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The Influence of Working Conditions on Perceived Work-life Balance

Abstract. *The influence of working conditions on employees' perceived work-life balance is examined using microdata from the 2021 European Working Conditions Telephone Survey (EWCTS), a nationally representative dataset covering over 70,000 respondents from 36 European countries. Given the subjective and multidimensional nature of work-life balance, the analysis combines descriptive statistics with machine learning techniques, employing an optimized artificial neural network to model the probability that individuals perceive compatibility between professional and personal responsibilities. The dependent variable reflects the perceived fit between working hours and family or social commitments, while explanatory variables capture professional characteristics, personal well-being, work-life interference, and demographic factors. Bayesian optimization (Optuna) is applied to identify the most effective neural network architecture, achieving good predictive performance (AUC = 0.794). Simulation experiments based on individual profiles are further used to assess how controlled changes in working conditions affect perceived balance. The results indicate that reducing working hours, limiting night work, increasing schedule flexibility, and enabling teleworking are associated with higher predicted perceived work-life balance, supporting the relevance of organizational policies focused on flexibility and employee well-being. Because the outcome is imbalanced, class-specific and balanced metrics are reported alongside the aggregate scores. A fixed-seed Monte Carlo Dropout sensitivity analysis provides 95% predictive intervals; the simulations remain illustrative model predictions rather than causal effects.*

Keywords: *work-life balance, Artificial Neural Network, European Working Conditions Survey, employee well-being, Bayesian optimization.*

JEL Classification: J81, I31, C45, J28.

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1. Introduction

The opportunity cost of earning a high salary in today's society often means giving up personal time, whether that's moments with family, leisure activities, or simply rest. Nowadays, when technology is present at every step, the boundaries

between the professional life and private life are becoming increasingly difficult to draw. Constant access to technology increasingly enables work to intrude into personal life, whether it is through mobile phones, social networks or online communication platforms. This reality reflects the increasingly common difficulty in clearly separating the two dimensions.

This paper aims to investigate the subjective perception of work-life balance, using the European Working Conditions Survey, special edition of 2021, analysed in the context in which economic pressures, organizational expectations and technology play a key role. This study combines a dataset from a nationally representative survey, which supports cross-national descriptive inference when the survey design is respected. At the same time, the integration of artificial neural networks is justified by the subjective and complex nature of how individuals perceive work-life balance, as these methods emulate, to some extent, the way the human brain processes information. The contribution lies in applying a standard MLP framework to a large cross-national survey and combining prediction with profile-level sensitivity checks, rather than in proposing a novel neural-network architecture.

The paper is organized as follows. First, the literature review discusses the main theoretical perspectives and empirical findings related to work-life balance, emphasizing the lack of a universally accepted definition and the diversity of approaches used to study this concept. Next, the model specification section presents the data source, the construction of the dependent and explanatory variables, and the preprocessing steps required for applying machine learning methods, followed by a detailed description of the artificial neural network architecture and the Bayesian optimization procedure. The results and discussion section then combines descriptive analysis with individual-level simulation experiments in order to illustrate how changes in working conditions and personal well-being factors affect the predicted probability of perceived work-life balance. Finally, the conclusions summarize the main results, discuss their implications for organizational policies, and outline the main limitations of the study together with possible directions for future research.

2. Literature Review

The term work-life balance was introduced in 1986, although the expression had already been used in everyday language for several years. However, initiatives aimed at ensuring this balance have existed since the 1930s (Meenakshi, 2013). The notion of work-life balance began to be debated in the literature with the emergence of major socio-economic changes, such as the increase in women's participation in the labour market, marking a transition from the traditional role of women in the household, to an equal involvement in the labour field. At the same time, professional and personal priorities have evolved over time, reflecting changes in the values and expectations of different generations. In addition, technological advances and increasing criticism of the 'overtime culture', which imposes an excessive

workload on employees, have amplified concerns about the impact of these practices on family life, health and overall well-being (Pawlicka et al., 2020).

The concept of work-life balance has no universally accepted definition and method of measurement (Kalliath and Brough, 2008), being interpreted differently depending on the chosen perspective. In the literature, this balance was analysed from several angles, with some researchers focusing on the distribution of time between work and personal life (Rapoport et al., 2002), while in other studies it was correlated with the level of satisfaction (Shaffer et al., 2015), the individual's well-being (Gropel and Kuhl, 2009), their performance at work (Preena, 2021) or quality of life (Greenhaus, Collins and Shaw, 2003). The absence of a clear definition and a standardised method of measurement underlines the complex nature of the concept of work-life balance.

One of the most well-known definitions of work-life balance belongs to Clutterbuck (2003), who states that work-life balance is the ability of an individual to effectively manages the various demands on their time and energy such that they can maintain their well-being and sense of personal fulfilment. On the other hand, researchers Greenhaus and Allen (2011) define work-life balance as "the extent to which an individual's efficiency and satisfaction in their work and family roles are compatible with their priorities in life at a given time". Kalliath and Brough (2008) state that the balance between the professional life and personal life reflects the way in which a person perceives the compatibility between professional responsibilities and those of his private life, in a way that supports personal evolution in accordance with his current priorities.

