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Diagnostic model for preschool workers' unwillingness to continue working

Developed using machine-learning techniques

Moemi Matsuo, PhD[a], Koutarou Matsumoto, PhD[b,*], Misako Higashijima, PhD[a], Susumu Shirabe, PhD[c], Goro Tanaka, PhD[d,e], Yuri Yoshida, PhD[e,f], Toshio Higashi, PhD[d], Hiroya Miyabara, PhD[a], Youhei Komatsu, PhD[a], Ryoichiro Iwanaga, PhD[d,e]

Abstract

The turnover of kindergarten teachers has drastically increased in the past 10 years. Reducing the turnover rates among preschool workers has become an important issue worldwide. Parents have avoided enrolling children in preschools due to insufficient care, which affects their ability to work. Therefore, this study developed a diagnostic model to understand preschool workers' unwillingness to continue working. A total of 1002 full-time preschool workers were divided into 2 groups. Predictors were drawn from general questionnaires, including those for mental health. We compared 3 algorithms: the least absolute shrinkage and selection operator, eXtreme Gradient Boosting, and logistic regression. Additionally, the SHapley Additive exPlanation was used to visualize the relationship between years of work experience and intention to continue working. The logistic regression model was adopted as the diagnostic model, and the predictors were "not living with children," "human relation problems with boss," "high risk of mental distress," and "work experience." The developed risk score and the optimal cutoff value were 14 points. By using the diagnostic model to determine workers' unwillingness to continue working, supervisors can intervene with workers who are experiencing difficulties at work and can help resolve their problems.

Abbreviations: AUROC = area under the receiver operating characteristic curve, K6 = Kessler Psychological distress scale, LASSO = least absolute shrinkage and selection operator regression, LR = logistic regression, ML = machine-learning, SHAP = SHapley additive exPlanations, XGBoost = eXtreme gradient boosting.

Keywords: diagnostic model, machine-learning (ML), mental health, turnover, work environment

1. Introduction

"Teacher turnover" is an umbrella term that refers to teachers who leave the teaching profession or move to another school.[1] In the past decades, a dramatic increase has been noted in the proportion of kindergarten teachers leaving the profession or transferring to other schools. The estimated cost of teacher turnover in public schools is over $7.3 billion a year in the US.[2] The importance of reducing turnover rate among preschool workers is increasing in developed countries,[3,4] including in East Asia.[5] For instance, Japan has been experiencing a shortage of kindergarten teachers.[6] Therefore, kindergartens provide insufficient childcare, causing parents to avoid enrolling their children. This situation may affect parents' ability to work.

A study suggested that "older age," "living with a spouse," "responsibilities related to care of younger children at work," "better mental health," and "higher work engagement" were significantly associated with a higher willingness to continue working.[7] It is believed that welfare benefits, individual support systems, balanced work conditions, and workers' high agreement with workplace childcare/education policies may be associated with reduced turnover.[7] Moreover, other studies suggest that early childhood teachers who are willing to continue working for >5 years provide significantly higher quality programs than those who are not willing to work for that length of time.[8] Taken together, empirical research has thus identified some key factors associated with reduced turnover (e.g., welfare benefits, individual support systems, balanced work conditions, and workers' high agreement with workplace

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[a] Faculty of Rehabilitation Sciences, Nishi Kyushu University, Kanzaki, Saga, Japan, [b] Biostatistics Center, Kurume University, Kurume, Fukuoka, Japan, [c] National Research Center for the Control and Prevention of Infectious Diseases Nagasaki University, Nagasaki, Japan, [d] Unit of Medical Science, Nagasaki University Graduate School of Biomedical Sciences, Nagasaki, Japan, [e] Center for Child Mental Health Care and Education, Nagasaki University, Nagasaki, Japan, [f] Faculty of Education, Nagasaki University, Nagasaki, Japan.

* Correspondence: Koutarou Matsumoto, Biostatistics Center, Kurume University, 67 Asahimachi, Kurume, Fukuoka 830-0011, Japan (e-mail: matsumoto_koutarou@kurume-u.ac.jp).

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childcare/education policies). However, a diagnostic model that calculates turnover rates is yet to be formulated. Therefore, this study develops a diagnostic model to analyze the unwillingness to continue working among preschool workers using machine-learning (ML) models. The models developed using ML techniques can be expected to predict turnover with a high degree of accuracy. The findings will help preschool administrations develop retention and replacement strategies by accurately diagnosing unwillingness to continue working in their faculty members.

