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An Analysis of the Subjective Well-Being in the Italian Regions Through an ANN Algorithm

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Abstract

This research aims to analyze the determinants of subjective well-being in the Italian regions. To this extent, a new ISTAT-BES database has been used, with data for the Italian regions between 2004 and 2021. An artificial neural network (ANN) experiment was conducted to explore the link among these variables. Empirical findings show that subjective well-being is positively associated with education, income, and social relations. Our results align with those provided by past studies on the determinants of subjective well-being. These results imply that governments should improve subjective well-being by increasing the level of investment in education, deepening economic growth, reducing income inequality, and promoting social relations.

Keywords Subjective well-being · Education · Inequality · Social relations · Italian regions · Artificial neural networks

JEL Classification D63 · I31 · I25

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Introduction

The study of happiness and individual well-being has been at the center of economic debate since Easterlin's paradox (Easterlin, 1974). The discovery that a marginal increase in income, beyond a certain threshold, is not associated with improving happiness opened a new field in economics. In the words of Easterlin:

Is there evidence that economic growth is positively associated with [...] human happiness? [...] The increase in output itself makes for an escalation in human aspirations and thus negates the expected positive impact on welfare. (Easterlin, 1974).

Easterlin questioned the positive relationship between income and happiness. He concluded:

[...] for the United States since 1946, higher income was not systematically accompanied by greater happiness. (Easterlin, 1974).

Further economic studies showed that Easterlin's paradox could be applied to either study on nations or to the analysis of individuals. Socioeconomic determinants and geopolitical and cultural factors can change the ultimate marginal income improvement associated with happiness maximization.

The question of subjective well-being (SWB) has obtained more consideration in literature due to the increase of social and psychological pathology associated with depression, anxiety, compulsive, and impulsive behavior together with the absence of self-evaluation. Inhabitants and employees in post-industrialized countries seem to be at the same time wealthier, at least in the sense of per capita income, and more dismal, in the sense of social and psychological disorders.

The missing positive relationship between income and happiness has received interest from the public sphere and the economics of incentives. The level of national gross domestic product (GDP), the structure of workforce participation, the degree of education and instruction, and the possibility of a generation of resilient human and social capital are all variables affected by decreasing human well-being in affluent economies. Economists have tried to take into account these complex psycho-economic relations promoting new methodologies to calculate GDP. Several researchers aimed to introduce measures able to capture human emotions about the SWB, subjective happiness, and subjective perspective of the future. The development of technologies and artificial intelligence can operate as an important ally in the attempt to create measures able to express public sentiment summarized by specific indexes. National statistical offices can estimate individual well-being by mining data through algorithms on a sample of selected citizens (Morelli et al., 2020).

Nevertheless, it is relevant to clarify the differences between the definitions of happiness and well-being. The concept of well-being includes happiness. The idea of happiness lacks social, relational, and psychological elements that are considered in well-being. Our study concerns the concept of well-being. We know that many empirical results centered on happiness, such as the Easterlin paradox, can only partially be referred to as well-being. In our view, well-being is a more complex concept with respect to happiness, even if it is only an approximation of the idea of *eudaimonia* as defined by Aristotle. In fact, in the idea of *eudaimonia*, there is harmony between individual and collective well-being based on the equilibrium of the private and public interests and actions.

SWB refers to an individual's self-reported evaluation of their life in terms of overall happiness and life satisfaction. It encompasses emotional experiences, cognitive judgments, and life assessments, making it a multidimensional construct. Factors influencing SWB include personal temperament, relationships, health, and socioeconomic status. Researchers often measure SWB through self-report surveys, capturing both hedonic (emotional) and eudaimonic (meaning and purpose) aspects of well-being. Key theories in positive psychology, such as the hedonic adaptation theory and the satisfaction set point, offer insights into the dynamics of SWB over time. Moreover, numerous studies underscore the significance of SWB in predicting mental and physical health outcomes, emphasizing its role as a crucial indicator of holistic well-being (Diener & Chan, 2011; Seligman & Csikszentmihalyi, 2000).

