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Developing Action Plans Based on Machine Learning Analysis to Prevent Sick Leave in a Manufacturing Plant

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Objective: We aimed to develop action plans for employees' health promotion based on a machine learning model to predict sick leave at a Japanese manufacturing plant. **Methods:** A random forest model was developed to predict sick leave. We developed plans for workers' health promotion based on variable importance and partial dependence plots. **Results:** The model showed an area under the receiving operating characteristic curve of 0.882. The higher scores on the Brief Job Stress Questionnaire stress response, younger age, and certain departments were important predictors for sick leave due to mental disorders. We proposed plans to effectively use the Brief Job Stress Questionnaire and provide more support for younger workers and managers of high-risk departments. **Conclusions:** We described a process of action plan development using a machine learning model, which may be beneficial for occupational health practitioners.

Keywords: Brief Job Stress Questionnaire, machine learning, mental disorders, occupational health, sick leave

Sick leave predicts mortality and work disability,[1,2] affects coworkers,[3] and causes economic costs.[4] The risk factors for sick leave reportedly include obesity, smoking, alcohol consumption, socioeconomic status, past sick leave, occupational stressors, and diabetes.[5–10] Evidence suggests that intervention for high-risk workers,[11–13] workplace mental health training for managers,[14] participatory workplace improvement programs,[15] and other interventions[16] are effective for workers' health promotion. These findings are helpful for occupational health practitioners; however, we hypothesized that analyzing real-world data within a specific workplace is warranted for developing appropriate countermeasures because they can vary depending on the type of industry and characteristics of workers.

Previously, we conducted community-based participatory research at a Japanese manufacturing company.[17] We analyzed the company's own data and implemented countermeasures to prevent employees' sick leave based on data analysis. The number of sick leaves due to mental disorders decreased after the project initiation. However, in this previous project, we had difficulties prioritizing the countermeasures for several risk factors of sick leave detected in the data analysis. Moreover, one of the findings in this analysis was inconsistent with a study by Tsutsumi et al.[18] Unlike that study, we found no significant association between sick leave due to mental disorders and high stress based on the Brief Job Stress Questionnaire (BJSQ). High stress was defined using the cutoff scores recommended in the Stress Check Program manual by the Ministry of Health, Labor and Welfare in Japan. The discrepancy might be because the appropriate cutoff on stress scores to predict sick leave can depend on the type of industry and characteristics of workers.

These findings from the previous project led us to hypothesize that machine learning models are suitable for resolving these limitations. Machine learning models can provide the relative importance of predictor variables and reveal nonlinear and nonmonotonic associations between the outcome and variables through partial dependence plots.[19] The variable importance can lead to prioritizing countermeasures to prevent sick leaves. In addition, the ability to reveal such nonlinear and nonmonotonic associations can waive the requirement for using a pre-determined cutoff. Although several studies applied machine learning approaches to assessment for sick leave,[20–23] these described no specific countermeasures based on the model.

On the basis of this hypothesis from our previous project, we conducted another project in which we applied a machine learning approach to predict sick leave and proposed health promotion countermeasures based on the results in partnership with stakeholders. This project report would be beneficial for occupational health practitioners to implement health promotion activities.

METHODS

Project Overview

This project was conducted using the methodology of community-based participatory research at a plant in a Japanese manufacturing enterprise. The worksite had approximately 3000 employees, 75% of whom were permanent (70% blue-collar and 30% white-collar workers) and 25% of whom were temporal workers. The project followed the problem-solving approach with the active participation of stakeholders, who were members of the health and safety management system, as conducted in our previous project.[17]

Figure 1 shows the overview of this project. We developed a machine learning model to predict sick leave and visualized variable importance and partial dependence plots. We then interpreted the results, performed additional analyses, and identified problems related to the current health promotion measures. Finally, we developed and proposed action plans for the company.

Predictor Variables

We used 17 predictor variables, including age, sex, department, job position, worksite, overtime hours, BJSQ scores (three items), the company's original questionnaire about harassment (three items), and results from periodic health examinations (five items).

