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ARTIFICIAL INTELLIGENCE IN HRM PROCESSES: GENERAL FRAMEWORK AND APPLICATION FOR PSYCHOLOGICAL CLIMATE MONITORING

The article considers the potential for the widespread use of artificial intelligence (AI) to address current challenges in the labor market and improve the efficiency of human resource management (HRM). It analyzes modern approaches to integrating relevant methods and tools into HRM practices. The study explores how AI can complement existing HR processes, creating a more data-driven and adaptive framework for decision-making. Companies are actively seeking ways to incorporate innovative solutions, so the results of this study can be seen as a step towards combining current HRM practices with AI's transformative potential to support effective management decisions. The paper presents powerful AI capabilities: mechanical AI, thinking AI, and feeling AI. Mechanical AI is best suited for automating tasks such as job creation, enrolment in training courses, reporting, monitoring career development, and performance evaluation. This type of AI significantly reduces administrative burdens, allowing HR professionals to focus on strategic decision-making and employee engagement. Thinking AI excels in analyzing CVs, learning outcomes, productivity, and career forecasting. Feeling AI focuses on analyzing applicant behavior, personalizing training programs, providing psychological support, and monitoring the workplace's psychological climate. To address challenges in emotional analysis, the article presents a conceptual model for sentiment analysis of data on the emotional state and satisfaction of employees. The paper includes specific recommendations for implementation and demonstrates the model's application on Glassdoor Job Reviews data using Python programming language. This approach illustrates how AI can enhance employee well-being while aligning HR practices with organizational goals.

***Keywords**: Human resource management, feeling AI, sentiment analysis, modeling, decision-making, company*

Problem statement. In today's business environment, the use of artificial intelligence (AI) algorithms in human resource management (HRM) is becoming increasingly relevant and important, as the rapid emergence and implementation of new technologies and the growth of data volumes require businesses to adopt new approaches to HR management. HRM is a fundamental function that controls talent acquisition, employee well-being, and productivity optimization in organizations. The use of AI in HRM helps to reduce the time and effort spent on routine administrative tasks, allowing HR professionals to focus on more strategic tasks, thereby reducing organizational costs. In addition, AI can provide better analytics and insights into employee performance, helping to identify team strengths and weaknesses. The use of AI can

also help improve communication and collaboration within a company through chatbots and automated support systems that can quickly answer employee questions. In addition, AI can help manage employee learning and development by providing individualized recommendations for learning materials and courses that meet their needs and career goals.

Analysis of recent research and publications. Studies on the AI integration in HRM processes have been analyzed by many researchers, including G. Sivabalan [1] and J. Lamri [2]. These works emphasize the impact of AI on recruitment. A significant body of literature, such as the publication by M. Rudra Kumar and V. K. Gunjan [3], S. R. K. Indarapu et al. [4], and A. Saxena et al. [5], highlights the application of machine learning methods to support processes in HCM. Simultaneously, researchers like P. Budhwar et al. [6], P. Korzyński et al. [7], and S. Chowdhury et al. [8] address the problems of using generative AI in HRM.

Identification of previously unresolved parts of the general problem. Despite the large number of publications on AI in HRM, the vast majority of works are devoted to highlighting the potential capabilities of this technology, while recommendations on the applied aspects of its use are not sufficiently covered in scientific publications. AI is already part of the methodological support of leading HRM information systems. However, for various reasons, the use of such systems is often impossible or impractical for small companies. Therefore, there is a need for methodologies to support the solution of certain important tasks using AI algorithms, including monitoring the psychological climate, which is proposed in this article. We propose a framework for HRM that demonstrates AI's capabilities to support key HRM processes in terms of mechanical, thinking, and feeling AI intelligences, and present a conceptual approach to the practical use of feeling AI algorithms.

Article objective. The purpose of this study includes theoretical and practical components. With regard to the theoretical component, the research aims to develop a framework for AI support of key processes in HRM, which implements the systematization of management tasks, taking into account certain AI capabilities. Another important goal of the research is to provide a more detailed overview of the framework elements related to the use of feeling AI algorithms, present a conceptual model and implement sentiment analysis for monitoring the psychological climate in the work environment.