SWB in Italy is a multifaceted construct influenced by various individual, social, and cultural factors. This country, renowned for its rich cultural heritage, has a distinctive approach to well-being that goes beyond economic indicators. The Italian way of life places considerable importance on social connections, family bonds, and a slower-paced lifestyle, contributing to a unique subjective experience of well-being. Additionally, the country's emphasis on leisure, art, and gastronomy adds layers to the subjective assessment of happiness and life satisfaction. However, challenges such as economic fluctuations, political changes, and the ongoing impact of global events may influence the dynamics of SWB in Italy. Research initiatives, including ISTAT's multidimensional approach, play a crucial role in comprehensively capturing the nuances of well-being, contributing to a more holistic understanding of the subjective experiences of individuals in the Italian context.

The present study has several elements of originality: (i) the use of a new dataset (ISTAT-BES) to analyze this topic; (ii) an interdisciplinary approach to the determinants of SWB, (iii) a model based on composite indexes able to shed light on a non-strictly economic foundation of SWB, and (iv) to the best of our knowledge, this is the first paper that applies an AI experiment through artificial neural network (ANN) analyses to these data. Our results show that SWB is associated with education, income, and social relations. Implications for policymakers include the necessity to rethink the welfare state and recalibrate the GDP growth process to widespread happiness among the population in democratic countries, especially in Western economies.

The remainder of this paper is organized as follows. The "Review of the Literature and Background" section provides a review of the literature on the determinants of happiness in an interdisciplinary approach. The "Materials" section provides the empirical model with an explanation of the variables and the theoretical framework. The "Empirical Results" section shows the results of the empirical analysis. The "Discussion" section discusses the empirical findings in light of previous literature. Finally, the "Concluding Remarks and Policy Implications" section presents conclusions and policy implications.

Review of the Literature and Background

Happiness and well-being have many dimensions. The economic literature affords many questions considering happiness either as a dependent variable or as an independent variable to explain the complex nexus among growth, development, and well-being.

SWB and happiness are closely related concepts, yet they involve distinct dimensions in the realm of positive psychology. Both involve an individual's overall evaluation of their life, including emotional experiences and cognitive judgments. Happiness typically refers to the emotional component of well-being, often characterized by positive affect and life satisfaction. On the other hand, SWB represents a broader construct that includes not only emotional well-being but also cognitive assessments of one's life. While the terms are sometimes used interchangeably, SWB encapsulates a more comprehensive perspective, incorporating elements beyond momentary happiness. Diener et al. (1999) delineated the nuances between happiness and SWB, emphasizing the need to consider both affective and cognitive facets when exploring an individual's subjective experience of well-being. Understanding these similarities and differences contributes to a more nuanced and comprehensive understanding of the factors influencing individuals' overall life satisfaction.

The determinants of SWB are multifaceted, encompassing various individual, social, and environmental factors. Personal factors, including genetic predispositions, personality traits, and cognitive styles, play a crucial role in shaping one's SWB. Additionally, social relationships and the quality of social support have a significant impact on well-being, with strong interpersonal connections contributing positively to SWB. Economic factors, such as income and employment, influence an individual's life satisfaction, while health and physical well-being also play a vital role (Diener et al., 2003). Cultural and societal norms, as well as individual values and aspirations, further contribute to the complexity of SWB determinants. Research in the field highlights the interplay of these factors, emphasizing the need for a holistic approach when understanding and promoting well-being (Helliwell et al., 2020).

Human abilities determine well-being and happiness, so that, according to the propensity to catch opportunities, adaptation inputs are born. Through the relationship between human abilities and adaptation, inputs are achieved in different well-being and happiness opportunities. A happy man determines a well-being *status*, but happiness must be considered and measured in the real context (daily life with its real available opportunities). It is important to underline that SWB includes happiness. For this reason, we focus the attention on happiness because it could be the tool for a full and fulfilling SWB.