The BJSQ is a self-administered questionnaire that comprises 57 questions measured with a four-point Likert scale and calculates total scores for psychological and physical stress responses (ranging from 29 to 116), job stressors (ranging from 17 to 68), and social support (ranging from 9 to 36).[18] This questionnaire is mandatory in

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Ethical considerations: The data analysis in this project aimed to investigate the cause of workers' health problems, which is one of the duties of an occupational health physician, as stipulated in the Industrial Safety and Health Law in Japan. The data used in the analysis were obtained per the regulations. Thus, ethical approval for this project was not required, as with our previous project. The company allowed us to conduct and report on this project, and written consent was obtained from the company. The office of the Ethics Committee at the University of Tokyo confirmed that the research ethics guideline is not applicable to this project. We conducted this project under the authorization of the University of Tokyo (study ID: 2022002NIe).

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Conflict of interest: Y.H.S. is an occupational health physician at this workplace. K.K. is a part-time physician of the company. K.Y. has no financial relationship with this company.

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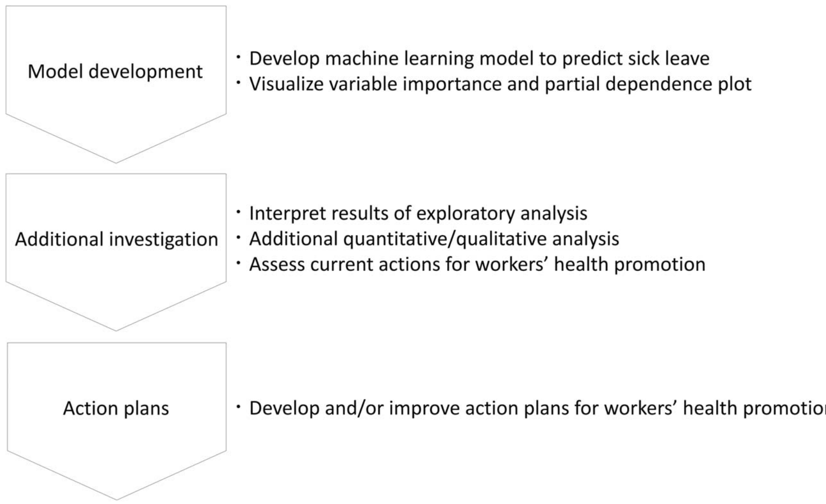

FIGURE 1. Flowchart of the project.

Japan for worksites with ≥50 employees from December 2015 according to the Stress Check Program as a national policy, and the employees complete the questionnaire annually.[24] We used scores from the three factors in the model development.

The periodic health examination in Japan includes questionnaires about lifestyles, physical measurements, laboratory blood tests (usually for employees aged ≥35 years), and urine tests.[25] Among the results, we used body mass index, systolic blood pressure, urine protein, alcohol consumption, and smoking status because they are reportedly relevant with sick leave[5,6,10] and were measured for all workers.

Outcome

The outcome was sick leave within a year from the measurement of the predictor variables. In this company, sick leave is defined as absence from work for at least 7 days owing to diseases diagnosed using the *International Statistical Classification of Diseases and Related Health Problems, 10th Revision*. The diagnosis information of medical certification was obtained from the company's occupational health management registers. We developed models for sick leave due to mental disorders and physical diseases, respectively.

Model Development

A random forest model was trained using data from April 2015 to October 2021. Three fourths and one fourth of the data were split into a training and test data set, respectively. Because the ratio of sick leave was low, which made for an imbalanced data set, we performed 1:4 random undersampling to train the model.[26] The hyperparameters were optimized by 5-fold cross-validation using the training data set with undersampling, with the area under the receiving operating characteristic curve (AUC) as an indicator for predictive accuracy. The AUC of the optimized model was quantified using the entire test data set. Thereafter, we developed the final model using all data with 1:4 random undersampling. The association between important variables, which were determined by variable importance based on the Gini index, and the incidence of sick leave was visualized through partial dependence plots.[19] All analyses were conducted using R version 4.1.1.

Additional Investigation and Proposing Action Plans

According to the partial dependence plots of the important variables in the prediction model, additional analyses, such as the cutoff determination for the BJSQ score and qualitative review for interview records of workers who took sick leave, were conducted as needed. On the basis of the analysis results and assessment, we developed action plans, examined the feasibility, and proposed the final plans.

Ethics Considerations and Authors' Roles

The data analysis in this project aimed to investigate the cause of workers' health problems, which is one of the duties of an occupational health physician, as stipulated in the Industrial Safety and Health Law in Japan. The data used in the analysis were obtained per the regulations. Thus, ethical approval for this project was not required,[27] as with our previous project.[17] The company allowed us to conduct and report on this project, and written consent was obtained from the company.