Kim et al. (2015) define the imbalance between personal and professional life as the phenomenon of overwork, in which work invades personal life, a phenomenon often encountered in countries with a long-term work culture, such as China and Japan. Based on these definitions, it is considered that the balance between personal and professional life is influenced by the experiences of each person, by their expectations from professional and personal involvement, and most importantly, by the priorities of each individual, all of which are delimited by the time variable. As priorities evolve throughout the different stages of life, the balance between work and personal life is dynamic and highly individual. This perspective is particularly relevant in the context of remote work, as highlighted by Vasilescu et al. (2024) in *Work-Life Balance when Working from Home*, where the flexibility associated with working from home may coexist with difficulties in maintaining clear boundaries between professional and personal life.

To capture the nuances of this perception and identify the determining factors, traditional methods of statistical analysis may be insufficient. In this context, computational models inspired by the structure and functioning of the human brain, such as neural networks, offer a promising alternative, an idea also supported by recent studies that propose a wide range of machine learning and data analysis techniques to better understand the mechanisms that shape work-life balance. A relevant example is provided by the research conducted by Pawlicka et al. (2020), which used methods from the field of Machine Learning to analyse the variables

associated with subjective perception of work-life balance. The research was based on an extensive dataset collected from 800 employees in Poland, including variables such as gender, age, education, marital status, number of children, length of service, number of hours actually worked, the existence of organizational solutions for work-life balance and subjective assessment of the material situation. The authors used an artificial neural network with two hidden layers to analyse this data and built an experimental framework based on simulated scenarios.

Authors such as Wang, Ma and Hu (2024) have analysed the relationship between mobile platforms, such as Slack, Microsoft Teams, and DingTalk, and the work-life imbalance, with the premise that the emergence of mobile platforms has blurred boundaries, "making it increasingly difficult for individuals to balance work and personal life." With the help of a co-emergence network analysis technique and using explainable AI methods, the non-linear relationships underlying the technology-induced work-life imbalance were analysed and behavioural patterns were detected.

3. Model Specification

3.1 Model Description and Hypothesis

The source of the data is Eurofound, which in 2021 organised a special edition of the European Working Conditions Survey (EWCTS), using the telephone interview to collect the responses. The total number of respondents who participated in the survey is 71,758 people, covering employees aged 16 and over, coming from 36 European countries. The survey covered all countries in the European Union, Switzerland, the United Kingdom, Serbia, Norway, Montenegro, North Macedonia, Bosnia and Herzegovina, Albania and Kosovo. The method of data collection was the computer-assisted telephone interview (CATI), and the average duration of the interview was estimated at 22 minutes.

The dependent variable used in this research refers to the employees' perception of the degree of work-life balance, reflected by the compatibility of the work schedule with family and social commitments. Survey participants assessed their compatibility between work schedule and family or social commitments, on a four-level Likert scale, from 'Very good' at 'Not at all'. Of the 63 variables available in the database, 25 were selected as independent variables, meeting three essential aspects in the analysis of work-life balance. More specifically, six variables that characterize personal life, nine variables that refer to professional life and six variables illustrating the interactions between them, to which are added four more demographic variables, all of them being described in Table 1.

Table 1. Description of the variables used in the research analyses

Category	Label	Description	Variable type
Dependent variable	work_life_balance	Perception of the balance between working hours and family obligations	Categorical, binary
Characteristics in the professional sphere	number_jobs; usual_hours_week; boss_gender; work_from_home; night; highspeed; autonomy_method; gender_freq; losejob	Workload, average number of hours worked per week; working methods; presence of night shifts; flexibility of working hours; staff at work	Categorical, binary Numeric
Characteristics in the personal sphere	rested, interesting; total_hour_housework; active; relaxed; cheerful	Self-assessment of the employee regarding the level of rest; well-being; relaxation and presence of an active and interesting life; the average number of hours allocated daily to household chores	Categorical, binary Numeric
Interference between the two spheres	wlb_tired; freetime_work; able_hour_off; wlb_concentration; presenteeism; health_risk	Self-assessment of the employee regarding the flexibility of leaving the workplace; working in free time, difficulty concentrating in daily life caused by work	Categorical, binary
Demographic variables	gender; age_groups; country; children	Gender; age; country and presence of children	Categorical, binary

Source: Authors' elaboration based on the Eurofound EWCTS 2021 questionnaire.

Given the categorical nature of most of the variables analysed (24 out of 26), it was necessary to recode them to ensure the validity of the machine learning model. The Likert variables allowed a direct transformation into binary format, but variables such as “*presenteeism*” and “*age_groups*” required a method capable of correctly representing the nominal nature of the categories. To this end, the One-Hot Encoding technique has been applied, which creates separate indicators for each category, avoiding the imposition of an artificial ordering and eliminating the risk of pseudo-ordinal relationships associated with label encoding (Al-Shehari and Alsowail, 2021; Bolikulov et al., 2024). The literature constantly emphasizes the superiority of this method in the preprocessing of categorical data from surveys, highlighting its contribution to improving the performance of classification algorithms (Raza et al., 2022; Rezapour and Hansen, 2022; Crowley et al., 2025).

Artificial neural networks (ANNs) emerged as early as the 1940s, when McCulloch and Pitts (1943) defined a formal model of the neuron. They are algorithmic systems inspired by the way the human brain works, being composed of processing units (artificial neurons) organized on several levels. The connections between neurons (assimilated to biological synapses) have scalable weights that can be adjusted during learning (Walczak and Cerpa, 2003). In *feedforward networks*, signals propagate from the input layer, passing through one or more intermediate layers, to the final layer, each layer serving as an input source for the next.