We split the literature into macro groups based on adaptation inputs (AI) of happiness. These are (1) happiness and community AI; (2) happiness and environmental AI; (3) happiness and psycho-clinical AI; and (4) AI against happiness. This organization allows us to introduce only the relevant papers for our analysis.

1) Happiness and community AI:

   - Happiness and good governance: Heliwell (2014)
   - Happiness and political affiliation: Dolan et al. (2008)
   - Happiness and terrorism: Metcalfe et al. (2011)

2) Happiness and environmental AI:

   - Predictors of happiness during life: Clark and Lee (2017)
   - Media and happiness: Benesch et al. (2010)
   - Happiness and sociality: Huppert (2009), Glaeser (2011), Ferguson (2016)
   - Happiness, income, and unemployment: Stutzer and Frey (2004)
   - Gender pay gap and happiness: Lalive and Stutzer (2010)
   - Happiness and unemployment: Clark et al. (2010)
   - Poverty and happiness: Clark et al. (2015)
   - Unfairness and happiness: d'Ambrosio et al. (2018)
   - Happiness and youth in Western Countries: Blanchflower and Oswald (2000)

3) Happiness and psycho-clinical AI:

   - The gene of happiness: De Neve et al. (2012), Saiz-Alvarez et al. (2014), Proto and Oswald (2017)

4) AI against happiness:

   - Against the political economy of happiness: Frey (2011, 2017), Frey and Stutzer (2017)
   - Errors in happiness prediction: Odermatt and Stutzer (2019)

In recent years, there has been a great interest in finding a single measure of well-being that includes socio-economic aspects, and there are several investigations (Lucas, 2008; Rentfrow et al., 2008) that use the level of education, income, health, and political freedom to stress the impact of personality on well-being, both at intra-regional and transnational levels. Due to its multidimensional dimension, and also the opportunity to connect well-being and happiness, in this paper, we try to empirically identify which variables could improve well-being at the country level (the macro group is Happiness and environmental AI).

Income is the main indicator for measuring the well-being of a country, and there are international standards for its measure. However, it cannot be used for giving information on individual quality of life because it does not include several indicators such as health, social relations, and education. From a theoretical point of view, it is possible to recall at least two strands of literature useful to investigate well-being. These are the capability approach (Sen, 1985), which considers the quality of life strictly connected with a set of human functioning, and the happiness approach (Grossi et al., 2012), which also supports the idea that happiness is linked to cultural dimension. Deaton (2008) used the Gallup World Poll and Gallup-Healthways index as indicators of well-being. However, all these studies are insufficient since well-being and happiness are multidimensional. The homeostasis approach (Cummins & Nistico, 2002) could be considered a wider study as it measures the level of well-being in an interdisciplinary way and a high income is related to a higher level of well-being and happiness. Therefore, the opportunity to consider other multidimensional indicators of well-being in addition to income, culture, human abilities, and so on, permits us to have a wider vision of its evolution so as to introduce ad hoc policies for reducing regional disparities and territorial gaps.

Some of the limits of the transnational analyses are the linguistic and cultural differences. Thus, in this work, we overpass these constraints by investigating only the Italian regions (Oswald & Wu, 2010; Rentfrow et al., 2009).

Starting from these considerations, this work presents a new methodological contribution using an AI approach. The use of the ANN experiment enables us to investigate individual-level and macro-level. Moreover, this study includes a great part of the previous analyses on Italy, reinforcing and enriching the results (Berloffa & Modena, 2012; Ferrara & Nisticò, 2015; Murias et al., 2012).

