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Using support vector machine modeling to compare differences in burnout between 24/7 caregivers and shift-based caregivers

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Abstract Elderly caregivers are a key group in the development of long-term care business, and their burnout problem is becoming more and more prominent. As the two main work arrangement methods, 24/7 system and shift system have different impacts on caregiver burnout. Based on the support vector machine model, this study compares and analyzes the differences in burnout between 24/7 caregivers and shift system caregivers. A random whole cluster sampling method was used to select 185 caregivers from 18 elderly care facilities in 6 districts of a city as the study subjects, and data were collected through a general information questionnaire and the Masler Burnout Inventory (MBI-GS), and analyzed by using the SPSS22.0 software and the support vector machine model. The results showed that the round-the-clock group (24-hour workday) was more likely to experience high levels of burnout than the shift-based group (12-hour workday) (OR=2.34, 95% CI: 1.63-3.49, p<0.001); The longer the working years, the more serious the burnout, and the burnout scores of caregivers who had worked for more than 3 years (50.73±13.12) were significantly higher than those of caregivers who had worked for less than 1 year (38.96±16.51); the prediction model based on the influencing factors had the highest accuracy, correctly predicting 150 cases; the number of hours of work per day (importance score of 80.19) and work stress (importance score of 70.40) were the main factors affecting caregiver burnout. The study suggests that rationalization of work system design can effectively reduce caregiver burnout, and it is recommended that senior care institutions adopt scientific work system arrangements and conduct regular burnout assessment and intervention.

Index Terms elderly caregivers, burnout, support vector machine, all-weather system, shift system, working hours

I. Introduction

With the increasing elderly population in China, especially the increasing number of empty nesters, elderly, unaccompanied, disabled, and semi-disabled elderly people, the problem of healthy aging for the elderly is becoming more and more prominent [1], [2]. The government strongly supports the model of combining medical care and institutionalized elderly care to improve the quality of elderly care, while caregivers are the main providers and main force of elderly care services [3]. However, at present, there is a shortage of human resources and overloaded workload of elderly caregivers in China, and there is also a strong willingness of elderly caregivers to leave their jobs, and it is positively correlated with burnout [4], [5].

Burnout, also known as job burnout, is the emotional overconsumption and cold service attitude and reduced sense of personal fulfillment shown by individuals in the process of dealing with work service objects [6]. The occurrence of burnout not only has a serious impact on the physical and mental health of practitioners, but also has an impact on their satisfaction, job performance, etc., and is one of the main reasons for practitioners to leave their jobs [7]-[9]. From a realistic point of view, caregivers in caring for the elderly living and living there are work factors such as high work intensity, cumbersome work content, long working hours, etc., and the profession shows a serious shortage of human resources, excessive workload and other characteristics [10]-[12]. As a result, senior care organizations have begun to introduce a flexible shift system, aiming to improve the working environment and welfare of caregivers [13], [14]. And by comparing the differences between 24/7 caregivers and shift system caregivers, the problem of caregiver burnout can be intuitively appreciated in order to formulate a solution strategy to promote the high-quality development of the nursing industry.

Under the background of accelerated population aging, the demand for elderly services continues to grow, and the professional development of elderly caregivers, as the core group of people who directly provide care services, is directly related to the quality of care for the elderly and the development of the elderly career. Elderly caregivers have professional characteristics such as professional independence, professional systematicity, completeness of