Each neuron calculates a linear combination of its inputs, often weighted and possibly biased, and then a nonlinear activation function such as 'sigmoid', 'hyperbolic tangent' or 'ReLU' is applied to produce an output signal. In the learning process, these weights are iteratively adjusted to minimize prediction error, allowing the network to generalize complex models (Walczak and Cerpa, 2003). The standard name in the literature for such a feedforward neural network with one or more hidden layers, in which each neuron is completely connected to those in the next layer, is called Multilayer Perceptron (MLP).

The Rectified Linear Unit (ReLU) is an activation function often used in neural networks, being mathematically defined by the formula:

$$f(x) = \max(0, x) \quad (1)$$

The activation function described in formula (1) indicates the assignment of 0 for negative inputs and is linear identity for positive inputs (Arora et al., 2018). In practice, ReLU is used in the hidden layers of neural networks, the main advantages being that it introduces non-linearity, but avoids the phenomenon of gradient saturation, since the derivative of the ReLU function is 1 for $x > 0$ and 0 for $x < 0$, so that positive signals propagate undistorted by amplitude. This behaviour helps accelerate the training of deep learning networks and decrease the gradient, compared to classic functions such as 'sigmoid' or 'tanh'. In addition, ReLU produces sparse (infrequent) activations, which can help the model learn more efficient representations (Arora et al., 2018).

Dropout is a regularization method introduced by Srivastava et al. (2014), which has the role of diminishing the overfitting of neural networks with many parameters. The method consists of randomly removing some neurons and their connections during the training of the network, which prevents the excessive coadaptation of internal neurons. At each training step, a different subnet is used, and the overall result can be interpreted as the average of the predictions of a large set of possible networks, using complementary sets of observations at each trained version. In the test phase, all neurons are reinserted and the entire network with scaled weights is used to approximate the effect. With this hyperparameter, overfitting is significantly reduced and network performance is improved for new observations (Srivastava et al., 2014).

Nadam (Nesterov-accelerated Adaptive Moment Estimation) is an optimization algorithm introduced by Dozat in 2016 that extends the Adam algorithm by integrating Nesterov momentum into parameter updating (Dozat, 2016). More specifically, Nadam calculates weighting corrections using both the first and second moments of the gradient and a Nesterov term that estimates the gradient at a future position of the parameters. By combining the advantages of adaptive learning rate with the benefits of introducing Nesterov, Nadam leads to faster convergence and trained models with greater accuracy. In practice, Nadam has proven to be useful because it can accelerate optimization and achieve superior performance to Adam or RMSprop models (Dozat, 2016).

The number of epochs is a hyperparameter that indicates how many times the entire training dataset is completely traversed by the model during the learning

process. Each epoch involves a complete passage of data through the network, both in the forward direction, called forward pass, and backward (backward pass), updating the weights of neurons according to the observed errors. After an epoch, the model has seen each observation in the training data once and adjusts its parameters accordingly, this process being repeated for a predefined number of epochs that allows the network to progressively learn the structure of the data (Azam et al., 2024; Dehgan et al., 2025).

In neural network training, the data used in model training is processed in batches of a fixed size, called 'batch'. The `batch_size` hyperparameter specifies the number of observations processed in the training in a forward and backward propagation step. As noted by Goodfellow (2017), the hyperparameter shows how many observations are sent over the network to calculate the error and update the parameters only once. Using it balances the cost of computing and stabilizes optimization.

For binary classification, binary entropy (log loss) is used as a cost function. This measures the difference between the original values $y_i \in \{0,1\}$ and the estimated probabilities. The loss function has the form: $\hat{p}_i$

$$L(y_i, \hat{p}_i) = -[y_i \log(\hat{p}_i) + (1 - y_i) \cdot \log(1 - \hat{p}_i)] \quad (2)$$

So, based on equation (2), if the dependent value is 1, then the loss includes $-\log(\hat{p}_i)$, and if the target value is 0, it contains $-\log(1 - \hat{p}_i)\hat{p}_i$. The goal of training is to minimize the average loss on the training dataset, and this criterion corresponds to maximizing the log-likelihood value for the Bernoulli distribution of classes (Terven et al., 2025). Basically, the model learns to increase the estimated probability for class 1 of each observation, penalizing wrong predictions.

For the implementation of the artificial neural network used in this work, the categorical variables were recoded by the One Hot encoding technique, and the numerical ones were normalized, ensuring compatibility with the MLP model described above. Subsequently, the Optuna Bayesian optimization algorithm was used with the aim of identifying the neural network architecture that maximizes the performance of the model in relation to the AUC score. This approach is consistent with recent studies in the literature, such as the study by Li, Zou, and Li (2024), in which the authors used Optuna to explore various combinations of activation functions, number of neurons, and dropout rates for an MLP applied in medicine.

The optimization was carried out using 50 iterations, each evaluating a different combination of parameters. The description of all included hyperparameters is available in Annex 1. For a more efficient representation, the model was designed so that, before building the neural network, it selects only the 20 most relevant variables for the binary classification problem. The data were divided into a ratio of 90% for the training stage and 10% for testing, in line with suggestions in the literature on the application of ANN (Pawlicka et al., 2020). The network architecture is described in Figure 1, where two hidden layers were selected, the first contains 35 neurons and a dropout rate of 0.281, and the second layer includes 59

neurons, both using the ReLU activation function. The model was trained using the Nadam optimization algorithm over 74 eras, using a learning batch size of 16.