2. Methodology

2.1. Study design

This was a cross-sectional study. The participants were recruited from several kindergartens (14 public kindergartens and 32 private kindergartens), authorized childcare institutions (8 public authorized childcare institutions and 44 private authorized childcare institutions), nursery centers (22 public nursery centers and 13 private nursery centers) across Nagasaki, Omura, and Goto in Japan. We developed the diagnostic models in accordance with the Transparent Reporting of a multivariable diagnostic model for Individual Prognosis or Diagnosis statement.

2.2. Participants

A total of 5415 questionnaires were sent to preschool workers in 2018, and 2304 (43%) of the distributed questionnaires were returned. Of these, 773 questionnaires with part-timers, 185 with those in managerial positions, and 344 with no response to the item about their willingness to continue working were excluded. From the rest of 1002 questionnaires, a total of 451 questionnaires with missing data were excluded for analysis (Fig. 1), and the remaining 551 questionnaires were used to develop the diagnostic model.

The participants provided informed consent in their workplaces. The study was approved by the Ethics Committee of Nishi Kyushu University (approval No. 21VDV15) and complied with the Declaration of Helsinki.

2.3. Outcome

Unwillingness to continue working was defined as the main outcome variable. The original questionnaire was used to measure the outcome (i.e., willing to continue working for ≥5 years or willing to continue working for <5 years).

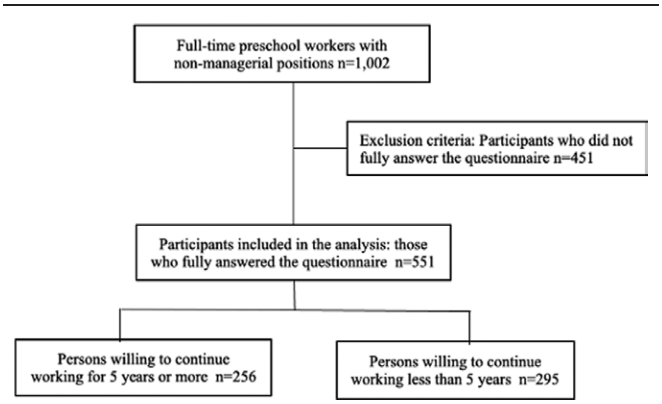

Figure 1. Flow chart of the research. The 551 participants who met the research criteria were divided into 2 groups. The first group included workers who were willing to continue working for ≥5 years, and the second group included those who were willing to continue working for <5 years.

Consequently, the participants were divided into 2 groups: those willing to continue working for ≥5 years and those willing to continue working for <5 years. All questionnaire responses were self-reported, anonymous, and returned in sealed envelopes. The questionnaire took approximately 10 minutes to complete.

2.4. Predictors

2.4.1. Demographic questionnaire. A general questionnaire was administered, which comprised 13 sections: gender, age, family environment, educational background, work experience, main responsibilities at work, type of workplace, current annual salary, desired salary, sum of overtime work for the last 30 days, sources of human relations problems, distressing aspects of childcare, and willingness to continue working in the present position for ≥5 years. Table 1 reports the comparative data from this questionnaire between participants of the 2 aforementioned groups.

2.4.2. Mental health. The Kessler Psychological Distress Scale (K6) was used to assess the mental health of preschool workers. The scale has been employed in annual government health surveys in the US, Canada, and the World Health Organization World Mental Health Surveys.[9] The scale assesses the frequency of experiencing psychological distress over a period of 30 days using 6 items. Participants responded to the items on a 5-point Likert scale (0 = not at all, 1 = rarely, 2 = sometimes, 3 = often, 4 = always). High K6 scores indicate a high level of psychological distress. The participants were categorized into 2 groups based on their scores: K6 < 13 or K6 ≥ 13. Scores in the K6 ≥ 13 category indicated that the participants frequently faced psychological distress.

2.4.3. Missing data. The rates of missing values for each variable used in the diagnostic model are shown in Table S1, Supplemental Digital Content, http://links.lww.com/MD/I316. The highest proportion of missing data was for the item assessing the sum of overtime work for the last 30 days, with 2 response options: overtime hours at the workplace (missing data n = 264) and overtime hours at home (n = 294). In the sensitivity analysis, to confirm the effect of the exclusion of missing values on the diagnosis results, we developed a diagnostic model by excluding variables with many missing values from the questionnaire. A flow chart of participant selection is shown in Figure S1, Supplemental Digital Content, http://links.lww.com/MD/I310.

