption, making it unsuitable for modeling complex physiological behavior. However, both algorithms still provide a scientific value as comparative models, highlighting that fatigue prediction requires nonlinear and ensemble-based approaches to achieve high accuracy.

These findings have strong implications for developing data-driven fatigue monitoring systems in process industries. First, the integration of subjective (MFI-20) and objective (HR) data provides a comprehensive overview of fatigue dynamics. The high accuracy of MFI prediction suggests that companies do not need excessive instruments; instead, focusing on the most representative indicators, HR and MFI-20 can make monitoring more efficient without compromising its accuracy. Second, the ability of RF to capture temporal patterns indicates that ensemble-based algorithms are highly suitable for development into decision support systems capable of generating early fatigue alerts using real-time data. Third, the results reinforce that fatigue is not solely a physiological issue but is also closely linked to cognitive and psychological aspects. Therefore, fatigue monitoring in industrial settings must be carried out holistically and continuously without relying solely on visual observations or self-reported feedback.

Overall, this study demonstrates that machine learning–based predictive models, particularly RF, offer an effective approach for monitoring and predicting worker fatigue using physiological and subjective indicators. The implementation of such predictive systems in industry has substantial potential to improve safety, reduce accident risks, and support more adaptive and evidence-based workforce scheduling and human resource management. In addition, future research will focus on strengthening the robustness and generalizability of the model by expanding the dataset to include a larger number of participants and more diverse operational contexts, particularly across different TA task categories and workload intensities. The next phase of development will also advance toward a multivariate predictive framework by integrating additional objective indicators such as Body Mass Index (BMI), blood pressure, oxygen saturation (SpO_2), sleep duration, physical activity level, and other fitness-related variables. These enhancements are expected to improve the physiological interpretability of fatigue responses across individuals and increase the model's applicability to different worker profiles. With a richer dataset, the study will further explore worker risk classification (high–medium–low) and extend the framework to critical operational units such as emergency response teams. Finally, the research direction will progress toward developing a prototype fatigue-monitoring dashboard, enabling real-time readiness assessment and supporting data-driven fatigue-management practices in industrial environments.

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