Because the outcome is imbalanced (58,648 perceived-balance cases, 81.7%, and 13,110 perceived-imbalance cases, 18.3%), the main ANN specification and the observed class distribution were retained, while evaluation was extended beyond aggregate scores. Precision, recall, and F1-score were calculated separately for classes 0 and 1, together with balanced accuracy and macro-F1. SMOTE was not applied because synthetic combinations of one-hot survey categories may be internally inconsistent, and under-sampling was not applied because it would discard observations.

For the uncertainty sensitivity check, the same architecture was re-estimated with fixed NumPy and TensorFlow seeds (20260818). Dropout was kept active for 1,000 stochastic forward passes for each selected profile, and the 2.5th and 97.5th percentiles define the reported 95% predictive intervals. These intervals describe model uncertainty conditional on the selected profile; they are not population confidence intervals and do not establish causality.

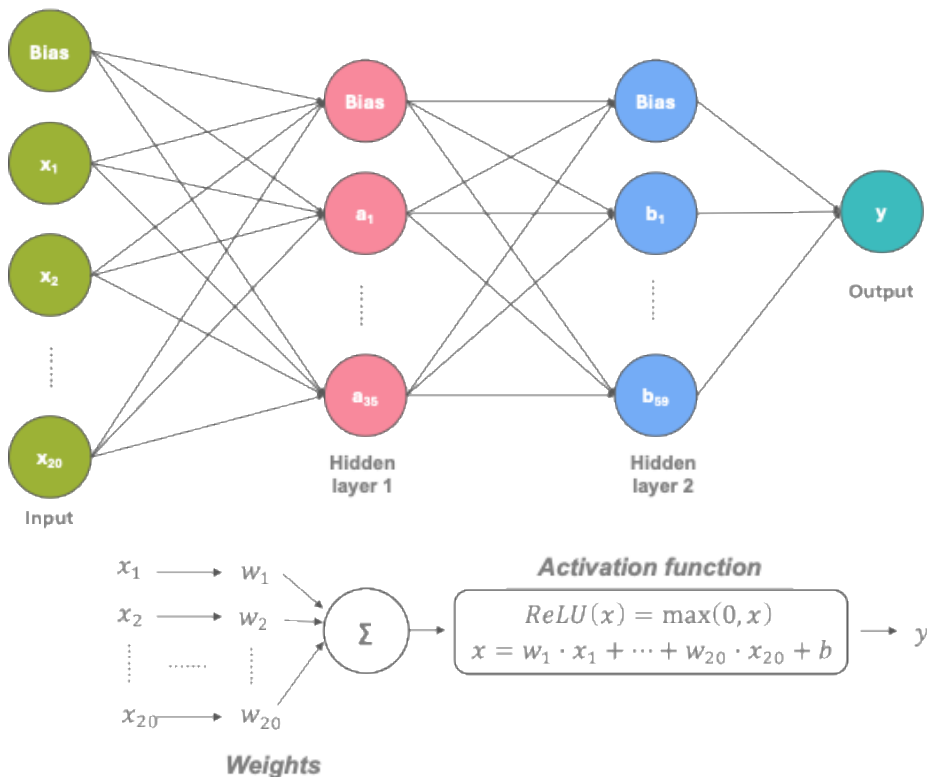


Figure 1. Architecture of the artificial neural network used in the analysis

Source: Own processing based on information from Yuan et al. (2022).

4. Results and Discussion

4.1 Descriptive Statistics

In order to carry out a descriptive analysis of the dataset from the European Working Conditions Survey in 2021, some relevant descriptive statistics are presented in Figure 2. A higher percentage of women, compared to men, said they felt an imbalance between personal and professional responsibilities, with the difference between the two groups being 10.4 percentage points. This denotes the involvement of women in several roles, being responsible for activities such as childcare and involvement in household chores.

Respondents largely stated that they felt cheerful (83%) and energetic (75%), but not as many admitted that they would be rested or relaxed, with the proportions being 63% and 70%, respectively, demonstrating that in 2021, in Europe, people perceived life as interesting, but sleep and leisure were lacking. While employees work an average of 39.8 hours per week, the time spent on household activities, childcare or family is almost 4 times less, spending an average of only 9.1 hours per week on such activities. This could be a first signal that employees are encountering problems in managing work and home activities. The dataset is not balanced, with people declaring a state of equilibrium predominating.