Research methodology. In the first part of our study, we systematize the findings of research in the field of AI application in HRM and, based on this systematization, develop a framework that demonstrates the potential of AI methods. Furthermore, we showcase an approach to leveraging feeling AI algorithms, particularly Natural Language Processing (NLP), for implementing sentiment analysis modeling. This approach can be practically useful for addressing relevant HRM tasks in companies that do not utilize advanced talent management systems in their operations. The implementation of the process of sentiment analysis of data on the emotional state and satisfaction of employees, including on the basis of their feedback, is presented below.

The first step in conducting an analysis is collecting data. The necessary information can be obtained through internal resources, such as corporate feedback platforms, regular anonymous surveys, posts on professional social networks, as well as external resources, such as Glassdoor or Indeed. A valuable source of internal resources can be the recordings of regular meetings between HR professionals and employees. Modern technologies for transforming relevant multimedia data into text and then structuring the text allow us to supplement the

surveys with important data. The collected data, usually in CSV or spreadsheet format, contains textual feedback and ratings on various aspects such as working conditions, management and compensation. This data is then loaded into specialized software for further analysis, such as Python as in our study.

The second stage involves pre-processing the gathered information, which is key to ensuring the accuracy of the subsequent analysis. This process includes cleaning, transforming and preparing data for modelling.

BERT (Bidirectional Encoder Representations from Transformers) and VADER (Value Aware Dictionary for sEntiment Reasoning) models that implement NLP technology can be selected for the next stage - modelling [9,10]. Once the data preparation is complete, the selected models are trained and tested to verify their effectiveness. The main metrics used to evaluate the model include accuracy, recall, precision and F1-measure. These metrics allow users to determine how well the model performs in classifying texts and how accurately it can predict the mood or tone of texts.

The final and most important stage is the analysis of the results. This stage involves the direct interpretation of the results in order to identify economically significant insights that can influence strategic decision-making in the company. HR analysts or HR managers analyze the results of the model, which include visualizations, sentiment distributions in employee feedback, the most frequently used words and phrases, and other text characteristics that help to understand the overall picture.

Research results. Systematization of research results in the field of AI application in HRM allows us to form a framework that demonstrates the potential of AI methods presented in terms of mechanical, thinking, and feeling AI intelligences. A corresponding approach to AI typification is proposed in [11,12]. We think it is very appropriate in the case of considering HR processes. Table 1 shows how different types of AI are used to improve key HRM processes.

Mechanical AI in HRM can automate many routine tasks related to collecting and processing data on employees, vacancies, training, and performance. For example, automating the collection of candidate data based on their CVs and social media allows for quick assessment of potential employees. Automated systems for processing employee performance data use algorithms to collect and analyze information about their achievements and productivity. Learning management systems automatically register employees for courses and training based on their professional needs and goals. In addition, time and attendance systems automatically collect data on working time usage, allowing for better project management and resource allocation.

Thinking AI provides a deeper level of analysis and insight. One of the key areas of its application is the analysis of data about employees, their skills and potential for career growth. This includes analyzing candidates' CVs and assessing their suitability for a vacancy, which greatly simplifies the recruitment process; analyzing employee productivity; forecasting staffing needs and developing individual staff development plans. This approach allows companies to not only retain key employees but also support their professional growth.

Table 1

Comparison of Mechanical, Thinking, and Feeling AI

HRM Processes	Mechanical AI	Thinking AI	Feeling AI
Recruiting	*Creating vacancies* Automatic creation and publication of job descriptions, which facilitates the work of recruiters.	*CV Analysis* Highlighting candidates' key skills and qualifications, allowing recruiters to weed out irrelevant CVs faster.	*Analysis of candidates' behaviour* Evaluation of candidates' behaviour during the interview, their answers, body language, and other nonverbal cues.
Personnel development	*Automation of enrollment in courses* Managing the enrollment process for professional training programs.	*Analysis of learning outcomes* Evaluation of the effectiveness of training programs.	*Adaptive learning plans* Providing personalized recommendations based on the professional needs of employees.
Talent management	*Automation of career development monitoring* Tracking the career progress and skills of employees.	*Career Forecasting* Assessment of employees' potential to predict their career development.	*Psychological support* Providing support and motivational recommendations based on an analysis of employees' emotional needs.
Performance management	*Automated Performance Evaluation Systems* Collect and process employee performance data for automatic report generation and feedback.	*Performance Analysis* Identification and analysis of employee productivity trends to objectively assess their achievements.	*Recognizing Emotional Impacts* Analyze emotional factors that affect performance and provide appropriate support.
Personnel control	*Reporting Automation* Generate reports on HR data for monitoring and managing personnel.	*Data Trend Analysis* Identify trends and patterns in HR data to respond quickly to changes.	*Psychological climate monitoring* Determining the level of psychological comfort and stress among employees to improve the working environment.