skills and uniqueness of the industry spirit, and their work covers a wide range of aspects such as life care, medical services and psychological comfort. However, the current nursing caregiver group is facing the increasingly serious problem of burnout, which is called “nursing professional cancer” and seriously affects their physical and mental health and work performance. Burnout is characterized by a combination of symptoms such as excessive depletion of emotional resources, indifference to work, and a reduced sense of accomplishment, and has become one of the main causes of staff turnover in the nursing profession. Existing studies have shown that burnout among elderly caregivers is affected by a variety of factors, including personal factors such as age, education, and monthly income, organizational factors such as work schedule and shift system, and sociological factors such as social support and social prejudice. Among them, working time system, as an organizational-level modifiable factor, has a significant impact on burnout. As the two main working arrangements in nursing care organizations, the differences in the effects of the all-weather care system (24 hours) and the shift system (12 hours) on caregiver burnout have not yet been systematically studied in a comparative manner. Existing data show that longer working hours and more intense labor are associated with higher levels of burnout and emotional exhaustion. Caregivers in nursing care facilities without shift system are more likely to suffer from burnout due to work pressure and lack of social activities in a highly stressful working environment for a long period of time. Support vector machine, as an efficient algorithm to deal with small-sample nonlinear problems, converts low-dimensional data to high-dimensional space through nonlinear mapping, which can effectively identify the patterns of burnout influencing factors and construct predictive models to provide scientific basis for intervention. Based on this, this study adopts the questionnaire survey method to collect the general information and burnout data of elderly caregivers, uses the support vector machine model to analyze the difference between the burnout of caregivers in the round-the-clock system and those in the shift system and their influencing factors, and constructs the burnout prediction model by comparing the burnout of caregivers in different working hours and filtering the key influencing variables by combining the recursive feature elimination method. The study intends to address the following issues: first, the magnitude and performance of burnout differences between caregivers in all-weather and shift systems; second, the extent of the impact of different working hours on the dimensions of burnout; and third, the identification of key variables affecting caregiver burnout. Through in-depth research on these issues, we can provide scientific basis and practical guidance for nursing institutions to optimize the design of work system, reduce burnout of caregivers, and improve the quality of nursing services.

II. Analytical foundations

II. A. Elderly caregivers

Elderly caregivers, as the main provider of elderly care services, are a special group that promotes the development of long-term care for the elderly. A scientific and reasonable definition of its connotation and extension is conducive to further clarifying its work responsibilities and promoting the development of long-term care and even social development [15], [16].

Elderly caregiver as a subordinate branch of the caregiver occupation, is a clearly defined occupational category. It must have its professional characteristics such as the independence of the profession, the systematic nature of professional knowledge, the completeness of the skill system, the uniqueness of the spirit of the profession and a high degree of professional autonomy.

This paper combines the professional characteristics of elderly caregiver, the connotation and extension of elderly caregiver is defined as follows: elderly caregiver is to life care, medical and psychological comfort as the main content of the work. To guide the elderly daily rehabilitation activities, provide psychological counseling and analysis, the elderly daily care as the necessary professional skills. The professionalism of the caregiver is based on a sense of professional identity, a sense of belonging to the organization, a sense of teamwork, etc., and on the premise of a care service plan, the caregiver has a high degree of autonomy in caring for the elderly.

II. B. Burnout

The phenomenon of burnout has become quite common in service-oriented industries, especially in the nursing field. Burnout can seriously affect the physical and mental health of caregivers and interpersonal interactions, and may even prompt caregivers to leave their jobs, so burnout is also known as the “cancer of the nursing profession” [17], [18].

Burnout is also known as job burnout, professional exhaustion and so on. Burnout is a group of syndromes caused by excessive consumption of emotional resources, gradual indifference to work, and reduced sense of accomplishment at work due to prolonged exposure to high work pressure.

At present, different burnout theories have been formed based on different research perspectives, and different burnout models have been formed according to their respective theories. At present, the following four burnout-

related models are widely used: Job Demand-Resource Model (JD-R), Job-Personal Matching Model (J-PFM), Work Situation-Personal Matching Model (P-E), and Effort-Reward Imbalance Model (ERI).

This paper here focuses on analyzing the Job Requirements-Resources model.

The Job Requirements-Resources Model assumes that the job specifics of any occupation will have an impact on burnout, and therefore its core theoretical assumption is that any occupation has specific factors that influence the occurrence of burnout. The Job Demands-Resources Model views job demands and job resources as potential factors in the development of burnout in workers, and the root cause of burnout is an imbalance between job demands and job resources. An imbalance in job resources complicates the fulfillment of job demands and leads to withdrawal from work, while an imbalance in job demands leads to the persistence of overburdening, which in turn leads to exhaustion.

II. C.Influences on burnout among elderly caregivers

(1) Personal factors

Age: Burnout gradually increases as the age of elderly caregivers increases. With age, the physical strength and energy level of elderly caregivers gradually decreases, making it difficult for them to effectively cope with the heavy caregiving burden of their work and making it easier for them to increase their sense of burnout. On the other hand, as older caregivers are about to leave their jobs, they will be less committed to their work, which in turn increases burnout.