Empirical research on the factors influencing SWB has burgeoned over the years, shedding light on the intricate interplay of various individual, social, and environmental elements. One critical determinant is personality, with traits like extraversion, neuroticism, and conscientiousness consistently linked to SWB (DeNeve & Cooper, 1998; Steel et al., 2008). Individuals with higher levels of extraversion tend to experience more positive emotions, contributing to their overall well-being. Neuroticism, on the other hand, is associated with lower life satisfaction due to heightened susceptibility to negative emotions. Conscientious individuals often report higher levels of life satisfaction, possibly because of their goal-oriented and disciplined nature.

Moreover, genetic predispositions also play a role in shaping SWB, as evidenced by twin and family studies (Lykken & Tellegen, 1996; Nes et al., 2018). These studies suggest a heritability estimate for SWB, indicating that a portion of individual differences in well-being can be attributed to genetic factors. While genetics may set a baseline for SWB, it is crucial to acknowledge the influence of environmental factors.

Income and economic status have long been scrutinized in SWB research, with a substantial body of literature exploring the relationship between wealth and well-being (Diener & Biswas-Diener, 2002; Easterlin, 1974). The findings reveal a complex picture—while a lack of resources can impede well-being, the association between income and SWB diminishes beyond a certain threshold. Instead, factors like financial security, autonomy, and a sense of control over one's life play pivotal roles in determining the well-being-income link.

Health is another crucial empirical factor influencing SWB. Physical and mental health conditions significantly impact an individual's overall life satisfaction (Keyes, 2007). Chronic illnesses, disability, and mental health disorders are associated with lower SWB, emphasizing the holistic nature of well-being. Conversely, good health, including regular physical activity and adequate sleep, is positively correlated with higher levels of SWB.

Social relationships and the quality of social support are integral components of SWB (Helliwell et al., 2018; Kawachi & Berkman, 2001). Positive social interactions, strong interpersonal connections, and a sense of belonging contribute to higher levels of life satisfaction. Marriage and stable relationships are often linked to increased SWB, although the quality of the relationship is more crucial than its mere existence. Loneliness and social isolation, conversely, are detrimental to SWB, highlighting the importance of social connectedness for overall well-being.

Cultural and societal factors also influence SWB, with variations across different societies and cultural contexts (Diener & Suh, 1999; Oishi & Diener, 2001). Collectivist cultures may prioritize family and community ties, associating them with higher well-being, while individualistic cultures might emphasize personal achievement and autonomy. Cultural norms and values shape individuals' aspirations and expectations, influencing their subjective evaluation of well-being.

Furthermore, life events and transitions have a significant impact on SWB (Diener et al., 2009; Lucas et al., 2003). Positive life events, such as marriage, the birth of a child, or career success, often lead to increased well-being, at least temporarily. Conversely, negative life events like job loss, divorce, or bereavement can have a lasting negative impact on SWB. The adaptation process, as suggested by the hedonic adaptation theory, implies that individuals tend to return to their baseline level of well-being after experiencing significant life events, highlighting the resilience of the human psyche.

Environmental factors, including living conditions and access to natural spaces, also contribute to SWB (Capaldi et al., 2014; White et al., 2013). The built environment, such as the availability of parks and green spaces, has been linked to higher levels of well-being. Urban design that fosters community engagement and walkability positively influences residents' overall life satisfaction.

Work and employment conditions are crucial empirical determinants of SWB (Clark et al., 2008; Warr, 2007). Job satisfaction, a sense of purpose at work, and a healthy work-life balance are associated with higher levels of SWB. Unemployment, job insecurity, and dissatisfaction at work, conversely, have detrimental effects on well-being. The role of autonomy, control, and a supportive work environment cannot be overstated in influencing the relationship between work and SWB.

Education also emerges as a significant factor in SWB (Diener et al., 2018; Layard et al., 2014). Higher levels of education are generally associated with increased well-being, possibly due to enhanced cognitive abilities, greater access to opportunities, and the fulfillment derived from intellectual pursuits. However, the quality of education and the pursuit of meaningful goals rather than the mere attainment of degrees are crucial in understanding the link between education and well-being.