The office of the Ethics Committee at the University of Tokyo confirmed that the research ethics guideline is not applicable to this project. We conducted this project under the authorization of the University of Tokyo (study ID: 2022002NIe).

Y.H.S., an occupational health physician at the company, organized the project, anonymized the data, and developed the action plans. K.K., a part-time physician of the company, supported the project as commissioned work through data analysis and action plan development. K.Y. provided academic advice for data analysis and action plans with permission from the company.

RESULTS

Descriptive Statistics

A total of 11,386 records were available, which included 89 cases of sick leave due to mental disorders and 126 cases due to physical diseases. The 1:4 random undersampling led to using 445 records for the final model of mental disorders and 630 records for physical diseases. Table 1 shows the descriptive statistics for 445 records used in developing the final model for mental disorders.

Compared with the overall turnover rate, except for retirement, which was disclosed in the company's sustainability report, that of workers who took sick leave was 2 to 8 times higher overall and 7 to 17 times higher among those who took sick leave because of mental disorders.

Machine Learning Model

The model for predicting sick leave due to mental disorders achieved an AUC of 0.882 (95% confidence interval, 0.833 to 0.930), a sensitivity of 0.933, and a specificity of 0.705. At this

TABLE 1. Descriptive Statistics for Records Used in the Model Development

Continuous Variables	Mean (SD)
Age, years	40.3 (11.8)
Brief Job Stress Questionnaire scores	
Stress response	58.8 (16.8)
Stressor	42.1 (6.9)
Support	19.8 (5.6)
Body mass index, kg/m^2	23.7 (4.0)
Systolic blood pressure, mm Hg	121.0 (13.7)
Categorical Variables	**n (%)**
Sex	
Male	407 (91.5)
Female	38 (8.5)
Job position	
Managers	27 (6.1)
Senior white-collar	56 (12.6)
Junior white-collar	23 (5.2)
Senior blue-collar	102 (22.9)
Junior blue-collar	154 (34.6)
Temporal workers	83 (18.7)
Overtime hours/month	
0–20	221 (49.7)
21–45	143 (32.1)
>45	31 (6.9)
Not available	50 (11.2)
Urine protein	
Negative	352 (79.1)
Trace	82 (18.4)
≥1+	11 (2.4)
Smoking	
Current	165 (37.1)
Past	63 (14.2)
Never	201 (45.2)
Not available	16 (3.6)
Alcohol drinking	
Everyday	125 (28.1)
Sometimes	164 (36.9)
Rarely/none	142 (31.9)
Not available	14 (3.1)

The data for 445 records, created by random undersampling and used in the model development for sick leave owing to mental disorders, are described. Information on departments, worksites, and the original questionnaire about harassment (three items) are waived for the company's privacy protection.

workplace, the total BJSQ stress response scores, age, and departments of workers were important for prediction, in this order (Fig. 2). The partial dependence plots, shown in Figure 3, indicated that workers with higher BJSQ stress response scores, those who were younger, and those who worked in certain departments (ie, either in departments A, C, or F) were at a higher risk of sick leave.

The model for predicting sick leave due to physical diseases showed an AUC of 0.607 (95% confidence interval, 0.469 to 0.744). Body mass index was the most important variable, and workers who were overweight were at a high risk of sick leave. However, we did not develop plans based on this result owing to its relatively low predictive accuracy.

Additional Analysis for Score on Stress Response

The high-stress workers in the workplace had been defined using the cutoff generally recommended in the Stress Check Program manual by the Ministry of Health, Labor and Welfare in Japan. The manual defines high stress as (a) a stress response score ≥ 77 or (b) a stress response score ≥ 63, together with the sum of stressors and support score ≥ 76.[18] However, this definition showed a sensitivity of 0.36 and a specificity of 0.88 (ie, Youden index of 0.24) for sick leave due to mental disorders at this workplace.

To determine the appropriate cutoff to detect high-risk workers for sick leave due to mental disorders, we conducted a receiver operating characteristic curve analysis of the BJSQ stress response scores. A score of 66 maximized the Youden index in the receiver operating characteristic curve, achieving a sensitivity of 0.65 and a specificity of 0.75 (ie, Youden index of 0.40). Furthermore, a receiver operating characteristic analysis for workers with a score ≥ 66 showed that a score of 82 maximized the Youden index among them.