Source: developed by the authors

Feeling AI is gaining popularity due to the growing trend of understanding and responding to people's emotional states, especially in the field of human resources. This type of AI is able to analyze speech, facial expressions, tone of voice, and other signals to determine emotional reactions, which opens up new opportunities for improving workplace interaction [13]. The application of feeling AI is multifaceted and covers all HRM processes. In recruitment, it is used to determine whether candidates are aligned with the organization’s values based on the analysis of their emotional reactions during interviews, which leads to a more objective selection

and improved decision-making accuracy. In addition, for employee development, feeling AI provides personalized recommendations that take into account their needs and skill gaps. This plays an important role in strategic planning of the organization's development and team efficiency.

One of the most important tasks in personnel control is monitoring the psychological climate in the team. Feeling AI can provide powerful support in determining the level of psychological comfort and stress among employees, which allows you to notice and respond to negative trends in time, thereby creating conditions for maximum efficiency and high results in the work process. Continuous monitoring based on feeling AI algorithms makes it possible to take proactive measures, thereby avoiding a decrease in labor productivity, threats of employee outflow, reputational losses, etc. The results of relevant management actions directly affect business efficiency and the competitive position of the company.

To implement the proposed conceptual model for monitoring the psychological climate in the team, we analyzed the Glassdoor Job Reviews dataset [14], which contains information on the work experience of employees across different companies.

Glassdoor is a widely used online platform that is useful for both employees and job seekers, as well as for employers [15]. On this platform, employees can leave feedback about the company, evaluating working conditions, salaries, benefits and work-life balance, etc. For job seekers, this allows them to make an informed choice by reviewing reviews of potential employers, while companies can post vacancies and use the platform to improve the hiring process.

The dataset for the following sentiment analysis contains a significant number of both categorical and numerical variables (**Помилка! Джерело посилання не знайдено.**).

Figure 1 demonstrates the change in the number of reviews left by users from 2008 to 2021. The graph shows that during the first few years, from 2008 to 2013, the number of reviews is low with a moderate increase. After 2014, the rate of increase in reviews accelerates markedly. The most noticeable growth is observed after 2019, when the number of reviews exceeds 100,000. This indicates a significant increase in user activity during this period, potentially due to external events that affected changes in consumer behavior or company operations. After 2020, the graph shows a certain stabilization, with the number of reviews remaining at a high level.

In the process of preparation for developing the model, duplicate records were removed to avoid biasing the results. In addition, a significant part of the data contained gaps, so the missing values in the text fields were filled with empty lines for further work.

Table 2

Data Types

Data	Type	Description
1	2	3
firm	object	The name of the reviewed company.
date_review	object	Review publication date.
job_title	object	Title of the position of the author of the review in the company.

1	2	3
current	object	Indicates whether the author of the review is a current employee of the company.
location	object	Company location.
overall_rating	int64	Overall assessment of the company.
work_life_balance	float64	Assessment of work-life balance in the company.
culture_values	float64	Assessment of the company's corporate culture and values.
diversity_inclusion	float64	Diversity and inclusion assessment of the company.
career_opp	float64	Assessment of career opportunities in the company.
comp_benefits	float64	Assessment of compensation and benefits provided by the company.
senior_mgmt	float64	Assessment of the company's top management.
recommend	object	Indicates whether the employee recommends this company to others.
ceo_approv	object	Indicates whether the author of the review approves of the activities of the company's CEO.
outlook	object	Prospects for the company's development.
headline	object	Brief description of the review about the company.
pros	object	Positive aspects of working in a company.
cons	object	Disadvantages of working in a company.

Source: developed by authors based on [14].