Coping strategies and resilience in the face of adversity are essential empirical factors influencing SWB (Ong et al., 2006; Tugade & Fredrickson, 2004). Individuals with effective coping mechanisms, such as problem-solving skills and positive reappraisal, tend to maintain higher levels of well-being even in challenging circumstances. The ability to bounce back from setbacks and maintain a positive outlook contributes significantly to long-term SWB.

In conclusion, the empirical factors influencing SWB are diverse and interconnected. Personality traits, genetic predispositions, income, health, social relationships, cultural context, life events, environmental conditions, work, education, and coping strategies collectively shape an individual's subjective evaluation of their well-being. Understanding these empirical determinants provides valuable insights for policymakers, psychologists, and individuals seeking to enhance overall life satisfaction and promote well-being. Future research should continue to explore the dynamic interactions among these factors and their implications for designing effective interventions that foster positive mental health and flourishing societies.

Materials

The empirical analysis aims to shed light on the determinants of SWB in Italy. A multidimensional approach to gauge equitable and sustainable well-being has been collaboratively devised by Istat, in conjunction with representatives from the third sector and civil society. This innovative approach aims to supplement indicators tied to production and economic activity with a comprehensive assessment of the fundamental dimensions of well-being, incorporating considerations of both inequality and sustainability. In total, 12 domains have been identified to intricately describe well-being in Italy. By embracing this holistic perspective, the measurement framework endeavors to offer a more nuanced and encompassing understanding of the factors contributing to the overall well-being of the population, beyond conventional economic metrics. The collaboration between ISTAT and various sectors highlights a commitment to capturing the complexity of well-being and fostering a more inclusive and sustainable approach to societal progress. Since 2017, a subset of 12 indicators from the framework for measuring equitable and sustainable well-being has become part of the economic planning cycle, as provided for in Law No. 163 of 4 August 2016. The indicators are analyzed in two stages of the economic and financial planning cycle, through two annual documents prepared by the Ministry of Economy and Finance (MEF), based on data provided by ISTAT.[1]

Descriptive statistics are provided in Table 3 (in the Appendix), while a visual inspection of the data series is given in Fig. (7) (for the correlation matrices) and Fig. 8 (for the variables' box plot), both in the Appendix.

By developing the framework above, and following Magazzino and Mele (2021), Magazzino et al., (2022a, b), and Mele et al. (2021), we propose and develop an ANN experiment to examine this topic.

In greater detail, the variables included in the model are as follows.

Subjective Well-Being

The SWB is the dependent variable and is used as a proxy for happiness in Italian regions. In particular, SWB is considered as the variable "Satisfaction For Your

[1] https://www.istat.it/it/benessere-e-sostenibilit%C3%A0/la-misurazione-del-benessere-(bes)/gli-indicatori-del-bes.
https://www.istat.it/en/well-being-and-sustainability.

Life" that is computed by ISTAT-BES as the percentage of people aged 14 who have expressed a life satisfaction score between 8 and 10 out of the total of people aged 14 and over. This variable can be considered as a proxy for SWB a perspective in the treatise of happiness. SWB is a global concept able to capture the economic and financial definition of happiness as well as to identify the limits of that complex social environment in which happiness prospers.

Education and Training

Education and training is a composite index in the ISTAT-BES database. It consists of five different variables: "Participation In Kindergarten," "People With At Least A Diploma," "Graduates And Other Tertiary Degrees," and "Participation In Continuous Training" minus the value of "Early Exit from the Educational And Training System". The variable is relevant since education and training can be considered as a proxy for income that should be associated with happiness and individual well-being.

Income and Inequality

Income and inequality are a composite index based on six independent variables built by ISTAT. In particular, the variable is based on the level of "Average Income Available Per Capita" minus "Inequality of Dispensable Income" minus "Serious Material Deprivation" minus "Low-Quality Home" minus "Great Economic Difficulty" minus "Very Low Work Intensity."

