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Employee Productivity Modeling Using Competencies, Burnout, and Performance: A Fuzzy Logic and Econometric Analysis

Lev S. Mazelis [1], Gleb V. Grenkin [1], Kirill I. Lavrenyuk [2]

[1] Vladivostok State University, Vladivostok, Russia

[2] Smart Space (Samokat.tech), St. Petersburg, Russia

Abstract. In this study, we investigated the factors influencing the development of organizational human capital that directly or indirectly affect employee productivity. These factors include indicators of competency development and the level of individual burnout. We developed a two-stage economic–mathematical model to quantitatively describe the influence of employee competencies on key performance indicators (KPIs), considering burnout, which is determined by the values of loyalty, engagement, and satisfaction. The initial data for this study, obtained from self-assessments of competencies and burnout from employees in the information technology (IT) and human resources (HR) sectors within seven major Russian companies, were calibrated by the supervisors of the respondents. Additionally, the initial data included the actual KPI values of the employees. First, we constructed a fuzzy model based on a weighted integral competency indicator with optimal weight coefficients, which divided the integral indicator values into unevenly sized categories. These categories were used to predict KPI achievements. Second, using a weighted least squares method, an econometric model of the dependence of the KPI on employee burnout indicators was constructed to explain the dispersion of the KPI values (among employees in specific competence categories in the fuzzy model) around the expected KPI. This model predicts employee KPI achievements depending on the input competencies and burnout levels. This model was applied to create an optimal portfolio of well-being activities to improve employee competencies, reduce burnout, and achieve target KPI values.

Keywords: competency, key performance indicator, burnout process, fuzzy optimal classification

1. Introduction

Recently, socioeconomic changes have led organizations to transform their operations into flexible and rapidly adaptable management systems. This is due to the restructuring and increased cost of logistics, aggressive growth of salaries for in-demand specialists, etc. Organizations must cope with technological changes and constant competition for consumers and resources. In this environment, the key factor for success is employee competency. Organizations need highly qualified and professional employees capable of efficiently performing their responsibilities.

In addition to competency, emotional and physical well-being is another important factor affecting employee performance. Often occurring with increased stress and workloads, burnout can seriously undermine the productivity and well-being of employees.

Therefore, understanding the correlation between competencies, burnout, and performance is critical for organizations. This knowledge will help organizations develop employee management strategies to effectively leverage their competencies, prevent burnout, and create a positive corporate environment.

However, under limited organizational resources, when making decisions about implementing various strategic initiatives, it is not advisable to rely solely on qualitative assessments. It is recommended to rely on predictive metrics, which can be obtained through quantitative modeling of relationships based on retrospective data. To mitigate existing uncertainties in the external and internal environment of an organization, a fuzzy set approach can be employed to model the relationships.

2. Literature Review

We identified several questions in our literature review that directly or indirectly address the effect of employee competencies on performance, considering burnout.

1. What is the effect of employee competency?

Kim & Jung (2022) studied the influence of organizational culture and employee competency on their perceptions of stressful situations and productivity. Jia (2023) modeled the correlations between innovations in human resource management, employee competencies, and innovation efficiency within enterprises. Daniali et al. (2022) modeled the professional competencies of employees. They evaluated the effect of competency development on the recruitment, hiring, appointment, and promotion of individuals, which ultimately influence the ability of an organization to achieve its goals. Kurniawan et al. (2023) studied the direct and indirect effects of employee competencies and job responsibilities on their motivation to be effective in their jobs. Sabuhari et al. (2020) analyzed the influences of employee flexibility, competency, adaptation to organizational culture, and job satisfaction on their productivity.

Thus, several studies have shown the effect of employee competencies on productivity. However, how specific employee competencies affect the completion of specific tasks still needs to be explored. Some studies have highlighted the negative effect of burnout on labor productivity due to increased workplace stress. However, this has not been sufficiently studied.

2. What influences employee productivity?

Diamantidis & Chatzoglou (2019) studied environment-related factors (i.e., learning culture, leadership support, dynamics of environmental changes, and organizational climate), work-related factors (i.e., work environment, job autonomy, and workplace communication), and employee-related factors (i.e., internal motivation, skill flexibility, qualification level, proactiveness, adaptability, and goal orientation) and their effects on employee productivity. Sitopu et al. (2021) analyzed the influence of motivation, work discipline, and rewards on employee productivity. Similarly, Riyanto et al. (2021) analyzed the effects of motivation and job satisfaction on productivity in the IT sector. Buil et al. (2019) examined the role of organizational identity and work engagement in the relationship between transformational leadership, work efficiency, and organizational civic behavior. Song et al. (2019) analyzed the positive influence of social networks on employee and team efficiency in the workplace.