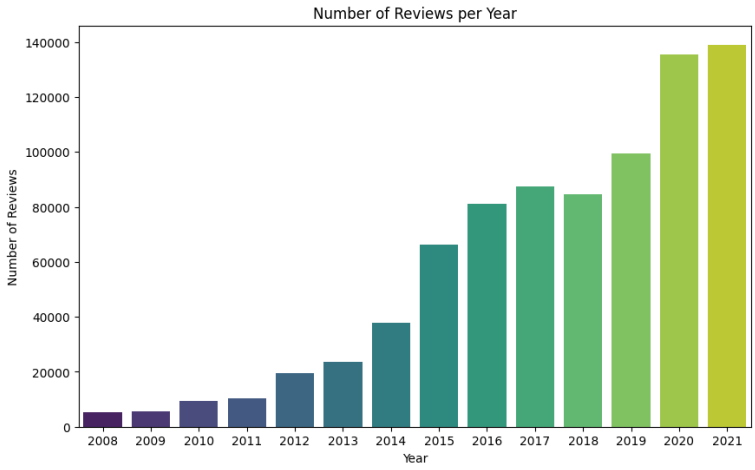

Fig. 1. Number of reviews in the dataset

Source: developed by the authors based on [14].

When preparing the text data, the Regular Expressions (re) library was used to remove punctuation, convert text to lowercase, and remove redundant characters. This step was necessary to improve the quality of further analysis and training of the model based on textual feedback.

In order to reduce computational resources and speed up the model training process, 6000 records were randomly selected from the total dataset using the sample() method, and this sample was used for further training and testing of the model. During the process of preparing the data for modelling, an imbalance check was performed to check whether the number of positive and negative reviews was equal. As a result of this action, it was discovered that there

were 3654 positive reviews, while there were 2346 negative reviews. If a model is trained on an uneven dataset, it tends to learn to predict the predominant class in most cases.

To balance the data in the dataset, we chose the undersampling technique, which involves reducing the number of records of the predominant class by selecting random records. As a result, a sample was created with the number of both positive and negative reviews equal to 2346.

To classify sentiments in reviews, we first selected the BERT model and performed the following steps.

At the first stage, the data is split into training, validation and test samples using the train_test_split function from the scikit-learn library. The main textual data set is represented in the headline column, which contains the titles of the reviews, and the label column represents the class labels used for classification (1 for positive and 0 for negative reviews). The split is performed in two steps. Firstly, the main dataset is split into a training set of 70% and an intermediate set of 30%, the intermediate set includes data for testing and validation. After that, the intermediate sample is divided into test and validation subsamples in the proportion of 40% and 60% respectively.

The next step was tokenization of the text using the pre-trained BertTokenizer tokenizer based on the Bert-base-uncased model. The maximum sequence length was set to 216, and the text sequences were truncated to this value. This allowed us to ensure the same length for all texts, which is a requirement for the BERT model.

Next, the text data was encoded into a format that can be used by the BERT model using the batch_encode_plus method. The encoding was performed for three different sets: training, validation and test samples.

For this task, the TFBertForSequenceClassification model was used, which was loaded from the pre-trained bert-base-uncased parameter set. This model is specially designed for sequence classification where each text is assigned a specific label. The model was trained on the tokenized and encoded input_ids vectors from the training set, which were prepared earlier. The training process lasted for 5 epochs with a battle size of 32. A validation sample was used to evaluate the model performance at each epoch. The model evaluation showed that the BERT model achieved an accuracy of 70.21% on the validation sample.

The VADER model was also applied in the next step, with an overall accuracy of 76.51%. According to the evaluation results (Table 3), VADER has the best performance in all major metrics, such as precision, accuracy, recall, and F1-score, indicating its superiority in the classification tasks of this dataset.

However, despite the fact that BERT demonstrates slightly lower results, this model is a powerful tool for more complex texts with a deep emotional context. Whilst VADER demonstrated higher accuracy, it has certain limitations in terms of deeper contextual analysis.

Table 3

Evaluating the Performance of VADER and BERT Models

Model	Accuracy	Precision	Recall	F1-score
VADER	76,51%	78,81%	76,51%	73,52%
BERT	70,21%	70,28%	70,21%	70,19%

Source: developed by the authors.

In the following, we analyzed the word clouds for negative and positive reviews generated by both models (Figure 2, 3).

Fig. 2: Word cloud for positive (left) and negative (right) sentiments using BERT model
Source: developed by the authors.

In Figure 2 (left), the frequency of using the words ‘best’, ‘career’, ‘excellent’, ‘opportunities’, ‘experience’, ‘culture’ indicates that employees are quite positive about the company's work environment, opportunities for development and other benefits, such as rewards. Common uses of the word ‘learning’ reflect that employees value opportunities for professional growth and training in the company.