Level of education and professional qualifications: The level of education and professional qualifications of caregivers also affects burnout. Research shows that caregivers with high levels of education and professional qualifications have lower levels of burnout. Elderly caregivers with high professional qualification levels have more professional knowledge and skills training, and have a clearer orientation and perception of the elderly service position, and are able to correctly recognize the value of their competence as elderly caregivers, thus increasing work motivation and reducing burnout.

Monthly income: An increase in monthly income can reduce burnout. Elderly caregivers with higher monthly income have lower burnout in the 3 dimensions of emotional exhaustion, depersonalization, and personal accomplishment. If the heavy work is not proportional to the income, caregivers are prone to the imbalance of unequal pay for the same work, which may affect their work motivation and thus aggravate burnout.

Organizational factors: at present, the working hours of most elderly care institutions are not reasonably designed, and the working hours of some of them are >12 h a day. While most of the elderly caregivers are mainly middle-aged and elderly women, they have certain disadvantages in physical activities, and the continuous long-time and heavy caregiving work may easily lead to work overload.

Studies have found that longer working hours and more intense labor are associated with higher levels of burnout and emotional exhaustion, as well as turnover rates. Shift systems can also affect burnout. Caregivers in nursing facilities without a shift system were more likely to experience burnout. The reasons for this may be analyzed as caregivers in elderly care facilities without shift systems do not have colleagues who can work in shifts, spend most of their time with the elderly, and lack social activities outside of working hours, which, coupled with long hours of highly stressful work environments, can easily lead to job stress, which in turn can lead to burnout.

(2) Sociological factors

Elderly caregivers with high social support have lower burnout. Research shows that there is a negative correlation between social support and burnout of elderly caregivers.

Influenced by traditional social concepts, elderly caregivers are prejudiced by society as a whole. Most people believe that elderly caregivers as a group are uneducated and of low quality, and therefore cannot receive the respect and support they deserve. This makes elderly caregivers believe that their work is worthless, have a low sense of personal fulfillment, and are prone to burnout.

II. D.Support Vector Machines

(1) A support vector machine is a solution algorithm for small-sample nonlinear problems for structural approximation minimization, which is widely used because of its simplicity and ease of implementation.

For the set to be solved (x_i, y_i), where $x_i \in R^n$ is the input vector, and $y_i \in R^n$ is the output vector, the regression theory is to transform the sample space from low-dimensional to high-dimensional through the introduction of a nonlinear mapping $\phi(x)$, for the solution of the nonlinear problem, the estimation function $f(x)$ is transformed as follows Form:

$$f(x) = W \cdot \phi(x) + b \tag{1}$$

where W is the weight coefficient, b is the bias term of the function, and $\phi(x)$ is the nonlinear mapping function.

In the application of SVM to solve the problem, the estimation function is used to solve the nonlinear regression problem, and when the linear problem transformation is performed during the solution process, α , the training set, is already existing by default. To find W and b, the parameters ξ_1 and ξ_2 are introduced as follows:

$$\begin{aligned} &\min Q = \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}(\xi_1 + \xi_2) \\ &s.t.\begin{cases} y_i - W\phi(x) - b = \varepsilon + \xi_1 \\ W\phi(x) + b - y_i = \varepsilon + \xi_2 \\ \xi_1, \xi_2 \geq 0 \end{cases} \end{aligned} \tag{2}$$

where $\|\omega\|^2$ is the descriptive function and C is the penalty factor.

$f(x)$ is responsible for processing the data, which cannot be estimated directly due to the presence of the precision factor ε, so the relaxation factors ξ_1 and ξ_2 are introduced to solve the regression function. During the prediction model run, the location of the loss function $F(x)$ is sought by the SVM. To expect the value of the risk function $R(f)$ to be minimized, the loss function is needed to solve it. Where the decision function equation can be represented using data points with sparse properties and the loss function $F(x)$ is expressed as:

$$F(x) = \sum_{i=1}^{n}\left[y - f(x,w)\right]_+ + \frac{1}{2}\|\omega\|^2 \tag{3}$$

where the loss is 0 when a single sample is correctly categorized and the interval is greater than y, otherwise the loss is $y - f(x,w)$. The $f(x,w)$ expression is determined by the specific problem, and the accumulation of all losses forms part of the $F(x)$.