2.5. Statistical analysis

We compared differences in the baseline variables using the χ^2 test, Fisher exact test, or Mann–Whitney *U* test, as appropriate. To develop the diagnostic model, we compared the diagnostic performance of 3 algorithms: 1 logistic model and 2 ML models. For the logistic model, variable selection was done using the backward method using Akaike Information Criterion. For the 2 ML models, we used the regularization method (the least absolute shrinkage and selection operator regression model)[10] and the ensemble decision tree model (eXtreme Gradient Boosting [XGBoost]).[11] Details of the ML programs are shown in the supplementary material, (see Supplementary Data – R programs, Supplemental Digital Content, http://links.lww.com/MD/I319, which explain the contents of the R-program).

The discriminating ability of each model was assessed by the area under the receiver operating characteristic curve (AUROC), sensitivity, and specificity. The calibration performance of each model was assessed using the calibration plot. We performed a stratified 5-fold cross-validation for internal validation (Figure S2, Supplemental Digital Content, http://links.lww.com/MD/I311).

Table 1

Comparison of variables between workers' willingness to continue working for ≥5 years and <5 years.

Variables	Willingness to continue working for ≥5 yr n = 256	Willingness to continue working for <5 yr n = 295	*P* value
Gender, n (%)			
Female	251 (98)	290 (98)	1.00
Male	5 (2)	5 (2)	
Age (in yr), n (%)			
20–29	85 (33)	191 (65)	<.01*
30–39	62 (24)	66 (22)	
40–49	57 (22)	22 (7)	
>50	52 (20)	16 (5)	
Family environment, n (%)			
Living alone/Transfer without family	43 (17)	35 (2)	.13
Living with a spouse	109 (43)	52 (18)	<.01*
Living with children	108 (42)	38 (13)	<.01*
Living with parent	91 (36)	193 (65)	<.01*
Living with spouse's parent	9 (4)	7 (2)	.59
Living with brother/sister	36 (14)	71 (24)	<.01*
Living with others	17 (7)	18 (6)	.93
Educational background, n (%)			
Lower than bachelor's degree	191 (75)	174 (59)	<.01*
Bachelor's degree/or higher	65 (25)	121 (41)	
Work experience (yr)	12 (4–22)	5 (2–10)	<.01*
Main responsibilities at work, n (%)			
0–2 yr old childcare or other	134 (52)	92 (31)	<.01*
3–5 yr old childcare or education	122 (48)	203 (69)	
Type of workplace, n (%)			
Kindergarten	46 (18)	74 (25)	<.01*
Authorized childcare institution	52 (20)	84 (28)	
Nursery center	156 (61)	129 (44)	
Others	2 (1)	8 (3)	
Mental health			
K6 < 13, n (%)	235 (92)	220 (75)	<.01*
K6 ≥ 13, n (%)	21 (8)	75 (25)	
Current annual salary			
<2 million yen	33 (13)	64 (22)	<.01*
2 million yen–3 million yen	106 (41)	170 (58)	
3 million yen–4 million yen	81 (32)	54 (18)	
4 million yen–5 million yen	26 (10)	4 (1)	
≤5 million yen	10 (4)	3 (1)	
Desired salary			
<2 million yen	4 (2)	7 (2)	<.01*
2 million yen–3 million yen	44 (17)	76 (26)	
3 million yen–4 million yen	89 (35)	124 (42)	
4 million yen–5 million yen	78 (30)	65 (22)	
≤5 million yen	41 (16)	23 (8)	
Sum of overtime work for the last 30 d			
At workplace (h)	10 (3–20)	15 (8–40)	<.01*
At home (h)	6 (2–20)	10 (3–30)	.02*
Cause of human relation problems, n (%)			
Boss	51 (20)	137 (46)	<.01*
Colleagues	71 (28)	88 (30)	.65
Subordinates	20 (8)	26 (9)	.79
Guardians	70 (27)	79 (27)	.96
Children	22 (9)	47 (16)	.01*
Others	7 (3)	1 (0)	.03*
Distressing aspects of childcare, n (%)			
Nothing	71 (28)	54 (18)	.01*
Children's behavioral problems	97 (38)	136 (46)	.06
Children's human relations problems	32 (13)	71 (24)	<.01*
Children's emotional breakdowns	68 (27)	95 (32)	.18
Governance of whole classes	32 (13)	58 (20)	.03*

Data are expressed as median (interquartile range), or number (%).

K6 = Kessler Screening Scale for Psychological Distress.