Bataineh (2019) analyzed the correlations between work–life balance, happiness index, and employee productivity.

Thus, any internal or external factor that directly or indirectly influences an employee’s physical or emotional state will affect their productivity, effectiveness, and efficiency. Employee burnout also affects work productivity. Various causes, such as a misalignment between expectations and reality, multitasking, and work monotony, contribute to this. We discuss these in more detail below.

3. How does burnout affect productivity?

Ouyang et al. (2022) examined the preconditions of emotional burnout related to satisfaction with job tasks and the psychological atmosphere in a company. Matani & Bidmeshki (2020) explored the components of burnout and their correlations with employee performance indicators. Rughoobur-Seetah (2023) identified and evaluated factors (particularly emotional burnout) influencing employee work efficiency in the post-COVID-19 era. Fastje et al. (2023) studied the effect of overtime hours in a productivity-oriented work environment on the emotional burnout of employees. Kalandatzis & Hyz (2021) described professional burnout among employees in the banking sector under adverse economic conditions. Wulantika et al. (2023) studied the effects of social support and professional burnout on employee productivity. Moreover, some studies have examined burnout from different perspectives (Gong et al., 2019; Rony, Pardosi, 2021; Wu et al., 2019).

Therefore, burnout is one factor that influences and typically decreases employee productivity. The specific causes of this decrease in productivity are not known. In this study, we hypothesized that burnout affects employee performance by reducing the full utilization of their competencies. Thus, the higher their burnout level, the less an employee can fully leverage their competencies.

Previously, we developed a model (based on expert assessments and assumptions) of the competency development process of employees and its effect on key performance indicators (KPIs). However, these do not account for the influence of burnout on productivity (Mazelis & Lavrenyuk, 2017).

Based on our literature analysis, previous theoretical and methodological research on this topic involved some shortcomings and assumptions. Thus, this study aimed to address these issues, which are as follows. 1) The effect of employee competency on various components of labor productivity has yet to be fully determined, affecting organizational performance and efficiency indicators. 2) The influence of employee burnout on productivity and full competency utilization has not been fully considered. 3) Uncertainties and risks have yet to be fully accounted for in studies on the effect of employee competencies on labor productivity when they experience burnout.

Thus, there needs to be more models describing the influence of employee competencies on labor productivity and an organization's overall performance when employees experience burnout. Furthermore, when there are resource constraints, high competition for resources, risks, and uncertainties, we need methods to facilitate the development of employee competencies and reduce burnout levels. Consequently, this will contribute toward achieving target KPIs for individual employees and the organization.

3. Research Objective and Tasks

In this study, we aimed to develop an econometric–mathematical model that quantitatively describes the influence of employee competency levels on their KPIs, accounting for burnout.

To achieve this objective, we performed the following tasks. 1) We developed a model to describe the impact of employee competencies on their KPIs. This model allows the categorization of employees (via the integrated competency level indicator generated by the model) into specific categories for each KPI within the fuzzy framework. 2) We developed a quantitative assessment method to measure the influence of employee burnout on achieving target KPIs by fully utilizing employee competencies.

4. Model

Let us consider an organization's personnel performance over a certain time interval, assuming that changes in the achieved KPIs by employees occur both because of high competencies and low burnout levels. These factors can vary because of well-being initiatives.

The values of model variables were determined based on employee surveys and subsequent expert calibration of assessments by line managers. Thus, there was uncertainty in the initial data. We used a fuzzy set approach to account for this uncertainty when categorizing objects based on competency levels. This approach allows the assignment of each employee to two adjacent categories with membership values. Furthermore, this approach enables econometric modeling of achievement of target KPI values to consider the informativeness of points within a category based on the membership values of employees in that category.

The assessment was performed using linguistic variables, such as “Not important”, “Minimal importance”, and “Below-average importance”. Subsequently, these linguistic variables were converted into fuzzy numbers to mitigate the subjectivity and fuzziness of the respondents' answers.

We developed a model to assess the expected KPIs achieved by employees, given their competency assessments and burnout indicators. The model development was divided into two stages as follows.

1. The development of a fuzzy model based on a weighted integral competency development indicator with optimal weight coefficients. The model divides the range of the integral indicator into unevenly sized categories. This division is made by minimizing the intragroup spread of the KPI. For a set of employees, the model enables a fuzzy classification based on their integral competency development indicator values and assigns them to designated ranges. These ranges are interpreted as categories of employee competencies. Thus, each employee is fuzzily classified into competency categories, and an expected KPI value characterizes each.