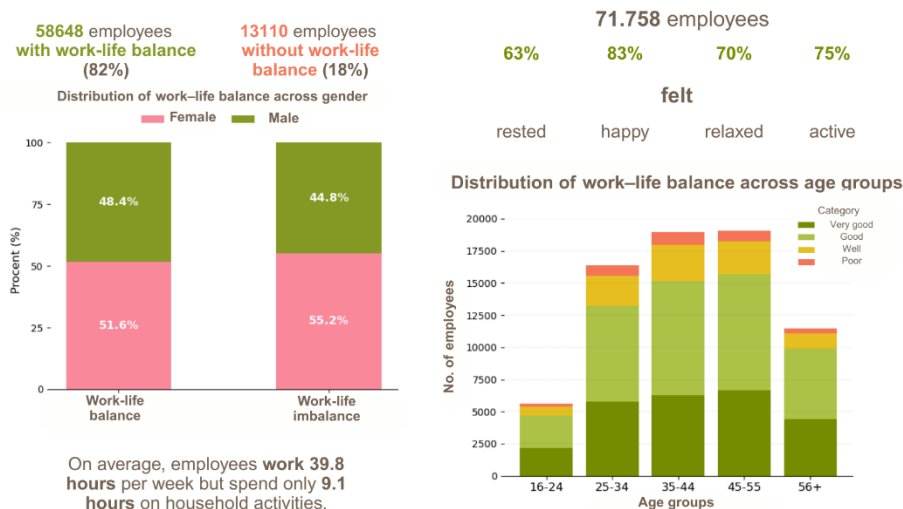


Figure 2. Infographic with descriptive statistics based on data from the EWCTS 2021 survey

Source: Own processing in Canva using the EWCTS 2021 database.

As for the perceived balance at the generational level, the data highlight a clear trend according to which adults in generation X (41–56 years old) and generation Z (16–24 years old) most frequently declare a balance between personal and professional life, compared to the other age groups. Millennials (25–40 years old) are

the generation in the middle of their professional career, which tends to perceive an imbalance more often, possibly due to uncertainties about the future of work and the lack of a consolidated professional routine, to which is added the beginning of a family life. People from the baby boom generation (over 56 years old) declare a relatively high proportion of balance, which may reflect both the transition to retirement and the expertise acquired in time management. A possible sociological explanation is related to the way in which each generation values work and personal time, depending on the context in which it was formed.

4.2 Training an Artificial Neural Network

To meet the goal set for this research, an artificial neural network was trained. It was then used to carry out simulations applied to individuals extracted from the analyzed sample, in order to examine the model response of controlled changes in relevant variables on the probability of achieving a work-life balance. The variables selected for these simulations are characteristics associated with the work environment that can be directly influenced by organizational policies, such as the average number of hours worked per week, working hours in inappropriate hours or the possibility of obtaining a free hour to solve personal problems. Through these analyses, the aim is to illustrate potentially relevant changes that can support the well-being of employees, directly contributing to increasing their performance and, implicitly, to improving the economic results of the respective company.

The simulations are interpreted as profile-specific sensitivity analyses: they show how the fitted ANN prediction changes when selected inputs are modified while all other inputs are held constant, rather than estimating the causal effect of an organizational intervention.

Table 2. Performance indicators for the trained artificial neural network

AUC	Accuracy	Precision	Recall	F1-Score
0.794	0.835	0.847	0.975	0.906

Source: Own processing in Python.

The architecture of the neural network used in the analysis is detailed previously, the artificial neural network being made up of two hidden layers, the first with 35 neurons, and the second with 59 neurons, a 'ReLU' activation function, the problem being one of classification. The performance obtained after training is presented in Table 2, where an AUC score of 0.794 stands out, which indicates a good performance of the model to differentiate between respondents who perceive a balance between the professional and personal spheres and those who do not. The F1 score value of 0.906 reflects a good balance between the precision of the model and its ability to correctly identify positive cases, being a useful indicator in contexts where both false positive and false negative errors can have important implications for organizational interventions.

The class-specific fixed-seed reproducibility run confirms the reviewer's concern. On the held-out test set, class 0 (perceived imbalance; $n = 1,311$) had

precision = 0.647, recall = 0.196, and F1 = 0.301, whereas class 1 (perceived balance; $n = 5,865$) had precision = 0.845, recall = 0.976, and F1 = 0.906. Balanced accuracy was 0.586, macro-F1 was 0.603, and ROC-AUC was 0.792. The originally reported high Recall and F1-score therefore largely reflect majority-class performance and should not be interpreted as evidence of equally strong discrimination for both classes.

The graph showing the evolution of loss function and AUC score during neural network training is available in Appendix 2. The loss on the validation data remains low and stable across epochs, indicating effective generalization. In parallel, the AUC values on both training and testing confirm the model's ability to correctly differentiate between classes.

Experiment 1. Adjustment of the work schedule and improvement of the subjective state

In order to better understand how certain individual traits can influence the perception of the balance between professional and personal responsibilities, a specific case was examined in which the artificial neural network model estimated a 50% probability that the employee would consider that he had such a balance. This value indicates a situation of equilibrium uncertainty, in which the model cannot clearly decide a positive or negative perception, rather attributed to a person who does not know how to assess his sense of balance. According to the values associated with this employee, he declares that he works, on average, 60 hours a week, works at night and considers that the work carried out at work has a negative impact on his health, and he is from Romania. He also does not feel relaxed and does not perceive everyday life as interesting, although he has flexibility in his work schedule, which allows him to solve his personal problems even during working hours.

Reproducibility note. The original narrative and Figure 3 identify Romania, whereas linking the code-selected observation back to the submitted dataset returns Bosnia and Herzegovina. The original figure has been retained unchanged. Country was excluded from the ANN, so this label discrepancy does not affect the prediction and no country-level inference is intended.