Additional Analysis for Younger Workers

To examine stressors among young workers who took sick leave because of mental disorders, we reviewed their records of interviews with physicians at this workplace. Diagnoses, medical histories, family histories, social histories, stressors in the workplace, and stressors outside the workplace were collected. The review revealed that (1) 60% of these workers implied factors outside the workplace or had no apparent association with stressors in the workplace, (2) 30% had problems with their supervisors, and (3) 30% had problems in their work environment.

DISCUSSION

Summary of the Machine Learning Analysis

Using real-world data from the workplace, we developed a machine learning model to predict sick leave. The model achieved sufficient predictive accuracy and showed that higher scores on the BJSQ stress response, younger age, and certain departments were important predictors for sick leave due to mental disorders. Here, we introduce and discuss the action plans according to these results.

Interpretation and Plans for Workers With a High Score on Stress Response

The higher risk of sick leave due to mental disorders among workers with higher scores on the BJSQ stress response was consistent with the previous study by Tsutsumi et al.[18] Interventions for the screened high-risk workers reportedly reduce the incidence of sick leave due to mental disorders and improve workers' stress symptoms and presenteeism.[11–13] According to the results and evidence, we planned to use the results of stress response scores on BJSQ more effectively (Table 2).

First, using the result from the additional analysis, we planned to define moderate-stress workers as those with a score ≥ 66 on the BJSQ stress response and severe-stress workers as those with a score ≥ 82. This would efficiently detect workers with a high risk of sick leave due to mental disorders.

Next, the feedback document of the BJSQ used in the company includes no information on the risk of sick leave due to mental disorders. In addition, the self-care information in this document seems insufficient. Thus, we planned to revise the document by including (a) an explanation of the risk of sick leave using the new definition of moderate/severe-stress workers; (b) a recommendation for consultation service by an occupational health physician, nurses, and Employee Assistant Program (EAP); and (c) sufficient self-care information such as stress coping.

Finally, at this workplace, few high-stress workers reached face-to-face guidance by an occupational health physician, which is stipulated in the regulation.[24] They are required to share the BJSQ results with the employer when applying the face-to-face guidance to enable the employer to improve the workload, working conditions, and work environment under the regulation. However, this requirement seemed to cause the fear of stigma. Thus, we proposed (a) explaining the

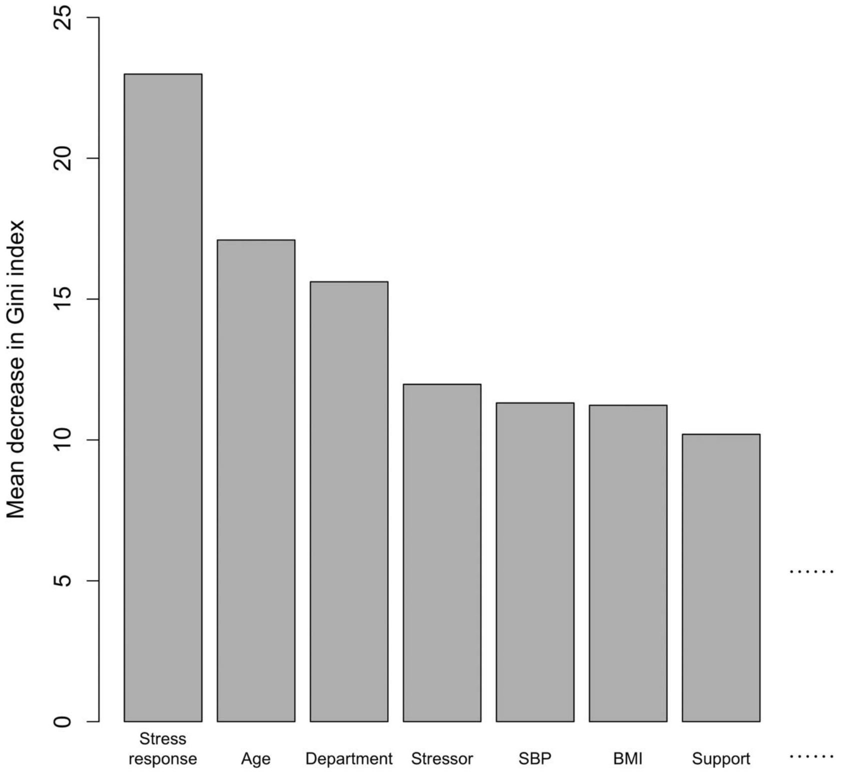

FIGURE 2. Variable importance in the machine learning model to predict sick leave due to mental disorders. Only the top important variables in the model are visualized. Stress response, stressor, and support correspond to the total score from the Brief Job Stress Questionnaire. BMI, body mass index; SBP, systolic blood pressure.

confidentiality, objective, and person to share the results when recommending the face-to-face guidance and (b) informing alternative options of the consultation service without the requirement for sharing the results, such as referral to occupational health physician, nurses, and the EAP.