Expectation function:

$$R(x) < R_\alpha + R_\beta \tag{4}$$

where R_α is the empirical risk. R_β is used to measure the complexity of $f(x,w)$.

$R_\alpha + R_\beta$ determines the maximum value of $R(f)$. The inner product of the feature space can be obtained through the kernel function. The kernel function location is in the low-dimensional space, eliminating the need to solve the problem for the cumbersome high-dimensional space problem, which is modeled by the SVM transformation:

$$\begin{aligned} &\max \sum_{i=1}^{n}\alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{i=1}^{n}\alpha_i\alpha_j y_i y_j k(x_i, x_j) \\ &s.t.\sum_{i=1}^{n}\alpha_i y_i = 0, \alpha_i \geq 0, i = 1,2,\cdots,n \end{aligned} \tag{5}$$

When the Lagrangian functions are combined, the problem being solved is eventually optimized as a dyadic problem with the following expression for $f(x)$:

$$\begin{aligned} &f(x) = \sum_{i,j=1}^{n}(\alpha_i - \alpha_i^*)k(x_i, x_j) + b \\ &s.t.\sum_{i=1}^{n}\alpha_i y_i = 0, \alpha_i \geq 0, i = 1,2,\cdots,n \end{aligned} \tag{6}$$

When the Lagrangian functions are combined, the problem being solved is eventually optimized as a dyadic problem with the following expression for $f(x)$:

$$f(x) = \sum_{i,j=1}^{n}(\alpha_i - \alpha_i^*)k(x_i, x_j) + b \tag{7}$$

where α_i and α_i^* are Lagrange factors. $K(x,x^*)$ is the radial basis function.

In this paper, the basis function in the support vector machine is chosen as $k(x_i, x_j)$ of the above equation, which can be written as:

$$K(x,y) = \exp\left(-\frac{\|x_i - x_j\|^2}{\delta^2}\right) \tag{8}$$

where δ^2 is the kernel function parameter.

The core point of SVM algorithm is to find the appropriate penalty factor C and kernel function parameters δ^2.

(2) Appropriate selection of kernel function is the guarantee that the support vector machine can transform the data dimension.

The kernel function of the support vector machine is basically defined as follows: if there exists a set X on the space R^n, then $K(x,x^*)$ existing on the space $R^n * R^m$ is called the kernel function, and its expression is:

$$K(x,x^*)=\left\{\phi(x),\phi(x^*)\right\} \tag{9}$$

If the kernel function is a symmetric function, which can be written as $K(x_1,x_2)$, for $\forall f(x)\neq 0$ and $\int f(x)^2dx<\infty$, there are:

$$\iint K(x_1,x_2)f(x_1)f(x_2)dx_1dx_2\geq 0 \tag{10}$$

When applying SVM models, the choice of different kernel functions can result in the differentiation of experimental results. This difference depends more on the parameter values of the chosen kernel function than the kernel function itself. However, choosing the most appropriate kernel function when solving different quadratic classification problems can indeed improve the optimization accuracy and convergence speed of SVM.

Currently, the radial basis kernel function (RBF) is chosen because of its ability to be expressed in a simple model for solving the optimal classification problem. RBF kernel function expression:

$$K(x_1,x_2)=\exp\left(-\frac{\|x_1-x_2\|^2}{\sigma^2}\right) \tag{11}$$

The radial basis kernel function was chosen to be able to perform a nonlinear to linear transformation of the initial data of the sample with the expression:

$$f(x)=\sum_{x_i\in Nsv}(\alpha_i-\alpha_i^*)K(x_i,x_j)+b \tag{12}$$

The prediction accuracy of SVM model is greatly affected by the parameters of penalty factor and kernel function, which are too large or too small to cause sample overfitting or underfitting. The selection of the two should not be interfered by human factors, so this paper selects a hybrid algorithm to optimize the penalty factor and kernel function in the SVM prediction model to obtain the optimal configuration.