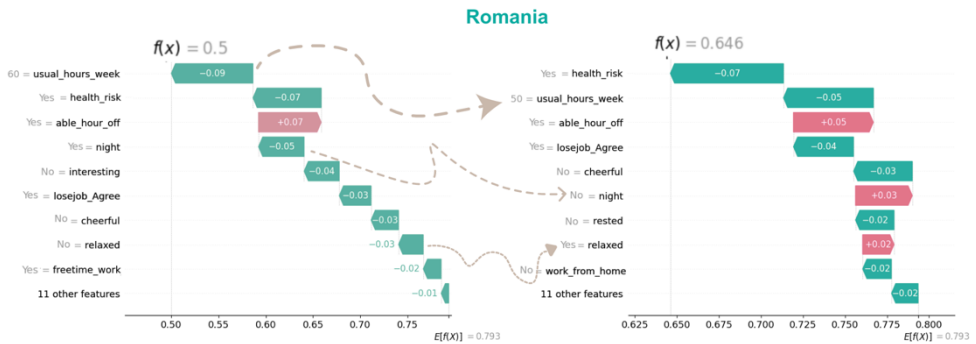


Figure 3. Change in work-life balance prediction for an individual after adjusting for four explanatory variables

Source: Self-processing in Python using the trained artificial neural network.

Starting from this profile, four variables relevant to this employee were modified in order to assess their association with the predicted probability estimated by the model. More specifically, the average number of hours worked per week was reduced to 50, night work was eliminated, and both the perceived level of relaxation and the extent to which daily life is perceived as interesting were improved. The results of these adjustments, presented in Figure 3, indicate an increase in the probability of perceived work–life equilibrium to 64.6%, corresponding to a gain of more than 14 percentage points compared to the initial prediction. These findings can inform several organizational recommendations aimed at improving employees’ professional quality of life. For instance, companies could introduce internal regulations limiting paid overtime to a maximum of 10 hours per week in order to discourage excessive working hours and support more efficient time management. In addition, employers could invest in automation technologies to reduce the need for night shifts, particularly in areas such as cybersecurity, where continuous monitoring is often required outside standard working hours. Finally, to enhance employees’ level of relaxation, organizations could implement well-being initiatives during working hours, such as massage sessions, sports activities, or other recreational events. Involving employees in identifying the activities they find most relaxing could further increase the effectiveness and acceptance of such initiatives.

Uncertainty sensitivity check. In the fixed-seed refit of the same architecture, the observed and modified profiles had predicted probabilities of 35.5% (95% predictive interval: 12.7%-46.9%) and 67.3% (48.4%-71.4%), respectively. Because the submitted training run did not fix random seeds, these reproducibility estimates supplement, but do not replace, the original point estimates shown in Figure 3.

Experiment 2. Introduction of teleworking and elimination of night hours

For the second experiment, an employee for whom the neural network model estimated a high probability of perceiving a work-life balance was analysed, more precisely 81.8%. The purpose of this simulation was to examine the model response

to changes in relevant factors, including for people who are already in a for people who are already in a favourable situation. According to the initial profile, this employee stated that he works, on average, 40 hours a week, carries out activities for work during the night, does not benefit from the possibility of working from home, does not feel rested, but does not perceive that the professional activity would affect his health, stating however that he feels relaxed, and he is from Belgium. The simulation took place in two stages. In the first stage, only the possibility of working from home was introduced, keeping all other variables constant, and later, the variable referring to the night schedule was also modified, eliminating it. Thus, the cumulative effect of the two amendments was assessed.

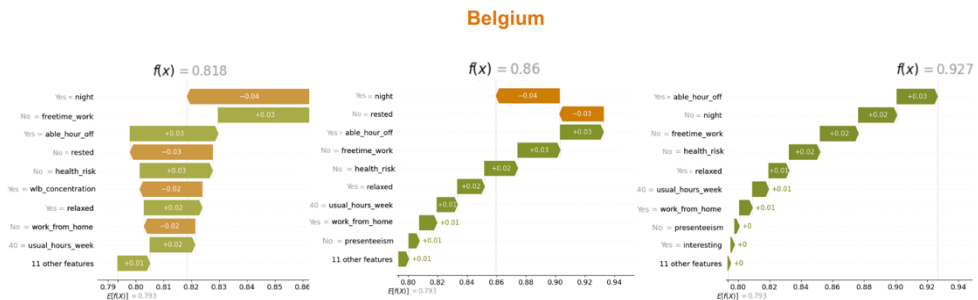


Figure 4. The effect of successively changing two variables on the prediction of work-life balance for an employee

Source: Self-processing in Python using the trained artificial neural network.

The results are presented in Figure 4, which illustrates the evolution of the estimated probability following each successive change. Initially, the predicted probability of perceiving work-life balance was 81.8%. After introducing the possibility of working from home, as shown in the middle panel of Figure 4, the estimated probability increased to 86%, indicating a higher predicted probability associated with greater flexibility in organizing both professional and personal activities. When the second change was added, namely the elimination of night working hours, the estimated probability further increased to 92.7%, highlighting a substantial cumulative change of the two interventions. These findings suggest that companies could improve employees' perceived work-life balance by implementing flexible work arrangements where job characteristics allow, particularly by facilitating access to teleworking options, and by limiting night work as much as possible or compensating for it through additional benefits. Such compensatory measures could include extra leave days or extended breaks during working hours, which may help offset the negative effects associated with atypical work schedules and contribute to overall well-being.