Social Relations

Social relations are a composite index based on eight independent variables built by ISTAT. The composite index is built by summing "Satisfaction With Family Relationships," "Satisfaction With Friends," "People You Can Count On," "Social Participation," "Civic and Political Participation," "Voluntary Activities," "Financing Association," and "General Trust." All data are collected through interviews. Social relations are able to increase the level of human capital, social capital, and civic capital boosting economic growth, social resilience, and institutional development, respectively. Social relations are important also in the development of links among people able to generate knowledge, competence, and attitude implicitly. For example, some communities are more devoted to produce immaterial goods such as technological innovations, and their ability to generate value-added is not only based on professional skills, but also on social relations among groups of people with particular productive capabilities. Social relations have the ability to increase happiness and individual well-being through a very large spectrum of variables interconnected shaping the environment, the culture, and the moods of a population towards the same idea of psychological states such as joy and enthusiasm.

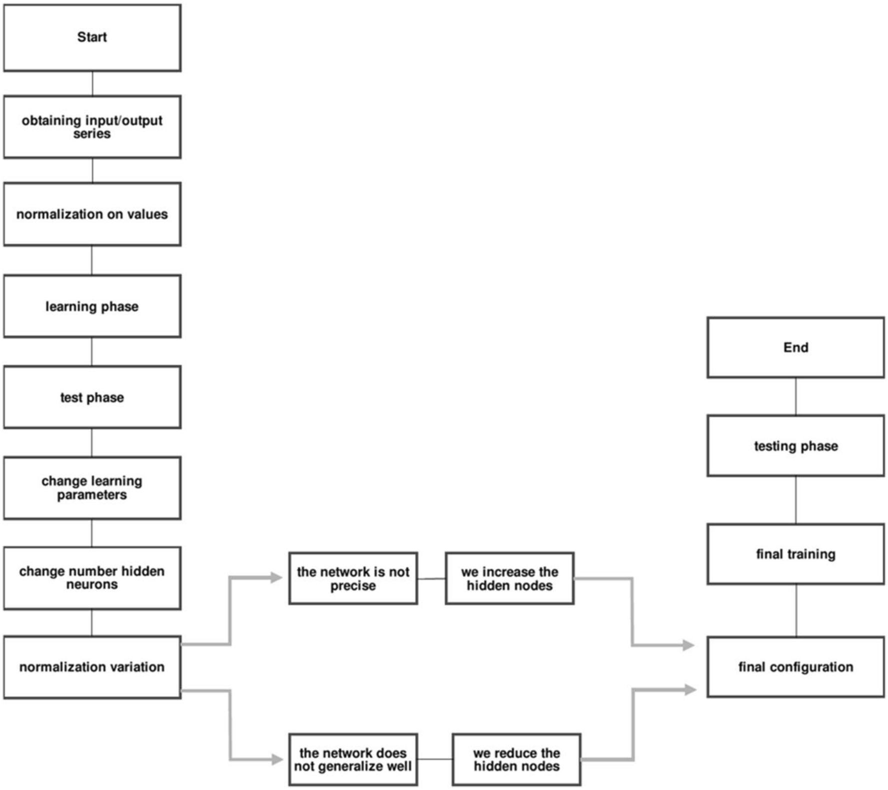


Fig. 1 The ANN process. Source: our elaborations in YaD

Empirical Results

In this section, we conduct an AI experiment with the use of ANNs. Therefore, we start from the assumption that each experiment must be reproduced and verified by different estimation techniques. We use the same dataset used for panel data analysis, implemented with an automatic learning algorithm developed in the Oryx 2.0.8 protocol. If the predictive analysis confirms panel data one, the results can be considered valid not only in a stationary state but also concerning the variation of the epochs. The use of ANNs, as a subset of the machine learning (ML) tools, follows a precise implementation scheme for building the network and obtaining results. In Fig. 1, we synthesize the process.