III. Differences in burnout among caregivers with different working hours

III. A. Research Program

III. A. 1) Research methodology

(1) Sample source and sampling method

The method of random whole cluster sampling is adopted. Three senior care institutions (including public senior care institutions and private senior care institutions) were sampled in each of the six districts of a city, making a total of 18 senior care institutions as the study site.

(2) Inclusion criteria:

a. Willingness to participate in this study.

b. Currently working as an elderly caregiver and have been in this job for >6 months.

c. Caregivers providing direct care.

d. Normal reading and writing comprehension skills, no previous and current mental illnesses or disorders of consciousness.

(3) Exclusion criteria:

a. Refusal to participate in this study.

b. Elderly caregivers who are on leave of absence and out for further training and study.

In this paper, during the period from August 20, 2024 to October 20, 2024, the elderly caregivers in the elderly care institutions in 6 districts of the city who met the nativity criteria were selected as the study subjects. The questionnaire survey, mainly through the paper questionnaire distribution, a total of 192 questionnaires were issued, 185 questionnaires were recovered, and the final effective recovery rate was 96%.

(4) General information questionnaire

The questionnaire contains entries such as the caregiver's gender, age, education level, marital status, having children or not, specialty, title, years of working experience, nature of the working organization, number of people caring for the elderly, training, and income.

(5) Burnout Scale

The Masler Burnout Scale (MBI-GS) was used for burnout. The scale was divided into 3 dimensions: emotional exhaustion, work attitude (cynicism), and achievement. A 7-point Likert scale was used: 0 for “never” and 6 for “every day”. The total burnout score was calculated according to the following formula:

$$\begin{aligned}Burnout=&\left(0.4\times Emotional\ exhaustion\ dimension\ score\right)\\&+\left(0.3\times Personality\ score\right)+0.3\times(6-Achievement\ score)\end{aligned} \tag{13}$$

where a score of <1.5 was defined as no burnout. A score of ⩾1.5 was classified as burnout. 1.5 to 3.5 was classified as mild to moderate burnout. ⩾3.5 was categorized as high burnout. The scores for the three dimensions of emotional exhaustion, work indifference, and no sense of work accomplishment were delineated with the same criteria as burnout.

(6) Data collection

In order to improve the recovery rate, each question is intended to be simple, clear, specific and easy to understand. The survey was distributed by the researcher on the spot, explaining to the respondents in detail the purpose of the survey, the content and the requirements for filling out the questionnaire, which was filled out anonymously. The rated subjects filled in the questionnaire on their own and independently, but if the rated person's literacy level was too low to understand or read the content, it could be read out to him by the survey researcher, item by item, so that the rated person could make the rating alone. The appraisee is told to complete the questionnaire within 30 minutes and check that there are no missing or multiple choices. The questionnaire is collected on the spot after completion and no modification is accepted.

(7) Statistical Methods

EXCEL was used for entry and SPSS22.0 software was used for statistical analysis. Frequencies and percentages statistically described the general demographic information of the elderly caregivers. Mean ± standard deviation described the burnout characteristics of elderly caregivers. The t-test or one-way ANOVA was used to compare the differences in burnout among elderly caregivers with different demographic characteristics.

(8) Quality control

a. Mature and authoritative survey scales that are widely used were selected on the basis of comprehensive search, reading of literature and consultation with experts.

b. Pre-experiment before the formal survey, adjusting the font size, language expression and time according to the subjects.

c. Select elderly caregivers from different elderly care institutions in different regions as research subjects to ensure the comprehensiveness of the survey.

d. Uniform instructions to the researcher, explaining the purpose and significance of the study to the subjects, eliminating their concerns while obtaining their verbal informed consent, and anonymous on-site collection within the specified time.

e. Strictly exclude unqualified questionnaires, such as missing, logical confusion. It was determined that the rate of empty items >5% was considered as missing.

III. A. 2) Burnout prediction model based on support vector machine

There are three prediction models constructed in this paper. They are primary screening prediction model based on basic information, prediction model based on influencing factors and prediction model based on basic information and influencing factors.