**P* < .05, χ^2 test or Mann–Whitney *U* test or Fisher exact test.

In addition, we used the SHapley Additive exPlanations (SHAP), interpretability method of ML, to visualize the relationship between years of work experience and willingness to continue working, as "work experience" was not an important predictor in the logistic regression (LR) model but was in the XGBoost model. SHAP is an excellent method for visualizing the contribution of predictors by applying Shapley values, which are guaranteed to be fairly distributed in cooperative game theory.[12] The XGBoost model was used to calculate the SHAP values.

The variable importance of ML models, the variables selected by backward method of the LR model, and the results of SHAP were used to narrow down the predictors for the final diagnostic model (Figure S3, Supplemental Digital Content, http://links.lww.com/MD/I312). Finally, the model was developed using an LR model and scored based on the standardized regression coefficients.

Two-sided *P* values <.05 were considered statistically significant. All statistical analyses were performed using the R statistical software (Version 4.1.0).

3. Results

3.1. Participants and baseline variables

The data of 551 analysis subjects were used to develop the diagnostic model. In total, 256 participants reported being willing to work for ≥5 years. Among these, 251 were women and 5 were men; 33%, 24%, 22%, and 20% were in their 20s, 30s, 40s, and >50, respectively. Meanwhile, 295 participants reported being willing to continue working for <5 years (290 women and 5 men; 65%, 22%, 7%, and 5% were in their 20s, 30s, 40s, and >50, respectively). First, we investigated the differences between the 2 groups in terms of baseline variables. As shown in Table 1, the 2 groups significantly differed on several variables, such as age and family environment. Moreover, the variable scores of the included and excluded participants were also compared; the values for 15 variables were significantly different ($P < .01$–$< .05$; Table S2, Supplemental Digital Content, http://links.lww.com/MD/I317).

3.2. Discrimination and calibration of each diagnostic model

We evaluated AUROCs in diagnosing unwillingness to work through ML models using least absolute shrinkage and selection operator regression or XGBoost, and the LR model with all available data. The ML models demonstrated a higher AUROC than LR, albeit by a small margin (Table 2 and Fig. 2). Regarding the calibration of each model, we plotted observed probability against diagnosed probability for the outcome. Calibration plots showed general concordance with some exceptions between diagnosed and observed probabilities in all the models (Figure S4, Supplemental Digital Content, http://links.lww.com/MD/I313). In the sensitivity analysis, the discrimination and calibration performances were also evaluated in the same manner; the results were similar to the main analysis (Table S3, Supplemental Digital Content, http://links.lww.com/MD/I318 and Figure S5, Supplemental Digital Content, http://links.lww.com/MD/I314).

3.3. Predictors for the outcome

Thereafter, we evaluated the predictors that contributed to the diagnosis within each of the diagnostic models (Fig. 3). The variables "human relation problems with boss," "not living with children," and "mental health; K6 ≥ 13" were identified as important predictors across all diagnostic models. "Work experience" was identified as an important predictor in the ML models but not in the LR model. Similar results were obtained in the sensitivity analysis (Figure S6, Supplemental Digital Content, http://links.lww.com/MD/I315).

3.4. Visualization using SHAP

We further performed SHAP analysis, as "work experience" was an important predictor in the XGBoost model. Although the risk of unwillingness to continue working was low among newly employed participants, the risk increased from the first to the tenth year in the job. Furthermore, the risk of unwillingness to continue working decreased after the tenth year of employment and saturated after the twentieth (Fig. 4).

3.5. Developing the final model

We developed 3 LR models by referring to the important variables identified in the ML models and the variables selected in the backward method of the LR model and SHAP analysis. Model 1 employed the 3 variables "human relation problems with boss," "not living with children," and "mental health; K6 ≥ 13," which were identified as important predictors in all the diagnostic models. Models 2 and 3 added "work experience"