In Figure 2 (right), the widespread use of words such as ‘bad’, ‘worst’, ‘terrible’, ‘poor’ indicate serious negative impressions that some employees have. It may also be noticed that the words ‘management’ and ‘manager’ are frequently used, which may point to problems with management or dissatisfaction with management decisions.

Fig. 3: Word cloud for positive (left) and negative (right) sentiments using VADER library
Source: developed by the authors.

Cloud for positive sentiment in Figure 3 also shows that the words ‘opportunity’, ‘career’ and ‘experience’ are widely used in the reviews, which indicates that employees see opportunities for learning, development and career growth in the company. Frequent mentions of ‘benefits’ and ‘balance’ demonstrate that employees value work-life balance and the benefits provided by the company.

In the cloud with negative sentiments, the words ‘poor’, ‘avoid’, ‘terrible’, ‘bad’, ‘boring’ are often found, which indicates dissatisfaction with working conditions and given tasks.

Furthermore, the word ‘management’ is often mentioned in a negative context, which may imply problems with management or dissatisfaction with management methods.

The results obtained from the application of the above-mentioned models provide HR professionals with an assessment of employee attitudes, forming an understanding of what causes dissatisfaction or anxiety in the team, and of what inspires employees to achieve their

maximum potential. Such an assessment can take the form of a regular report on the overall psychological state of employees in the company. The report may include detailed information on the content of the issues that are important to most employees. Based on such information, it is appropriate to create certain indicators of employee satisfaction to develop proactive measures to eliminate potential problems in the company. It is also worth creating dashboards with such indicators, such as satisfaction, loyalty and engagement.

Visualizations, graphs, ratings, reviews by sentiment, the most commonly used words and bigrams, reviews with unusual emotional coloring will help you better understand the expectations and needs of employees. Relevant visualizations may include the Average weekly (monthly) sentiment score graph, which displays weekly (monthly) averages of the emotional tone of employee reviews. The X-axis represents weeks, and the Y-axis represents emotional coloring from -1 (most negative) to 1 (most positive); The most common and high-frequency words in the review data - a cloud of words that are most often found in reviews; Common words around 3 most frequent words; Top 20 Bigram Frequency and others. It's important to use these visualizations in conjunction with other psychological climate research methods to get a more comprehensive view, and to monitor the dynamics of changes in the word cloud to understand how employees' opinions and moods change over time. In addition, this visual representation can be very effective in stimulating discussions or new ideas during team discussions about HR activities.

If this approach is used regularly, the model needs to be updated periodically to ensure that the modelling results are in line with reality. It is recommended to choose the frequency of updating depending on the size of the company. For example, for small businesses with a small number of employees, it is advisable to update the model every 6-12 months, which will be sufficient to maintain accuracy. For medium-sized companies with more than 50 employees, it is appropriate to update the model every 3-6 months. In this case, fluctuations in employee sentiment may be more frequent, and more frequent updates will allow you to respond more quickly to these changes.

In the case of using the model in large companies with more than 500 employees, due to the much larger number and frequency of data changes, it will be advisable to update the model on a monthly basis. Such a procedure will ensure timely analysis of a large amount of data on the emotional state and satisfaction of employees, allowing you to identify new trends and respond quickly to potential problems. In addition, more frequent updates will help to maintain flexibility and accurately track changes in employee attitudes towards their work.

Conclusions. The need for widespread use of AI potential is driven by current labor market challenges and increased requirements for HRM efficiency. Companies are actively looking for ways to incorporate relevant methods and tools into their practices, so the results of this study can be seen as a step towards combining current HRM practices and AI potential to support relevant management decisions. The paper presents a framework that includes powerful AI capabilities: mechanical AI for automating repetitive actions, thinking AI for processing data for decision-making, and feeling AI for analyzing interactions and human contacts.

Competition for talent in the labor market forces companies to pay special attention to employer reputation and internal processes, so AI algorithms, including feeling AI, are becoming indispensable tools for quickly identifying problems and making strategic decisions to maintain a high level of competitiveness. Therefore, the focus of this study is on the characteristics and

possibilities of implementing feeling AI algorithms, in particular through the implementation of sentiment analysis. Powerful talent management systems have already included relevant algorithms to support their functionality. However, such systems are available to a limited circle of large companies, while the issue of rapid implementation of effective new approaches concerns all business representatives, therefore, the recommendations for implementing sentiment analysis to monitor the psychological climate proposed in this paper are in demand and relevant.