Among them, the initial screening prediction model based on basic information is characterized by demographic variables. Burnout as the dependent variable, divided into by the willingness to low to high, divided into five categories, and multi-category decision function transformation, two categories were established SVM model.

The prediction model based on influencing factors is to take the influencing factors as the characteristics (job involvement, compensation and benefits, job stress, job autonomy, training, support of organization members, professional growth, family responsibilities), burnout as the dependent variable, do the research on the role of eight characteristic items for the classification of burnout, and establish the SVM model.

In contrast, the prediction model based on basic information and influencing factors is to build an SVM model with all independent variables as characteristics and burnout as dependent variable.

III. B. Analysis of results

III. B. 1) General information on caregivers in nursing facilities

The results of the general information showed that there were more female caregivers, accounting for 82% of the total. Age was generally older, with the largest number of caregivers in the 40-55 age group at 45%. Literacy was generally low, with the largest proportion of caregivers with junior high school education at 43%. In terms of marital status, married caregivers accounted for the largest number. In terms of the number of children, caregivers with one child accounted for the most. In terms of monthly income level, the number of caregivers with a monthly income level of more than 4,500 RMB was high, accounting for 47%. 92% of the caregivers did not have chronic diseases and were in good health in general. 90% of the caregivers had no religious beliefs.

III. B. 2) Basic occupational profile of caregivers in nursing facilities

The basic occupational profile of nursing facility caregivers is shown in Table 1 (N=185).

In the occupational profile of nursing caregivers in nursing care institutions, 91.89% of the caregivers possessed the nursing caregiver's license. In terms of the time spent in nursing care, the number of people who had been practicing for more than 3 years amounted to 44.32%, while those who had been practicing for less than 1 year accounted for only 13.51%. In terms of working time in the organization, most of the caregivers have worked for a shorter period of time, with 42.16% of them working for 1 to 2 years. In terms of leaving experience, 62.16% of the caregivers in the nursing care institutions have left their jobs.

The number of elderly people cared for by the caregivers in the nursing care institutions were all higher, with the largest proportion of caregivers caring for 6~7 elderly people. The daily working hours of the caregivers were basically more than 10 hours, with the percentage of those working 10 hours or more reaching 56.22%. 45.95% of the caregivers did not work overtime.

Table 1: The basic career of the nursing personnel of the pension institution

Variable	Options	Frequency (N)	Composition ratio(%)
Whether there is a pension nurse's qualification certificate	YES	170	91.89
	NO	15	8.11
Working hours of nursing care	6months~1year	25	13.51
	1~2years	61	32.97
	2~3years	82	44.32
	3years and above	17	9.19
In native working hours	6months~1year	53	28.65
	1~2years	78	42.16
	2~3years	42	22.70
	3years and above	12	6.49
Has the allowance of the pension care officer's departure experience	Have	115	62.16
	Nothing	70	37.84
The number of elderly people currently caring	1	14	7.57
	2-3	27	14.59
	4-5	46	24.86
	6-7	52	28.11
	8 or more	46	24.86
Daily hours	8 hours and below	25	13.51
	9 hours	56	30.27
	10 hours or more	104	56.22
Average overtime week	Never work overtime	85	45.95
	1-4hours	56	30.27
	5-8hours	29	15.68
	Over 8 hours	15	8.11

III. B. 3) Correlation analysis between working hours and burnout situation

In this paper, the all-weather work system and shift work system are converted into 24-hour work hours and 12-hour work hours. The correlation analysis of all-weather system, shift system, and 7-8 hour system with burnout was conducted. The correlation analysis of working hours and burnout situation is shown in Table 2. After controlling for the effects of age, gender, education, income, and marital and childbearing status, the results of the multifactorial analysis showed that the all-weather group (working 24 hours) was more prone to a high degree of burnout among caregivers of nursing homes compared with the group with an average working hours of 7~8 per day (OR=2.34, 95% CI: 1.63~3.49, P<0.001). High emotional exhaustion was more likely to be felt in the classification of burnout (OR=3.96, 95% CI: 2.43~6.79, P<0.001). According to the data in the table, it can be obtained that round-the-clock caregivers are more likely to feel burnout than shift-based caregivers.