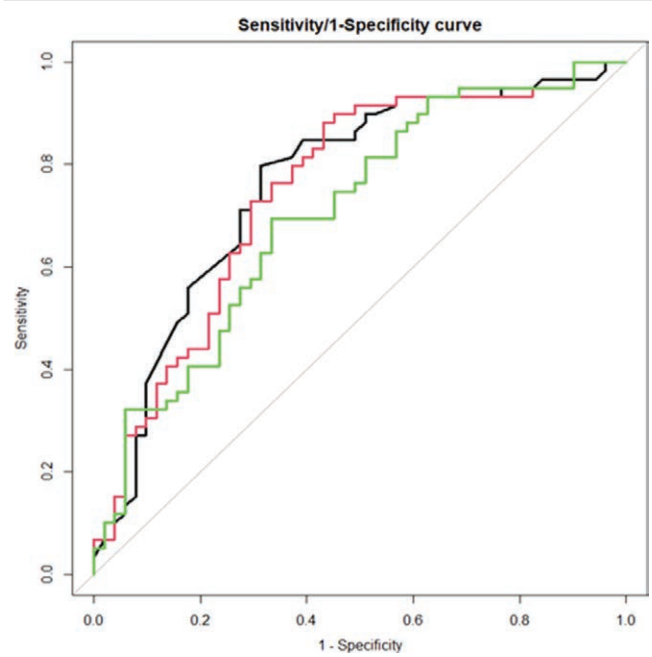

Figure 2. Sensitivity/1-specificity curve. The ROC curves for the 3 diagnostic models are shown. The black curve indicates the result of XGBoost. The red curve indicates the result of LASSO. The green curve indicates the result of LR. AUROC = the receiver operating characteristic (ROC) curve, LASSO = least absolute shrinkage and selection operator regression, LR = logistic regression, SHAP = SHapley Additive exPlanations, XGBoost = eXtreme Gradient Boosting.

Table 2

Discriminative ability of diagnostic models.

	AUROC	Sensitivity	Specificity
LR model	.755 ± .042	.705 ± .076	.719 ± .084
LASSO model	.760 ± .038	.770 ± .088	.683 ± .076
XGBoost model	.769 ± .033	.793 ± .094	.679 ± .158

The mean and standard deviation of each metric after stratified 5-fold cross-validation are shown.

AUROC = area under the receiver operating characteristic curve, LASSO = least absolute shrinkage and selection operator regression, LR = logistic regression, XGBoost = eXtreme Gradient Boosting.