The economic value of the proposed approach to the implementation of sentiment analysis lies in the possibility of quick and precise diagnosis of problem areas within any organization, which, in turn, allows HR professionals to respond promptly to a decrease in the level of satisfaction or an increase in staff turnover. This allows us to reduce the costs associated with high rates of resignations, recruitment and adaptation of new employees. In addition, such models will help companies to improve their analysis of external factors, including the employer's reputation in the labor market, for example, through public platforms such as Glassdoor. Based on this information, organizations can make decisions and develop strategies to improve their image both externally and internally.

The presented practical results are the beginning of a comprehensive study, which involves, first of all, a thorough study of the stage of data collection for analysis, as to unlock the potential of the proposed approach, it is important to develop a procedure for systematic data collection within the organization and from external sources. These data may include regular (at least once every 3 months) anonymous employee surveys, analysis of emails, comments in professional social networks, results of personal communications with HR specialists, and labor productivity indicators. Using this range of data, it will be possible to gain a deeper understanding of the team environment and the real opinions of employees, and as a result, help the company take effective steps towards positive change.

The other important area of development of this research is developing the software that will allow regular monitoring of the psychological climate based on data from both internal and external sources, and based on the results of the modeling; generate the necessary reports, trend graphs, ratings and understanding of the mood. This can be a powerful tool for small companies, as the introduction of psychological environment monitoring into daily work processes will not only help to identify and solve problems in a timely manner but will also have a positive impact on the overall atmosphere in the team.

The conducted research confirms that AI is a transformative mechanism in the HRM sector. The impact of AI is evident in the optimization of numerous HR processes, and the focus of such management is shifting to creating and maintaining a productive working environment where employees feel comfortable and work efficiently.

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ШТУЧНИЙ ІНТЕЛЕКТ В ПРОЦЕСАХ УПРАВЛІННЯ ЛЮДСЬКИМИ РЕСУРСАМИ: ЗАГАЛЬНІ ЗАСАДИ ТА ЗАСТОСУВАННЯ ДЛЯ МОНІТОРИНГУ ПСИХОЛОГІЧНОГО КЛІМАТУ

У статті розглядається потенціал широкого застосування штучного інтелекту (ШІ) для вирішення актуальних викликів на ринку праці та підвищення ефективності управління людськими ресурсами (human resource management, HRM). Аналізуються сучасні підходи до інтеграції відповідних методів і інструментів у практики HRM. Дослідження вивчає, як ШІ може доповнити існуючі процеси HRM, створюючи більш орієнтовану на дані та адаптивну основу для прийняття рішень. Компанії активно шукають способи впровадження інноваційних рішень, тому результати цього дослідження можна розглядати як крок до поєднання сучасних практик HRM із трансформаційним потенціалом ШІ

для підтримки ефективних управлінських рішень. У статті представлено потужні можливості ШІ: механічного ШІ, мислячого ШІ та емоційного ШІ. Механічний ШІ найкраще підходить для автоматизації завдань, таких як створення вакансій, реєстрація на навчальні курси, складання звітів, моніторинг кар'єрного зростання та оцінка ефективності. Цей тип ШІ суттєво знижує адміністративне навантаження, дозволяючи фахівцям з HRM зосереджуватися на стратегічному прийнятті рішень та залученні працівників. Мислячий ШІ досягає успіху в аналізі резюме, результатів навчання, продуктивності та прогнозуванні кар'єри. Емоційний ШІ зосереджується на аналізі поведінки кандидатів, персоналізації навчальних програм, наданні психологічної підтримки та моніторингу психологічного клімату на робочому місці. Для вирішення проблем пов'язаних з аналізом емоцій стаття пропонує концептуальну модель для аналізу настроїв на основі даних про емоційний стан і задоволеність працівників. У роботі надано конкретні рекомендації щодо впровадження та продемонстровано застосування моделі на основі даних з оглядів про роботу компаній на платформі Glassdoor із використанням мови програмування Python. Цей підхід ілюструє, як ШІ може сприяти благополуччю працівників, одночасно узгоджуючи практики HRM із цілями організації.

Ключові слова: *управління людськими ресурсами, емоційний ШІ, аналіз настроїв, моделювання, прийняття рішень, компанія*