2. We constructed a linear model within the fuzzy framework depicting the relationship between the KPIs and employee burnout to explain the deviation in the KPIs from the expected values. This method considers the employee’s membership degree to a particular category. The model uses a weighted least squares method, with the weights determined by the membership degree of points to the relevant competency category.

We utilized KPIs and burnout indicators averaged over short intervals to analyze the employees. Specifically, one year was divided into quarter intervals.

Let us introduce the following parameters and variables:

i – employee index within the organization, where $i = 1, 2, \ldots, I$;

j – competency index of the employee, where $j = 1, 2, \ldots, J$;

m – KPI index, where $m = 1, 2, \ldots, M$;

l – burnout indicator index, where $l = 1, 2, 3$;

s – interval index for changes in the integral competency development indicator, where $s = 1, 2, \ldots, S$;

c_{ij} – level of development of the j-th competency for the i-th employee;

b_{il} – the value of the l-th burnout indicator for the i-th employee;

k_{im} – the value of the m-th KPI for the i-th employee;

C_i – integral competency development indicator for the i-th employee;

t_s – right boundary of the s-th interval for changes in the integral competency development indicator; and

u_{is} – degree of point C_i belonging to the s-th interval of changes in the integral competency development indicator.

We isolated one of the KPI indicators with index m and denoted its value for the i-th employee as $K_i = k_{im}$. Our goal was to identify the dependence of K_i on the competency levels c_{i1}, c_{i2}, …, c_{iJ} using multiple piecewise constant regression, taking into account the fuzzy membership of the integral competency development indicator $C_i = w_1 c_{i1} + w_2 c_{i2} + \ldots + w_J c_{iJ}$ to the designated intervals.

For the chosen partition of the numerical axis into S intervals $[t_0, t_1]$, $[t_1, t_2]$, …, $[t_{S-1}, t_S]$, where $t_0 = \min_i C_i$, and $t_S = \max_i C_i$, we can determine the membership function of the i-th employee to the s-th interval $[t_{s-1}, t_s]$ using the following formula:

$$u_{is} = \begin{cases} \dfrac{C_i - a_{s-1}}{a_s - a_{s-1}}, & C_i \in [a_{s-1}, a_s], \\ \dfrac{a_{s+1} - C_i}{a_{s+1} - a_s}, & C_i \in [a_s, a_{s+1}], \\ 0, & \end{cases}$$

where $a_s = (t_{s-1} + t_s)/2$ is the midpoint of the s-th interval. Thus, the membership coefficient u_{is} linearly depends on C_i in the intervals between the midpoints of the intervals, and the membership coefficient for the s-th interval is 1 at the midpoint a_s of the s-th interval and 0 at the midpoints of the neighboring intervals a_{s-1} and a_{s+1}.

We introduced the objective function (1) to determine the optimal weight multipliers w_1, w_2, …, w_J simultaneously with the optimal partition of the set of values of the integral competency development indicator into intervals $[t_{s-1}, t_s]$:

$$f(w_1, \ldots, w_J, t_0, \ldots, t_S) = \sum_{s=1}^{S} \sum_{i=1}^{I} u_{is} (K_i - d_s)^2 . \tag{1}$$

We then minimized this function with respect to the parameters w_j, t_s, and d_s. The coefficients u_{is} were determined using the values of the integral competency development indicator $C_i = w_1 c_{i1} + w_2 c_{i2} + \ldots + w_J c_{iJ}$ and the coordinates of the interval boundaries t_s. The numbers d_s, at which the function f reaches its minimum value at fixed values of w_j and t_s, can be expressed using the following formula:

$$d_s = \frac{\sum_{i=1}^{I} u_{is} K_i}{\sum_{i=1}^{I} u_{is}}.$$

The values of d_s were calculated as the weighted average of KPI values, reflecting the characteristic level of KPI within a given competency category. The weight multipliers, u_{is}, signify the uncertainty associated with assigning each observation to the competency category.

After obtaining the desired boundaries of the intervals t_1, t_2, …, t_{S-1} and the optimal weight multipliers w_j, we can explain the spread of KPI values K_i within each interval relative to the mean d_s, based on the values of burnout indicators b_{il}. To achieve this, we first selected the interval number s and assigned each observation a weight equal to the membership degree in this interval u_{is}. Then, we solved the weighted least squares method problem and built a multiple linear regression to reconstruct the dependence of K_i on b_{il} with parameters W_0, W_1, W_2, and W_3, ensuring the minimum of the objective function

$$g_s(W_0, W_1, W_2, W_3) = \sum_{i=1}^{I} u_{is} \left(K_i - (W_0 + W_1 b_{i1} + W_2 b_{i2} + W_3 b_{i3})\right)^2 .$$

5. Numerical Methods

We propose solving the problem of minimizing the objective function (1) by using an iterative method, where each iteration has two stages: 1) optimize the interval boundaries t_s with given multipliers w_j and 2) optimize the multipliers w_j with given interval boundaries t_s.