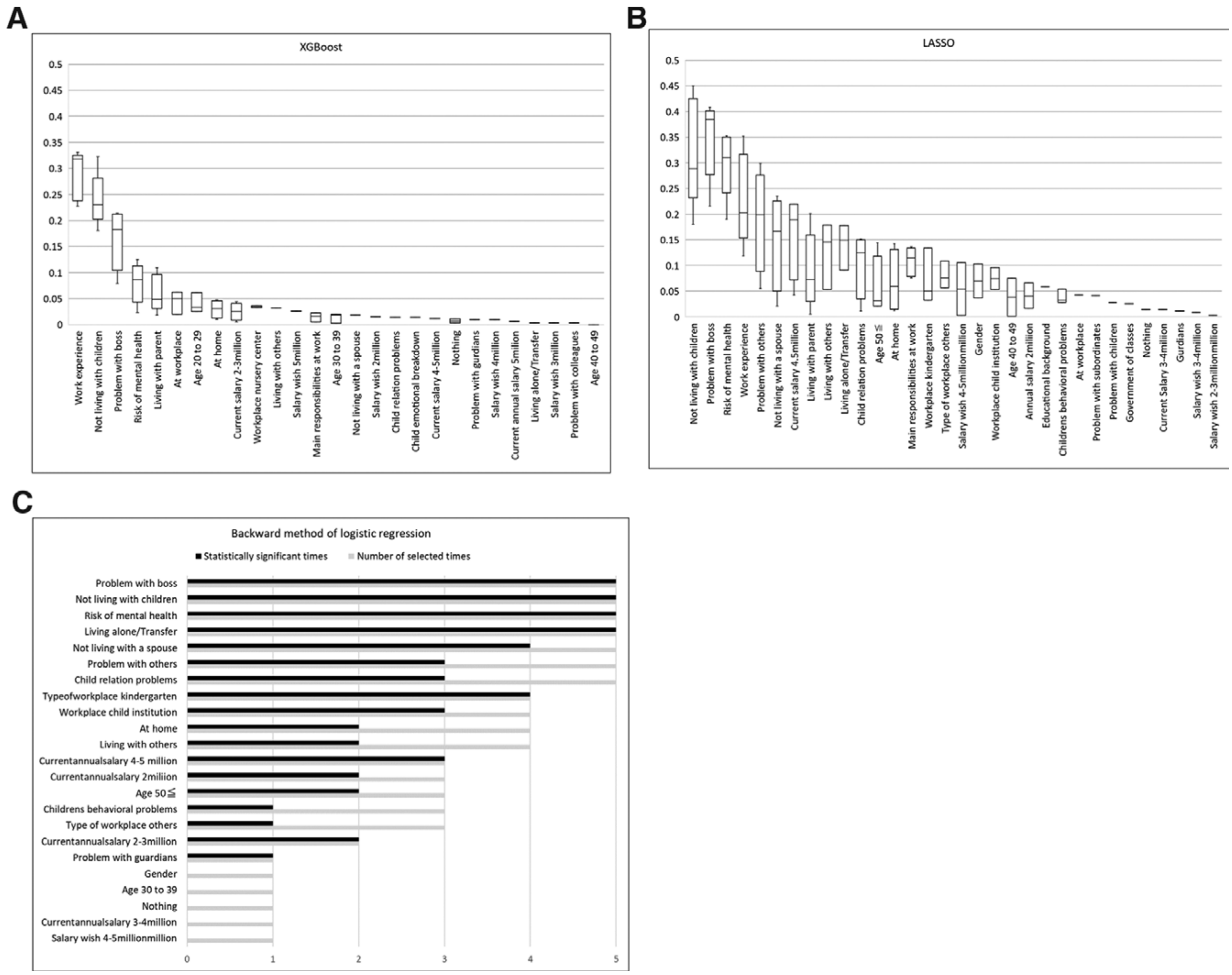

Figure 3. Variable importance of each diagnostic model. (A) Indicating variable importance by XGBoost. (B) Indicating variable importance by LASSO. (c) Indicating the number of times the predictors were selected and significant in the backward method of LR. LASSO = least absolute shrinkage and selection operator regression, LR = logistic regression, XGBoost = eXtreme Gradient Boosting.

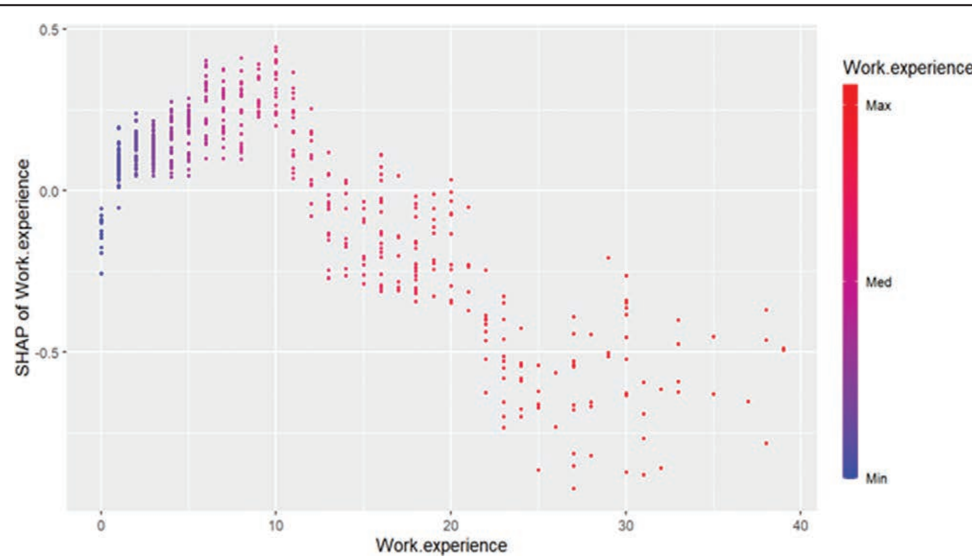

Figure 4. SHAP dependence plot for willingness to continue working and work experience. Each dot is a person. The x-axis is their work experience, and the y-axis is the SHAP value attributed to their work experience. Higher SHAP values represent higher risk of unwillingness to continue working due to work experience. SHAP = SHapley Additive exPlanations.

to the above 3 predictors, with Model 3 further classifying the value of "work experience" by referring to the SHAP analysis results. The discrimination performance of Model 3 was the best among the 3 LR models (Table 3).

Finally, we developed a risk score, referring to the standardized partial regression coefficients of Model 3 (Table 4). ROC analysis (Youden index method) was performed using the developed risk score and the optimal cutoff value was 14 points (Fig. 5).

4. Discussion

This study developed a diagnostic model to analyze the unwillingness to continue working among preschool workers. The major findings of this study were as follows. All the diagnostic models showed generally good discrimination and calibration performance. The ML diagnostic models performed better than the LR model; however, the difference was not much. SHAP analysis using the XGBoost model revealed a non-linear relationship between work experience and unwillingness to continue working. Thereafter, a risk score was developed using an LR model after adding categorized job experience, considering its non-linear relationship as a predictor. In addition, similar predictive performance and factors were observed in the sensitivity analysis, suggesting that the influence of bias due to missing data is low.