Therefore, after uploading the dataset in Oryx, we have adapted the data series to an ML process through logarithmic and differential transformations. In fact, the higher the volume of data, the greater the capacity of analysis of the automatic intelligence system. The values are then normalized through the training selection procedure, which also begins a first test phase. In this phase, we evaluate the presence of omitted variables or outliers, which might cause false values of the NN. Subsequently, starting from the results obtained with the first test, we

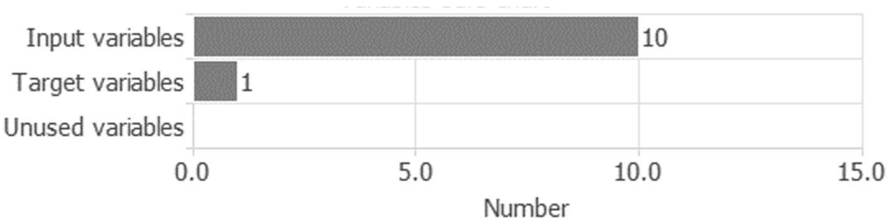


Fig. 2 Variables' bars chart. Source: our elaborations in Oryx

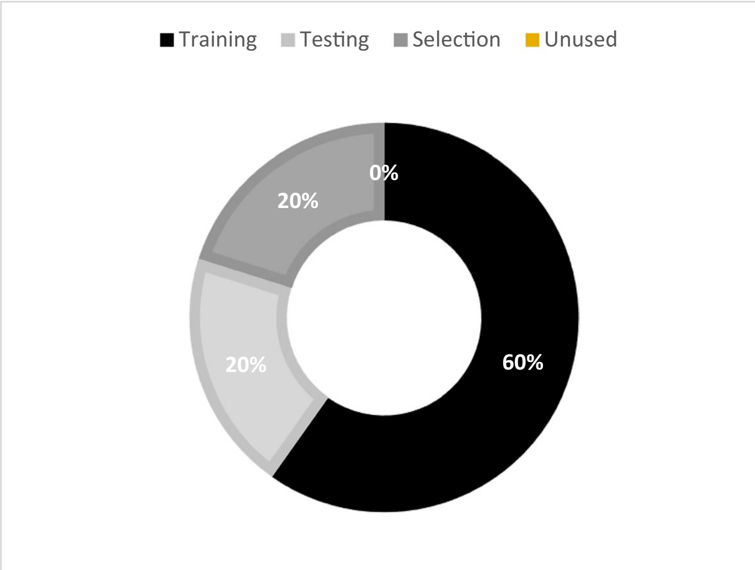


Fig. 3 Instances' pie chart. Source: our elaborations in Oryx

choose the suitable number of hidden neurons that will be an integral part of the network. The next step is to launch the algorithm for creating the NN. The result obtained is carefully analyzed, and we verify the precision and generalization of the obtained network. In this phase, we apply several different optimizations to our algorithm (gradient descent, quasi-Newton method, and conjugate gradient) capable of performing the NN. This optimization allows us to obtain the optimal configuration of the NN, which will be subjected to a new level of training. Finally, we run tests that perform the NN both on the order of neurons and on the inputs that generated the final target.

Now, the ANN results can be analyzed. In total, the NN considered ten inputs (with four omitted inputs) and 1 target[2], (Fig. 2).

[2] For further details, see the Appendix.