Stage 1 was implemented using the gradient descent method. With the given coefficients w_j, we obtained points (C_i, K_i). We could determine the membership degree to the s-th interval u_{is} for each point, depending on the choice of boundaries t_s. Monotonicity constraints were imposed on the boundaries: $t_1 \le t_2 \le ... \le t_{S-1}$.

Then, we obtained the relationships between the components of the gradient of the objective function:

$$\frac{\partial f}{\partial t_p} = \sum_{s=1}^{S} \sum_{i=1}^{I} d_s \left(d_s - 2K_i\right) \frac{\partial u_{is}}{\partial t_p}$$

To calculate the partial derivatives $\frac{\partial u_{is}}{\partial t_p}$, we found expressions for the derivatives of the membership degrees with respect to the coordinates of the interval centers $\frac{\partial u_{is}}{\partial a_p}$ and used the formula $\frac{\partial u_{is}}{\partial t_p} = \frac{1}{2} \frac{\partial u_{is}}{\partial a_p} + \frac{1}{2} \frac{\partial u_{is}}{\partial a_{p+1}}$.

The calculated partial derivatives $\frac{\partial f}{\partial t_p}$ were multiplied by the gradient method's step parameter, and all values of t_s were adjusted by this amount. Subsequently, corrections were made to ensure the monotonicity constraint. Initial approximations were taken from the weight coefficients of the multiple linear regression model, and the interval boundaries were calculated for the crisp piecewise constant regression problem.

Stage 2 was implemented using the built-in optimizer from the SciPy library, employing the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm with automatic gradient computation.

6. Initial Data

The research sample consists of I = 219 sets of c_{ij} for J = 38 competencies, b_{il} for L = 3 indicators, and k_{im} for M = 4 metrics. The respondents in the sample who provided the information are current employees of seven Russian companies (such as Samokat, Avito, and Gazprom-Media) and are primarily from the information technology (IT) and human resources (HR) sectors. Our previous study details the metrics (Mazelis et al., 2023). The list of competencies is as follows:

systems thinking (j = 1);
creative thinking (j = 2);
critical thinking (j = 3);
empathy (j = 4);
clarity of expression (j = 5);
presentation skills (j = 6);
focus on the main points (j = 7);
logical reasoning (j = 8);
memorability (j = 9);
motivational skills (j = 10);
delegation skills (j = 11);
control skills (j = 12);

stress resistance (j = 13);
adaptability (j = 14);
reflection (j = 15);
proactivity (j = 16);
ambition (j = 17);
execution skills (j = 18);
IT project management (j = 19);
IT product management (j = 20);
business analysis (j = 21);
system analysis (j = 22);
IT architecture (j = 23);
UX/UI design (j = 24);
coding (j = 25);
software testing (j = 26);
software configuration and deployment (j = 27);
software maintenance and support (j = 28);
HR project management (j = 29);
HR product management (j = 30);
personnel administration (j = 31);
recruitment (j = 32);
onboarding (j = 33);
compensation and benefits (C&B) (j = 34);
learning and development (L&D) (j = 35);
HR brand (j = 36);
HR analytics (j = 37);
corporate communication (j = 38).

In the study, we assessed personnel competencies using the 180-degree method with the beehive tool. In the first stage, employees self-evaluated their competencies. In the second stage, their direct supervisors calibrated their assessments. Finally, the employees and supervisors met one-on-one to discuss the final assessment for each competency.

We utilized the online service anketolog.ru to assess burnout levels. The survey consisted of 23 questions to evaluate loyalty, satisfaction, and engagement, forming the basis for calculating the degree of burnout for individual employees. Notably, the assessment involved the use of linguistic variables.

The retrospective values for the employees who participated in two prior assessments were used as the KPI data.

7. Results

Let us present examples that illustrate how to assess the influence of employee competency values on their KPIs, considering the level of burnout determined by satisfaction, engagement, and loyalty values.