Although models that diagnose unwillingness to continue working have been developed,[13–15] and some counterplans were suggested,[16] diagnostic models using ML have not. For the first time in our study, we used ML to develop a model to diagnose the unwillingness to continue working in preschool workers. However, contrary to our intention, we were unable to develop high-performing models; furthermore, there were minimal differences in the performance of the ML models compared to the LR model. The XGBoost model, which we expected to have a particularly high diagnostic performance, is a type of decision tree ensemble model that has desirable features, such as the ability to automatically handle non-linear relationships and interactions and missing values as they are. However, due to internal processing complexities, overfitting may occur when the number of data or events is small. Therefore, we focused on the advantage of capturing the non-linear relationship of the decision tree ensemble learning models (XGBoost, etc.) and visualized it using the SHAP method. Consequently, we found a non-linear relationship between job experience and high turnover intentions. Nevertheless, an LR model has become the gold standard for calculating risk scores because of its ease of interpretation and good diagnosis performance. In the future, this new method of calculating risk scores, which combines the advantages of ML methods with previously used methods, is expected to become the gold standard.

Multiple previous studies have discussed the predictors associated with the willingness to continue working. In some studies, the importance of psychological predictors such as mental health and human relations have been suggested.[5,17] In addition, the importance of work conditions such as salary and workload have also been suggested.[13,18,19] In this study, "not living with children," "human relation problems with boss," and "high risk of mental distress" were important predictors of unwillingness to continue working, whereas the variables of "gender," "age,"

Table 4

Standardized regression coefficients for the final LR model and risk score points.

Characteristic	Standardized regression coefficients	Score
Not living with children	.576	6
K6 ≥ 13	.465	5
Human relation problems with boss	.427	4
>20 yr of work experience	Reference	0
11–20 yr of work experience	.519	5
2–10 yr of work experience	.876	9
0–1 yr of work experience	.45	5
Total		34

Risk scores were generated by multiplying the standardized regression coefficient by 10 and rounding.
K6 = Kessler Screening Scale for Psychological Distress score, LR = logistic regression.

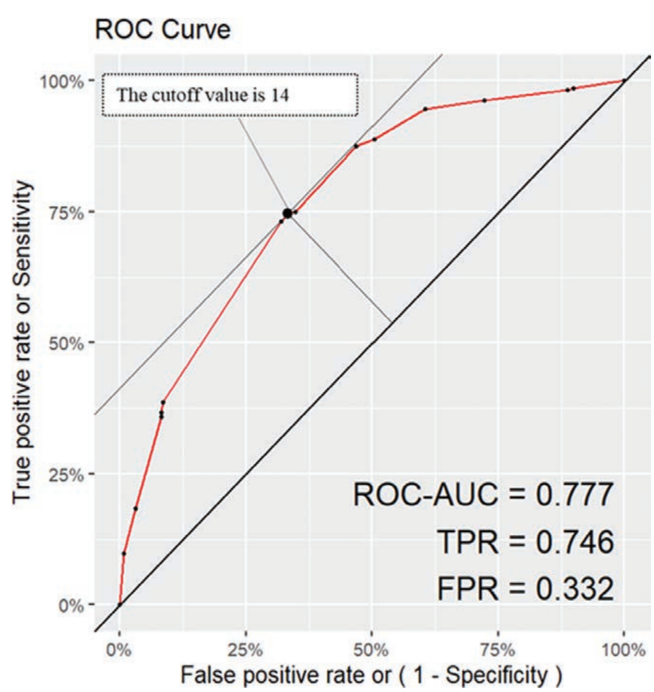

Figure 5. ROC curve and cut-off value for risk score. The results of the ROC curve for the risk score are shown. The optimal cutoff value using the Youden index method was 14 points. ROC = receiver operating characteristic.

Table 3

Discriminative ability of LR models built with variables of high importance.

	AUROC	Sensitivity		Specificity
LR Model 1	.741 ± .029	.685 ± .196	.700 ± .226	
LR Model 2	.763 ± .054	.851 ± .089	.599 ± .161	
LR Model 3	.774 ± .050	.790 ± .121	.654 ± .190	
LR Model 3	.774 ± .050	.790 ± .121		.654 ± .190

Model 1: not living with children, K6 ≥ 13, human relation problems with boss. Model 2: Model 1 + years of work experience. Model 3: Model 2 + categorized years of work experience; the mean and standard deviation of each metric after stratified 5-fold cross-validation are shown.
AUROC = area under the receiver operating characteristic curve, LR = logistic regression.