III. B. 4) Univariate Analysis of Factors Influencing Caregiver Burnout

The one-way ANOVA test of working hours on burnout of elderly caregivers is shown in Table 3, (N=185).

On overall burnout, the F value = 4.509 and the significance p-value of 0.045<0.05 indicate that there is a significant difference in burnout among caregivers with different working hours in elderly care.

Based on the results of multiple comparisons and in the mean scores, it can be seen that the level of burnout among caregivers with more than 3 years of working hours is significantly higher than that of caregivers with less

than 2 years of working hours, which indicates that the longer the time of working in elderly care, the more serious the burnout is.

Table 2: Correlation analysis of working length and job burnout

Variable	High level of burnout OR value (95%CI)	High level of emotional exhaustion OR value (95%CI)	High level of job apathy OR value (95%CI)	High level of lack of job fulfillment OR value (95%CI)
Working length				
7~8	1.00	1.00	1.00	1.00
12(Shift system)	1.65(0.53~5.12)	1.32(0.37~4.19)	1.11(0.64~10.52)	1.53(1.15~5.14)
24(All-day system)	2.34(1.63~3.49)*	2.65(1.73~3.56)*	2.89(1.15~2.82)*	2.51(1.07~2.05)*
Working length variation				
Invariant	1.00	1.00	1.00	1.00
Reduce	1.03(0.43~8.96)	0.86(2.69~6.17)	1.56(1.04~4.14)	0.93(0.91~1.95)
Increase	4.25(2.56~7.86)*	3.96(2.43~6.79)*	2.93(1.19~5.26)*	1.67(1.03~2.17)*

In the dimensions of emotional exhaustion, cynicism, and low achievement, the F-test values were 3.224, 3.018, and 2.997, respectively, and the significant P-values were all greater than 0.05. This indicates that there are no significant differences between caregivers who have been engaged in elderly care for different working hours in the dimensions of emotional exhaustion, cynicism, and low achievement.

In the emotional exhaustion dimension, based on the mean scores, it can be seen that caregivers with more than 3 years of working hours have the highest emotional exhaustion scores, followed by those with 2 to 3 years of working hours, and the lowest scores are those with 1 to 2 years of working hours, indicating that the longer the period of time spent working in elderly care, the more severe the emotional exhaustion.

Table 3: The single factor variance test of the job time of the nursing department

Working hours	N	Overall burnout	Emotional failure	Cynicism	Low sense of accomplishment
6months~1year	25	38.96±16.51	17.42±8.63	12.45±8.03	9.13±6.24
1~2years	61	40.15±15.22	16.75±9.04	14.13±6.08	9.25±5.87
2~3years	82	45.63±12.36	19.76±6.53	15.21±5.19	10.11±5.53
3years and above	17	50.73±13.12	22.19±5.78	16.34±4.76	12.47±7.83
F value		4.509	3.224	3.018	2.997
P value		0.045	0.051	0.127	0.125
Lsd Multiple comparison		4>1,4>2	/	/	/

III. C. Analysis of the results of burnout prediction based on support vector machine

In this paper, the sample data were sliced at the beginning of the model construction, and the ratio of its training set and test set was 8:2, in order to verify the prediction ability of the initial screening prediction model based on basic information (Model 1), the prediction model based on influencing factors (Model 2), and the prediction model based on basic information and influencing factors (Model 3), and the prediction results of its 185 cases of the test set samples are shown in Table 4.

It can be seen that Model 2 has the best prediction results in terms of the number of correct predictions, reaching 150 cases. Model 3 is the next best and Model 1 is the worst. Meanwhile, Model 2 has the best overall stability in terms of the comparison of the number of correct predictions for each degree of burnout.

In order to further analyze the degree of contribution of each variable to the prediction results during the model construction process of the primary screening prediction model based on basic information (Model 1), the prediction model based on influencing factors (Model 2), and the prediction model based on basic information and influencing factors (Model 3), this paper uses recursive feature elimination (RFE) in support vector machines to rank the importance of each variable in the models.