The constructed model, which determines the relationship between the KPI and competency values with S = 6 intervals, is presented in Fig. 1. The abscissa axis shows the integrated competency development indicator C_i. In contrast, the ordinate axis shows one of the KPIs, K_i. The color indicates the average values of the burnout indicators $(b_{i1} + b_{i2} + b_{i3})/3$. The vertical lines illustrate the division of integral competency indicator values into ranges. Horizontal dashed lines indicate the average values of the KPI, d_s. In Fig. 1, only five intervals are visible because the boundaries of the third range [62.3, 62.3] coincide, which may indicate a sharp discontinuity between points to the left and right of this boundary.

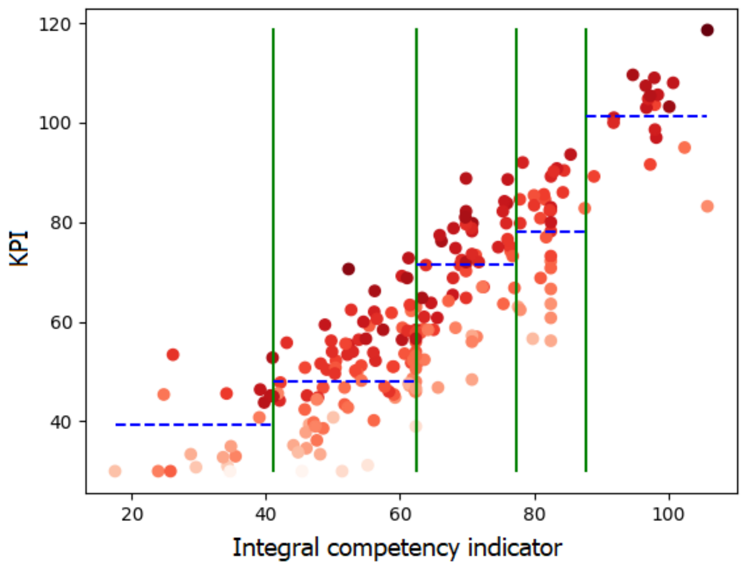

Fig. 1. Plot of pairs of values (C_i, K_i) with indications of the average burnout indicator (darker points correspond to higher values of this indicator)

Figure 1 shows that within each range, there is a dispersion of KPI values around the mean, and those above the mean are predominantly darker than points with KPIs below the mean. Therefore, other factors, such as burnout, can explain the KPI dispersion.

Figure 2 shows the relationship between multiple linear regression of the KPI and burnout indicators: the abscissa axis shows the integrated burnout indicator $W_0 + W_1 b_{i1} + W_2 b_{i2} + W_3 b_{i3}$, while the ordinate axis shows K_i. The color indicates the membership coefficients of the points to the second range of integral competency indicator values, with coordinates [41.1, 62.3]. Figure 2 shows that accounting for burnout adds significant corrections to the model.

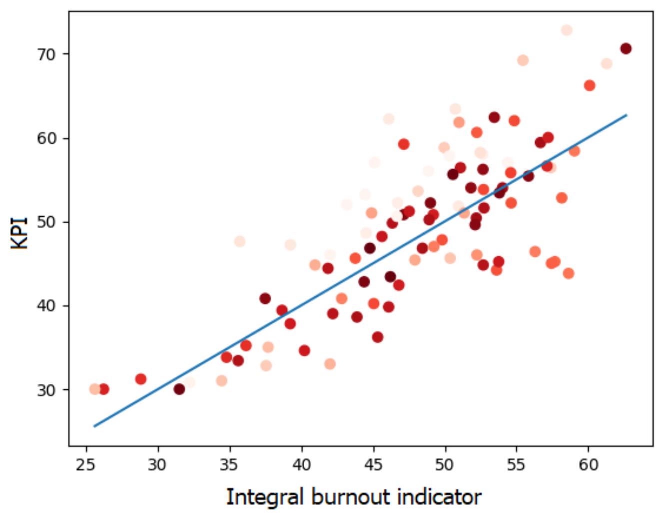

Fig. 2. Plot of pairs of predicted (horizontal) and actual (vertical) KPI values for points in the second range of the integral competency indicator; color denotes membership coefficients in this range (darker points indicate higher membership).

Table 1 shows the weight coefficients for the competencies.