"educational background," "main responsibilities at work," "type of workplace," and "salary" were not significantly correlated with willingness to continue working. Additionally, similar to Tayama et al,[6] we found that "work experience" also influenced unwillingness to continue working.

Generally, it is difficult for workers with children to leave the workforce, as they need the financial resources to meet their child-rearing responsibilities. Although many teachers report that one of the challenges to continuing working involves taking care of their own children, the current study suggests that workers without children are more likely to leave work. In recent years, gender equality has been promoted and employers are focused on supporting workers with children by providing family-friendly work conditions. Such work conditions could increase workers' satisfaction levels.[9,18] Conversely, under these work conditions, workers without children must work harder to make up for the absence of workers on maternal or paternal leave, with the same reward conditions (i.e., salary) in Japan. This may lead to increasing dissatisfaction among workers without children. These findings suggest that we should pay more attention to the actual reasons that workers without children are unwilling to continue working.

Studies have reported that human relation problems and difficulty caring for children were associated with a high risk of mental health issues among preschool workers,[8] whereas healthy interpersonal relationships can improve mental health.[20,21] Thus, better human relations may relate to better mental health. Moreover, programs such as relationship counseling could positively impact teachers' mental health.[20,21]

A cross-sectional study suggested that better mental health was significantly associated with a higher willingness to continue working.[22] Higher job satisfaction positively affects mental health, and higher job satisfaction and work engagement have been shown to lower turnover rates.[4,23–26] Another study suggested that better implementation of stress management plans by the government could have a beneficial impact on the broader psychosocial needs of workers.[27]

Although workers with more work experience have less role stress and are more satisfied,[28] the importance of work experience has not been discussed thoroughly in the literature. We found that the risk of unwillingness to continue working was low among newer employees; however, it increased from the first year to the tenth year in the job. Notably, the risk of unwillingness to continue working decreased after the tenth year of employment and saturated after the twentieth. These findings could reflect various aspects of workers' motivation; for instance, new employees have high motivation to work, but, over the years, they begin to face problems. Then, around the tenth year of employment, workers' motivation might change, especially if they get married or have children. After the twentieth year of employment, they might not consider leaving work because in Japanese society it is difficult to change workplaces as one ages. However, our findings warrant further research to comprehensively examine this predictor.

This study has several limitations. First, the participant selection may have led to biases, as all the participants were recruited from a single prefecture in Japan. Second, there were missing data in the baseline variables, which may have also led to selection bias. Third, the possibility of overfitting cannot be completely excluded, although diagnosis models constituted by the training set were fitted to the test set. In future research, the generalizability of our findings should be assessed in other social settings and other countries. Fourth, we did not collect data on how many children were enrolled in the participating institutions; the ratio of workers to children could not be calculated.

In developing a diagnostic model to predict one's willingness to continue working, "not living with children," "human relations problems with boss," "K6 $\geq$ 13," and "work experience" were identified as important predictors. The model was developed by integrating ML techniques with an LR model. Using the diagnostic model, supervisors can intervene for workers with difficulties at work and resolve their problems. The findings of this study will contribute to the prevention of worker turnover intention among preschool workers.

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Author contributions

MM contributed to the research concept, design, definition of intellectual content, literature search, data analysis, manuscript preparation, editing, and review. KM contributed to the definition of intellectual content, statistical analysis, and manuscript editing. MH, SS, GT, YY, TH, HM, and YK contributed to definition of intellectual content and manuscript review. RI contributed to the research concept, design, definition of intellectual content, manuscript editing, and review.

Conceptualization: Moemi Matsuo, Koutarou Matsumoto, Misako Higashijima, Susumu Shirabe, Goro Tanaka, Yuri Yoshida, Toshio Higashi, Hiroya Miyabara, Youhei Komatsu, Ryoichiro Iwanaga.
Data curation: Moemi Matsuo, Koutarou Matsumoto, Ryoichiro Iwanaga.
Formal analysis: Moemi Matsuo, Koutarou Matsumoto.
Investigation: Ryoichiro Iwanaga.
Methodology: Moemi Matsuo, Ryoichiro Iwanaga.
Project administration: Moemi Matsuo.
Supervision: Moemi Matsuo.
Validation: Moemi Matsuo.
Visualization: Moemi Matsuo
Writing – original draft: Moemi Matsuo.
Writing – review & editing: Moemi Matsuo, Koutarou Matsumoto, Misako Higashijima, Susumu Shirabe, Goro Tanaka, Yuri Yoshida, Toshio Higashi, Hiroya Miyabara, Youhei Komatsu, Ryoichiro Iwanaga.

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