Uncertainty sensitivity check. In the fixed-seed refit, the predicted probabilities were 67.1% at baseline (95% predictive interval: 56.0%-71.7%), 74.8% after enabling telework (66.4%-81.4%), and 80.5% after also removing night work (75.9%-87.8%). These values supplement the original Figure 4 and show that the

intervals overlap; the changes should therefore be interpreted cautiously as model sensitivity rather than intervention effects.

Figure 4 shows an increase of 4.2 percentage points after introducing teleworking and a further increase of 6.7 points after eliminating night work in the submitted model run. These increments are specific to the selected employee profile and are not assumed to be additive for other employees.

Experiment 3. The impact of overwork and lack of flexibility in the workplace

The third experiment involved the analysis of an employee for whom the neural network model estimated the lowest probability of perceiving a work-life balance, of only 18.8%. The profile of this employee indicates a difficult situation, characterized by a very high workload, the employee working, on average, 90 hours a week, to which is added the lack of possibility to agree on personal problems or the possibility of working from home, low level of relaxation and general satisfaction, as well as the feeling that the professional activity endangers his health and the employee is from Albania. Despite these factors, the employee declares that he does not have concentration problems, which may suggest a high tolerance for overwork, often associated with 'workaholic' people. The employee mentions that he continued to work even during the periods when he was sick, which may reflect an organizational culture in which work-life balance is not a priority.

Reproducibility note. The original narrative and Figure 5 identify Albania, whereas the country field linked to the code-selected observation is Kosovo. The original figure has been retained unchanged. Country was excluded from the ANN, so this label discrepancy does not affect the prediction and no country-level inference is intended.

In order to achieve a visible improvement in the estimated model score for this employee, simultaneous changes were required for seven variables, which underscores the importance of preventive measures to promote work-life balance. The purpose of this experiment is to highlight how important it is for the balance between the two spheres to be promoted from the early stages of professional life, before employees reach critical situations, associated with the emergence of the phenomenon of 'burnout', which involves an increased risk of resignation that is also reflected in the costs and performance of companies.

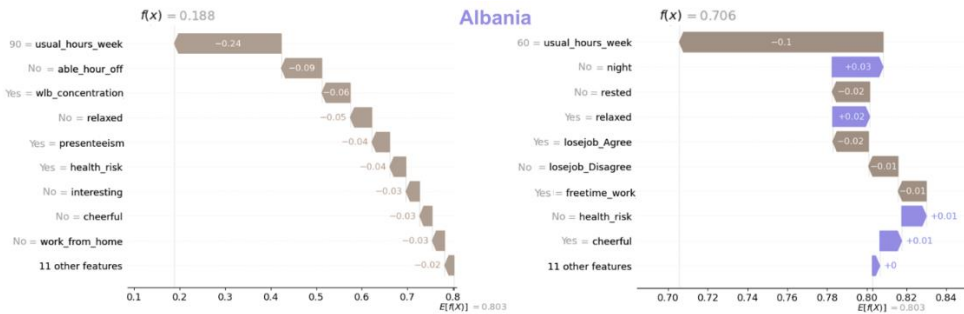


Figure 5. The effect of successively changing three variables on the prediction of work-life balance for an employee

Source: Self-processing in Python using the trained artificial neural network.

The results of the third experiment are presented in Figure 5, which illustrates the evolution of the estimated probability following the simultaneous modification of seven variables. Specifically, the average number of weekly working hours was reduced to 60, remote work was introduced, and employees were allowed to manage certain personal responsibilities during standard working hours. At the same time, the perceived health risks associated with professional activities were reduced, while levels of relaxation, positive mood, and interest in daily life were favorably adjusted for the analyzed employee. These combined changes led to a substantial improvement in the predicted probability of perceived work-life balance, suggesting that multifaceted interventions may be particularly effective. From an organizational perspective, these findings support several potential measures, including limiting paid overtime to a range of approximately 10 to 20 hours per week in order to reduce the risk of burnout, while still allowing flexibility for employees who voluntarily choose to work longer hours without being penalized. In addition, companies could implement policies that permit personal appointments during working hours, particularly for family- or health-related matters such as medical consultations or childcare responsibilities. Expanding opportunities for remote work, where job characteristics allow, could also contribute to improved balance, for instance by allocating a fixed number of days per week or per month for teleworking while maintaining regular in-office collaboration. Furthermore, organizations could support physical health through regular medical check-ups at the workplace, facilitating early detection of stress-related or overwork-related conditions. Finally, providing access to mental health services, such as weekly therapy sessions available to all employees, may help sustain psychological well-being and prevent emotional strain associated with prolonged occupational stress.

Uncertainty sensitivity check. In the fixed-seed refit, the baseline profile had a predicted probability of 9.5% (95% predictive interval: 0.8%-25.0%), while the seven-variable scenario had a predicted probability of 74.0% (69.2%-81.0%). These estimates supplement the original Figure 5. Because all seven inputs were modified together, their individual contributions cannot be isolated.

The combined scenario is associated with a higher predicted probability for this selected profile, as shown in Figure 5. The result is exploratory and does not establish that the seven changes would produce the same outcome in practice or in the wider employee population.