Table 1. Optimal weight coefficients of the integrated indicator

j	w_j	j	w_j	j	w_j	j	w_j
1	0.35	11	2.82	21	2.14	31	−0.69
2	1.33	12	−0.36	22	−1.3	32	2.19
3	−1.6	13	0.77	23	1.28	33	−1.45
4	1.59	14	1.38	24	−0.57	34	-2.09
5	−1.9	15	−1.14	25	1.07	35	1.77
6	0.93	16	1.12	26	0.42	36	−0.98
7	1.37	17	1.63	27	0.70	37	0.37
8	−1.02	18	3.81	28	−0.37	38	1.49
9	0.0036	19	2.67	29	4.99		
10	3.06	20	0.98	30	0.75		

Considering the data in Table 1, w_j can be interpreted as coefficients indicating the influence of various competencies on the integrated indicator and, consequently, on the employee's membership in a particular category. For example, the competencies with the greatest influence on the integrated indicator are "HR project management", "motivational skills", and "performance". The overall pattern is superficial because each competency influences KPI achievement. However, some competencies negatively affect the integrated indicator, specifically "logical presentation", "reflection", "systems analysis", and "compensation and benefits". Interestingly, this suggests that higher employee competencies are related to deep immersion in a specific activity, resulting in a lower likelihood of KPI achievement. One hypothesis for this is that many KPIs are formulated absurdly, and a disposition toward reflection by employees reduces the time available for the completion of tasks, leading to burnout and failure to achieve the KPI.

Table 2 displays the coefficients of the regression relationship between KPI and burnout for various categories of the integrated competency indicator.

Table 2. KPI regression coefficients depending on burnout indicators for different integrated competency indicator categories

W_l	s					
	1	2	3	4	5	6
W_0	13	9	18	22	11	40
W_1	0.24	0.21	0.11	0.09	0.36	0.35
W_2	0.22	0.25	0.24	0.29	0.30	0.29
W_3	0.0063	0.14	0.19	0.27	0.33	0.16

We evaluated the quality of regression models built for each category of the integrated competency indicator using the adjusted coefficient of determination, Fisher's F-test, and significance assessments of regression coefficients. The results are outlined in Table 3. All model coefficients are statistically significant at the 0.002 level, except for the W_1 coefficient on intervals 3 and 4 and the W_3 coefficient on interval 1.

The confidence intervals at a significance level of 0.95 were calculated for all significant coefficients of each model. For example, for the second category (s = 2, Table 3), the confidence intervals of the coefficients are as follows: $W_1 \in (0.107; 0.333)$, $W_2 \in (0.163; 0.339)$, $W_3 \in (0.058; 0.213)$.

We verified the adherence to the assumptions of the Gauss–Markov theorem:

- An analysis of exogenous variables confirmed the hypothesis of no multicollinearity in the dataset for the “burnout” variables because the variance inflation factor (VIF) values for all variables were below 7;
- Residual analysis of the constructed models using the Breusch–Pagan method revealed the absence of heteroscedasticity at the significance level of 0.05;
- The Shapiro–Wilk test, suitable for small and medium-sized samples, indicated that the distribution of residuals closely approximated a Gaussian distribution.

We used Cook's distance to check for anomalous values or outliers that could influence the regression coefficient estimates. Evaluating the effect of removing one (considered) observation indicated the presence of no more than two outliers in several constructed models. Excluding these specific data points allowed us to build models without outliers.

Table 3. Criteria for the quality of regression models

	s					
	1	2	3	4	5	6
R^2	0.748	0.775	0.648	0.695	0.698	0.711
F	31.63	68.90	37.00	41.72	50.24	24.84
Prob (F)	$2.4 \cdot 10^{-11}$	$9 \cdot 10^{-24}$	$1.8 \cdot 10^{-15}$	$2.4 \cdot 10^{-16}$	$1.7 \cdot 10^{-16}$	$8.4 \cdot 10^{-8}$

There is a correlation between KPI and burnout for different categories of the integrated competency development indicator. The weight coefficients W_l significantly differ for different categories.

Table 2 shows that the influence of indicators characterizing employee burnout (i.e., satisfaction, engagement, and loyalty) differs within each designated category. For instance, the loyalty indicator has almost no impact on the group in the category with the lowest integrated competency development indicator. However, as the integrated indicator increases (up to the fifth category), the influence of the loyalty indicator increases. Thus, one motivation for employees to achieve KPI is loyalty toward their company. Meanwhile, the free term has the most impact for the sixth category, indicating the need to explore further factors influencing employee performance in the categories with the highest integrated competency development indicators.

We calculated the square root of the weighted average (with fuzzy membership coefficients) of the squared deviation between the model KPI values and the actual values, considering burnout and without it. For the multiple linear regression model, where competency values are the only independent variables, the error was 8.8. For the constructed fuzzy model of multiple piecewise constant regression with correction using multiple linear regression (depending on burnout indicators) for each competency interval, the obtained mean squared error was 5.4. Of note, with an increase in the number of intervals to $S = 7$, the error was 5.5. The increase in error with increased intervals may be related to considering fuzziness in the optimized function.