Interpretation and Plans for Younger Workers

The higher risk of sick leave due to mental disorders among younger workers was consistent with the findings of a previous study.[28] The onset of mental disorders, such as adjustment disorders and major depressive diseases, can be triggered by psychosocial environments.[29,30] This could explain the higher risk among younger workers because they tend to experience substantial changes, such as the transition from education to employment. In addition, survivorship bias between younger and older workers, known as the healthy worker effect,[31] could also explain this result. Previous reports suggest that occupational stress affects the mental health of younger workers,[32] and support for cognitive and social skills among these workers is beneficial for their mental health.[33]

The additional qualitative analysis revealed that factors outside the workplace and problems with supervisors and work environments

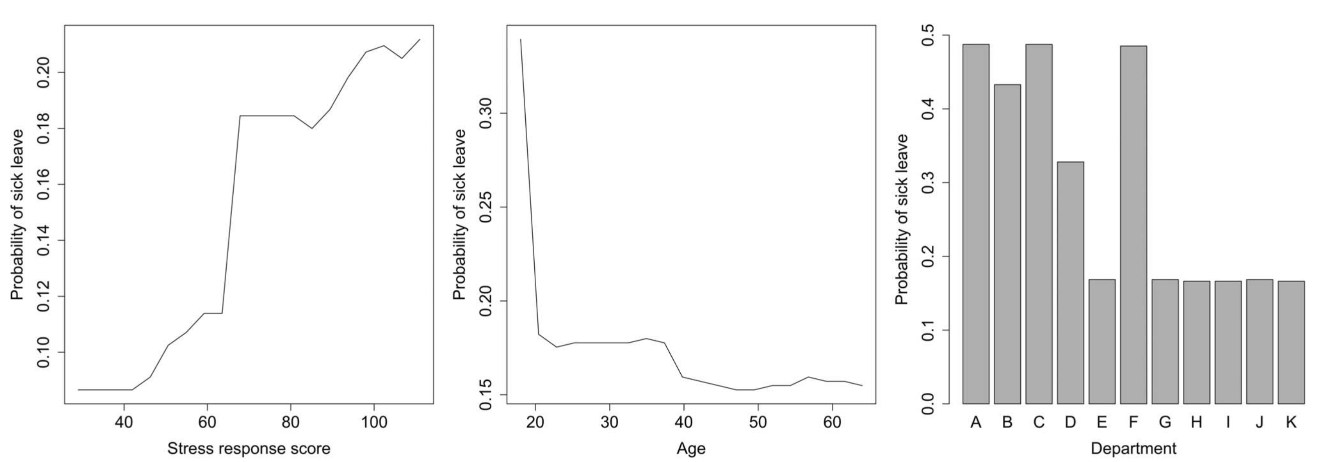

FIGURE 3. Partial dependence plots for important variables in the machine learning model to predict sick leaves due to mental disorders. The probability of sick leave on the *y* axis, which was generated by the model developed using 1:4 random undersampling, is not equal to the actual probability in the data.

TABLE 2. Summary of Action Plans Corresponding to the Results of the Analysis

Risk Factors	Proposal
Higher scores on the Brief Job Stress Questionnaire stress response	Redefinition of high-stress workers based on the receiver operating characteristic analysis
	Revising feedback documents
	Promoting consultation with occupational health physicians, nurses, and Employee Assistant Program
Younger workers	Increasing awareness of the Employee Assistant Program
	Training supervisors to learn appropriate management skills and leadership
	Promoting the participation of young workers to establish a productive and healthy work environment and organization
	Collaborating with the Personnel Administration section and the Safety and Health section
Certain departments	Recommending personalized actions for each manager and supervisor of the department
	Providing support by occupational health staff

were prevalent among younger workers. Thus, we proposed (1) increasing young workers' awareness of the EAP to obtain support to deal with stressors outside the workplace,[34] (2) training supervisors to learn appropriate management skills and leadership, (3) promoting the participation of young workers to establish a productive and healthy work environment and organization, and (4) supporting the Personnel Administration section and the Safety and Health section to implement several actions, such as the participatory workplace improvement program and the EAP referral for young employees (Table 2).