5. Conclusions

From the analysis of descriptive statistics based on data from the European Working Conditions Telephone Survey (2021), it emerges that work-life balance is perceived differently according to gender and age, which leads to the confirmation of the hypothesis extracted from the theories studied in the literature, according to which a person's priorities change throughout life, and the factors that bring fulfilment in life at a certain age do not correspond to those that lead to the feeling of satisfaction at an older age.

Women reported a higher proportion than men that they face an imbalance between the two spheres, which can be explained by their higher involvement in domestic or family care activities. The difference of 10.4 percentage points between women and men in terms of the perception of imbalance validates the theory of work-family boundaries formulated by Clark (2000). This theory highlights the difficulty of crossing between the two spheres in the case of less flexible boundaries, such as those encountered by women, who manage professional tasks and domestic responsibilities at the same time. In fact, it has been found that the weekly time allocated to work is, on average, four times longer than that dedicated to family care and household activities, which can generate difficulties in managing the two dimensions.

The results of the simulations using the artificial neural network showed higher predicted balance for the selected profiles when reducing the number of hours worked per week, eliminating night work hours, introducing the possibility of teleworking, and allowing employees to address personal matters during working hours. These scenario results are not causal estimates; the corresponding organizational measures should be evaluated before implementation. The results can nevertheless inform future research on organizational measures supporting flexibility, burnout prevention, and employee mental health. The analytical framework could be adapted at company level by applying an internal employee survey, the results of which can be used to identify ways to improve employee balance.

The present paper presents some important limitations that can influence the interpretation and generalization of the conclusions obtained. Firstly, the database used comes from the 2021 edition of the European Working Conditions Survey, and although a new edition took place in 2024, the related microdata has not yet been disseminated. Also, the fact that the survey was conducted in the post-pandemic period may affect employees' perceptions, as in the wake of the COVID-19 pandemic, employees are considered to be living in a new era. In addition, the implemented Machine Learning models could have been further optimized by

running a greater number of iterations within Bayesian processes, but technical limitations related to the capacity of the computer used restricted this possibility.

A further limitation is that random seeds were not fixed in the submitted training run, so exact individual simulation point estimates can vary across refits. The newly reported predictive intervals characterize uncertainty in a fixed-seed sensitivity analysis rather than survey-sampling uncertainty. In addition, strong class imbalance limits detection of the minority imbalance class; aggregate accuracy, Recall, and F1-score should therefore not be interpreted in isolation.

As future developments, the research could be extended by testing several neural network architectures, such as convolutional networks or recurrent networks, which can provide new insights into the relationship between personal characteristics and the perception of work-life balance. Also, redoing the analysis based on the latest dataset collected in 2024, which is not influenced by the immediate effects of the COVID-19 pandemic, would allow the conclusions to be validated in a more stable context. In addition, the integration of more machine learning algorithms for classification problems, such as SVM or logistic regression, could contribute to a broader comparative assessment of the performance of models. Another research direction is to expand the set of variables included in the analysis, in order to better capture the factors that influence the perception of balance felt by employees.

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Annex 1

Values tested and selected using the Optuna algorithm for ANN

Table 3. Hyperparameters tested and optimal configuration selected by Optuna

Hyperparameter	Test values	Values selected by Optuna
units_l0	(32, 128)	35
activation_l0	["relu", "tanh", "selu"]	'Relu'
dropout_l0	(0.0, 0.5)	0.2811553128779143
add_second_layer	[True, False]	True
units_l1	(16, 64)	59
activation_l1	["relu", "tanh", "selu"]	'Relu'
dropout_l1	(0.0, 0.5)	0.2546272178163222
add_third_layer	[True, False]	False
units_l2	(8, 48)	-
activation_l2	["relu", "tanh", "selu"]	-
dropout_l2	(0.0, 0.5)	-
Optimizer	["Adam", "Nadam"]	'Nadam'
Epochs	(50, 200)	74
batch_size	[8, 16, 32]	16

Source: Self processing in Python.

Annex 2

Evolution of loss function and AUC score during artificial neural network training

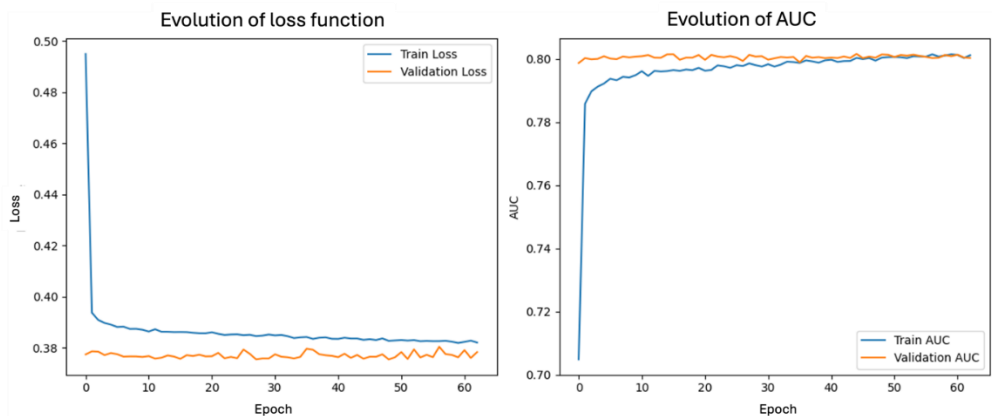


Figure 6. Evolution of training and validation loss and AUC during neural network training

Source: Self-processing in Python using the trained artificial neural network.