This model provides information about the uneven data distribution into categories based on the integrated competency indicator. Thus, we could study the impact of burnout on performance within specific categories. Thus, this procedure simplifies data analysis via fuzzy classification of employees into competency categories. Because competencies are a more static factor than burnout, well-being activities most suitable for these employees can be selected for each category.

8. Discussion

This study validated assumptions from previous studies regarding the importance of calibrating an employee's competency level depending on their degree of burnout. As the employee's burnout level increases, the effective utilization of their competencies decreases, and vice versa. Consequently, this also affects their progress toward achieving targeted KPI values. However, because previous studies did not fully consider the uneven effect of specific competencies on individual KPIs, it is practically impossible to identify a set of competencies requiring development based on target KPI values. The proposed model addresses this by identifying and using weighted coefficients in the integrated competency development indicator. Additionally, the model accounts for the implementation of existing competencies by the employee (rather than their current level of development), which is influenced by their degree of burnout. This is resolved through a two-stage approach, where the first stage models the influence of competencies on the KPI, and the second stage involves adjustment considering the degree of burnout. Existing uncertainties in assessing the impact of an employee's competencies on their KPI are accommodated by employing fuzzy optimal classification.

Thus, based on the obtained results and their validation by experts in the personnel management field from participating organizations, we found the proposed model to be an effective tool. It uses fuzzy classification of employees based on their competency development levels and facilitates the prediction of achievement of KPIs depending on input values of competencies and the degree of burnout.

Nevertheless, it is important to recognize certain limitations in employing the proposed model within an organization. For instance, a sufficiently large sample is required because of the many model parameters. Additionally, to create this sample, we must comprehensively assess employees in terms of their competencies and burnout levels, which can be resource-intensive. Furthermore, a performance review system must be implemented in the organization, with a transparent goal-setting system for each employee.

9. Conclusion

This study proposed a model that functionally describes the effect of employee competencies on KPIs, accounting for burnout levels. Shortcomings identified during our literature review were addressed in this study. Specifically, the influence of specific employee competencies on achieving their KPIs, considering burnout, was quantitatively described. Considering burnout, the fuzzy set approach was used to account for uncertainties and risks in assessing the influence of employee competencies on their productivity.

An optimization model was constructed. In the initial stage, employees were fuzzily classified based on the development of their competencies. In the second stage, an econometric model of the dependence of the KPI on employee burnout indicators was constructed for each competency category, considering each subject's membership in different categories. The model defined the integrated competency development indicator with optimal weight coefficients and optimally divided the integrated indicators into unevenly sized categories. The expected KPI value characterized each class. A numerical method for determining optimal parameters of the model was developed, i.e., weight coefficients of the integrated indicator, indicating the influence of each competency on the integrated indicator and the boundaries of category intervals.

The proposed model is theoretically significant because it facilitates the creation of a fuzzy optimal classification of employees based on their competency development levels. For each category, it confirms and quantitatively assesses the effect of burnout on employee performance by distributing employees according to their KPI values (Fig. 1). The fuzzy classification, combined with the construction of econometric models for each category, markedly enhances the accuracy of forecasting employee performance and reveals considerable differences in the influence of each burnout indicator (loyalty, engagement, and satisfaction) on achieving target KPI values depending on the employee's competency level.

This model can predict an employee's KPI achievement based on their input competencies and burnout levels, which can be obtained using standard human resource management tools, such as 360/180-degree evaluations and surveys.

The developed model is part of a study focused on developing an optimization model that, in the medium-term, shapes the structure of resource allocation invested by organizations for implementing well-being program activities. The optimization model will employ the integral indicator of achieving KPI as its objective function. The optimization variables will encompass investment volumes across different time periods for the various activities within the well-being program. In the conceptual model, investments initiate implementing or sustaining program activities. In turn, these activities influence the development of employee competencies and reduce their burnout levels. Burnout directly affects the effective utilization of an employee's competencies. In conclusion, employees attain specific KPI values depending on their level of competency development and burnout.

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References

Bataineh Kh. (2019), Impact of Work-Life Balance, Happiness at Work, on Employee Performance, *International Business Research*, Vol. 12, No. 2, 99-112.

Buil I., Martínez E. & Matute J. (2019), Transformational leadership and employee performance: The role of identification, engagement and proactive personality, *International Journal of Hospitality Management*, Vol. 77, 64-75.