Interpretation and Plans for the Heterogeneity Between Departments

Several workplaces had a high risk of sick leave due to mental disorders. A systematic review indicated that an organizationally focused job-stress intervention was beneficial at both individual and organizational levels.[35] In addition, psychosocial work environment improvement based on organizational analysis of the BJSQ results reportedly reduces workers' stress.[36]

At this workplace, the organizational analysis reports of the BJSQ for managers and supervisors contained no specific action plans optimized for each department, which could inhibit autonomic improvement activities. We therefore proposed (1) recommending personalized actions for each manager and supervisor through the organizational analysis report and (2) providing support by occupational health staff to implement the recommended actions, especially for the high-risk departments (Table 2). We planned to use action checklists developed in previous studies for this recommendation.[37,38] These include dozens of organizational actions for workers' mental health promotion developed based on interviews in Japanese companies and the KJ method among experts.

Discussion With Stakeholders

We shared the results from analyses with senior managers and the chief of the Safety and Health section and received feedback that the results were relevant to their needs and concerns. The action plans were also shared with the senior managers and the chief of the Safety and Health section, concluding that all of them were feasible and matched the cultural context of this plant. These favorable feedbacks would be attributable to the active participation of stakeholders from planning the analysis to developing action plans. As with our previous project,[17] this experience suggests the importance of collaboration with stakeholders.

We decided to hold regular meetings to implement the action plans. At the first meeting, we established the strategy for mental health promotion with the safety and health staff and occupational health nurses. Moreover, we will ensure the worker's participation in implementing these action plans through collaboration with the labor union and the joint health and committee in the workplace.

Implications From This Project

This project exemplified an application of machine learning analysis to occupational health practice. The random forest model allowed us to obtain the relative importance of variables, thereby enabling us to prioritize countermeasures. Furthermore, the model revealed a nonlinear association between the BJSQ stress response score and the incidence of sick leave, as shown in Figure 3. Such ability to analyze nonlinear relations was beneficial because the model can be developed without a requirement for a cutoff for the BJSQ scores. This allowed us to overcome the limitation of our previous project, which revealed no significant odds ratio of high stress defined using the cutoff generally recommended by the Stress Check Program manual.[17]

Notably, although the BJSQ also calculates scores for stressors and support,[24] these were less important than stress response scores, age, and department. The results implied that we should focus more on these important factors than the stressor, although stressors are generally an important factor for sick leave.[39] This result may partially support our hypothesis that analyzing real-world data within a specific workplace is important for developing countermeasures.

Limitations

There are some limitations to this project. First, we applied only the random forest model to the data because the model, which we trained first, achieved sufficient predictive accuracy; however, other machine learning algorithms, such as gradient boosting decision tree, might have achieved higher accuracy. Second, the transferability of this project to smaller workplaces was uncertain because machine learning algorithms usually require a sufficient sample size to train the model. Conducting analyses aimed at hypothesis verification using a propensity score to reduce the number of variables may be an option.[40] In addition, using outcomes other than sick leave, such as productivity, work capacity, and presenteeism,[41] may also overcome the sample size limitation. Third, the model for physical diseases showed a low predictive accuracy, which may be because sick leaves due to physical diseases were analyzed together. Stratified analysis for types of physical diseases should be conducted after more data are accumulated. Regardless of this limitation, the analysis showed a high risk among workers who were overweight, consistent with the findings of previous studies,[5,6] and suggested a need for intervention for them. Finally, this report only comprised the analysis and plan proposal. Thus, the implementation process has not yet been completed, and the effectiveness of the project remains unclear. However, effectiveness could be expected for this project, in which the data analysis has been improved compared with our previous project, which seemed to reduce the number of sick leaves owing to mental disorders.[17]

CONCLUSIONS

Action plan development based on machine learning analysis may be useful for occupational health practice. However, the project's effectiveness and implementation process remain unclear, and further investigation is warranted. In addition, a further project needs to be held in other workplaces to verify the transferability of this process.

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