Table 4: Test set prediction results

Corresponding model	Predictive result	The degree of occupational burnout (the likert 5 scale)					Total
		No	Not at all	Partly	Basically	Totally	
Model 1	Forecast correct number	5	15	56	12	0	88
	Actual number	6	36	91	52	0	185
Model 2	Forecast correct number	25	50	55	20	0	150
	Actual number	30	51	79	25	0	185
Model 3	Forecast correct number	10	50	56	10	0	126
	Actual number	24	66	78	17	0	185

In this paper, the recursive feature elimination (RFE) of support vector machine was used to rank the feature importance of the variables in each model. The importance measures of the permutations were calculated by training each support vector machine model.

In this paper, the three models were trained by Python software, while still setting the ratio of training set to test set to 8:2 and cross-validating the data to maximize the use of available data. According to the output results, the optimal output parameters of each model are shown in Table 5.

Table 5: Optimal output parameters for each model

Model	C	Gamma	Kernel
Model 1	6	0.001	poly
Model 2	20	0.002	rbf
Model 3	20	0.001	rbf

At the same time, since it is an analysis of feature explanatory power, the main focus is on the output results on the training set. During the training process, the order of importance of the three models on the respective variables in the training set is shown in Table 6.

The variables in Model 1 are monthly income, commuting time, age, marital status, gender, and education, respectively.

Table 6: The importance score results

Model	Variable	Importance score	Variable	Importance score
Model 1	Monthly income	55.29	Commuting time	16.04
	Age	40.12	Marital status	5.69
	Gender	1.69	Educational background	2.52
Model 2	Social support	55.28	Job autonomy	31.04
	Training	38.51	Sense of fairness	50.73
	Professional growth	40.66	Family responsibility	35.92
	Working pressure	70.40	Working hours per day	80.19
Model 3	Social support	53.69	Marital status	26.85
	Commuting time	43.21	Educational background	16.73
	Monthly income	56.04	Family responsibility	24.83
	Professional growth	37.23	Personal values	10.05
	Sense of fairness	29.46	Job autonomy	32.26
	Training	41.29	Working pressure	40.19
	Working hours per day	70.82	Age	42.32
	Compensation benefits	25.34	Working hours in the machine	15.88

The variables in Model 2 were social support, job autonomy, training, sense of fairness, career growth, family responsibilities, job stress, and hours worked per day.

The variables of model 3 are social support, commuting time, monthly income, professional growth, hours worked per day, sense of fairness, training, compensation and benefits, marital status, educational qualifications, family responsibilities, personal values, job autonomy, job stress, age, and hours worked in the organization.

Based on the output results, this paper finally selected job stress, hours worked per day, social support, monthly income, and age as the main characteristics of the high burnout group among elderly caregivers.

It is mainly based on the following two considerations. On the one hand, it is the rating height. In this paper, the variables with the top 5 importance ratings in each of the 3 models were selected for comparison. On the other hand is cross-model consistency this consistency implies the robustness of these variables in explaining and predicting burnout.

IV. Conclusion

The working hours of elderly caregivers were closely related to burnout, and caregivers in the 24/7 system were more likely to experience burnout than those in the shift system. Multifactorial analysis showed that the all-weather group (24-hour working hours) was more prone to high levels of burnout than the 7-8-hour working group (OR=2.34), and the difference was more significant in the emotional exhaustion dimension (OR=2.65). The degree of burnout was positively correlated with the number of years of work, and the burnout score of caregivers with more than 3 years of work (50.73) was significantly higher than that of caregivers with less than 2 years of work, indicating that the longer the work time, the more serious the burnout. Support vector machine-based prediction model analysis revealed that the influence factor-based prediction model (Model 2) performed best among the three models, correctly predicting 150 cases. Characteristic importance analysis determined that daily working hours (importance score 80.19), work pressure (70.40), social support (55.28), monthly income (56.04), and age (42.32) were the key variables in predicting burnout among elderly caregivers.

Elderly care institutions should optimize the design of the working time system to avoid excessively long working hours; establish a scientific shift system to ensure sufficient rest and social time for caregivers; strengthen the construction of the social support system and improve the remuneration; implement differentiated working arrangements according to the age characteristics; and carry out burnout assessment and intervention on a regular basis to build a multi-level prevention system, so as to reduce the risk of burnout and improve the quality of elderly care services. The following is a summary of the findings of the study.

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