Daniali S., Barykin S. E., Khortabi F. M. et al. (2022), An Employee Competency Framework in a Welfare Organization, *Sustainability*, Vol. 14, No. 4, 2397.

Diamantidis A. D. & Chatzoglou P. (2019), Factors affecting employee performance: an empirical approach, *International Journal of Productivity and Performance Management*, Vol. 68, No. 1, 171-193.

Fastje F., Mesmer-Magnus J., Guidice R. & Andrews M. C. (2023), Employee burnout: the dark side of performance-driven work climates, *Journal of Organizational Effectiveness: People and Performance*, Vol. 10, No. 1, 1-21.

Gong Z., Chen Y. & Wang Y. (2019), The Influence of Emotional Intelligence on Job Burnout and Job Performance: Mediating Effect of Psychological Capital, *Frontiers in Psychology*, Vol. 10, 2707.

Jia Z. (2023), The Relationship Between Human Resource Management Innovation and Enterprise Innovation Performance and the Mediating Role of Employee Competencies in SMEs in China. *SHS Web of Conferences*, Vol. 163, 02005.

Kalandatzis T. & Hyz A. (2021), Empirical Analysis of the Phenomenon of Job Burnout Among Employees in the Banking Sector, *International Journal of Service Science Management Engineering and Technology*, Vol. 12, No. 5, 116-132.

Kim J. & Jung H.-S. (2022), The Effect of Employee Competency and Organizational Culture on Employees' Perceived Stress for Better Workplace, *International Journal of Environmental Research and Public Health*, Vol. 19, No. 8, 4428.

Kurniawan A., Sanosra A. & Qomariah N. (2023), Efforts to Increase Motivation and Performance Based on Employee Competency and Job Characteristics, *JEFMS Journal*, Vol. 6, No. 7, 3153-3162.

Matani M. & Bidmeshki G. A. (2020), The Role of Burnout on Reducing Employees' Performance, *Journal of Management and Accounting Studies*, Vol. 6, No. 2, 39-46.

Mazelis L. & Lavrenyuk K. (2017), Devising a fuzzy model for compiling a plan of activities aimed at developing human capital in university, *Eastern-European Journal of Enterprise Technologies*, Vol. 3, No. 88, 35-44.

Mazelis L. S., Lavrenyuk K. I. & Krasko A. A. (2023), Modeling the Competency Development Process of Organization Employees to Achieve Target KPI Values, Intelligent Engineering Economics and Industry 5.0 (INPROM), Proceedings of the International Scientific and Practical Conference, April 27-30, 2023, 579-582.

Riyanto S., Endri E. & Herlisha N. (2021), Effect of work motivation and job satisfaction on employee performance: Mediating role of employee engagement. *Problems and Perspectives in Management*, Vol. 19, No. 3, 162-174.

Rony Z. & Pardosi H. D. (2021), Burnout digital monitoring on employee engagement at the company, *International Journal of Research in Business and Social Science*, Vol. 10, No. 7, 156-162.

Rughoobur-Seetah S. (2023), An assessment of the impact of emotional labour and burnout on the employees' work performance, *International Journal of Organizational Analysis*, https://doi.org/10.1108/IJOA-09-2022-3429

Sabuhari R., Sudiro A., Irawanto D. W. & Rahayu M. (2020), The effects of human resource flexibility, employee competency, organizational culture adaptation and job satisfaction on employee performance, *Management Science Letters*, Vol. 10, No. 8, 1777-1786.

Sitopu Y. B., Sitinjak K. A. & Marpaung F. K. (2021), The Influence of Motivation, Work Discipline, and Compensation on Employee Performance. *Golden Ratio of Human Resource Management*, Vol. 1, No. 2, 72-83.

Song Q., Wan Y., Chen Y., Benitez J. & Hu J. (2019), Impact of the usage of social media in the workplace on team and employee performance, *Information & Management*, Vol. 56, No. 8, 103160.

Ouyang Ch., Zhu Y., Ma Z. & Qian X. (2022), Why Employees Experience Burnout: An Explanation of Illegitimate Tasks, *International Journal of Environmental Research and Public Health*, Vol. 19, No. 15, 8923.

Wu G., Hu Z., Zheng J. (2019), Role Stress, Job Burnout, and Job Performance in Construction Project Managers: The Moderating Role of Career Calling, *International Journal of Environmental Research and Public Health*, Vol. 16, No. 13, 2394.

Wulantika L., Ayusari R. M., Wittine Z. (2023), Workload, social support and burnout on employee performance. *Journal of Eastern European and Central Asian Research*, Vol. 10, No. 1, 1-8.