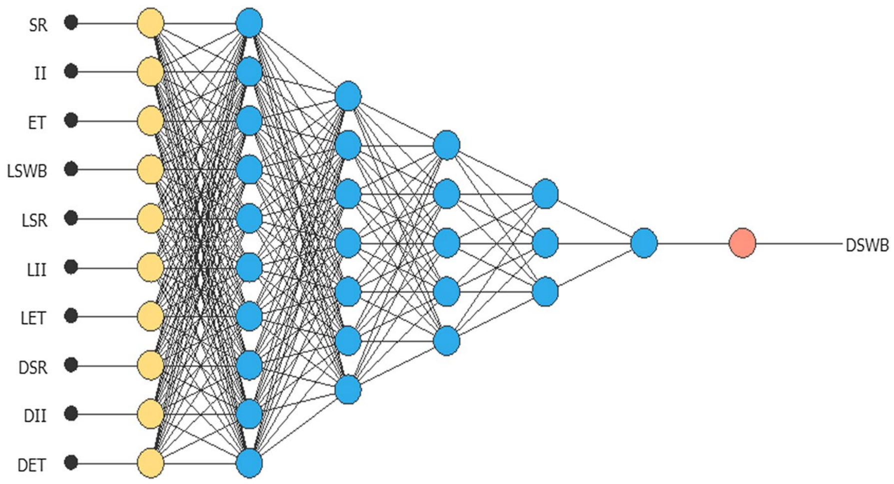


Fig. 4 ANN graph. Source: our elaborations in Oryx

Table 1 Confusion matrix

	Predicted positive	Predicted negative
Real positive	3,745	411
Real negative	812	3777
Classification accuracy	86.01%	
Sensitivity	82.30%	
Specificity	90.11%	
False positive	9.03%	

Source: our elaborations in Oryx

Through the pie chart in Fig. 3, we can observe in detail the use of all instances in the dataset.

The total number of instances is 378. The number of training instances is 226 (60%), the number of selection instances is 76 (20%), the number of testing instances is 76 (20%), and the number of unused instances is 0 (0%). These results can be explained as follows: the training instances have designed the best process for the neural algorithm. It has a design accepted 60 times out of 100, and its value is higher than a different algorithm (selection instance), and the same value as the testing instance. Thus, the algorithm suggests the construction of the first phase of NNs. Finally, after observing the behavior of our data concerning the processing in ML, we can analyze the results of the ANNs.

The ANN graph in Fig. 4 contains a scaling layer, a NN, and an unscaling layer. The number of inputs is 10, while the number of outputs is 1 (target). The input variables are SR-LSR (social relations index and its logarithm); II-LII (income and inequality index and its logarithm); ET-LET (education and training index and its logarithm); LSWB (logarithm of the subjective well-being index); DSR (first difference

Table 2 Effects of the inputs on the target (input on output)

Name	Value
SR	94.0000
II	96.2333
ET	89.7000
LSWB	4.3599
LSR	4.5452
LII	2.4020
LET	4.4597
DSR	0.1132
DII	− 0.1704
DET	0.0793

Source: our elaborations in Oryx

of the social relations index); DII (first difference of the income and inequality index); DET (first difference of the education and training index), respectively. The target generated by our neural network is DSWB which represents the first difference on the subjective well-being index. The complexity, represented by the number of hidden neurons, is 10:7:5:3:1. As we can see, the pre-set target is DSWB. It represents the best choice compared to 302,400[3] possible combinations of inputs, to generate a target necessary for the analysis. The confusion matrix in Table 1 confirms previous findings.

Table 1 shows the performance of our algorithm in generating the executive target. The predicted positive values, compared to the total of the analyzed values, are 81.2 times every 100 combinations between the inputs. Classification accuracy, sensitivity, and specificity values are very high (beyond 80%). Finally, we can see that the false positive, which is a rate that measures the percentage of incorrect positive forecasts on the total of negative instances, is quite good, with a value of 9.03%. Therefore, the analysis of the confusion matrix and the four tests carried out clearly confirm the goodness of the results obtained by the ANNs. In particular, the confusion matrix reestablishes the choice to generate a target corresponding to the DSWB variable.

The influence of each input on the generated target requires the extension of our algorithm with a protocol capable of breaking down the incidence of each input, concerning changes in the NN. To this end, we use the extension of AIT-Ltd in Table 2.

Table 2 represents the effect of each input on the output (target). The AIT-Ltd extension shows us the weight of neural signals from each input to the target in the whole process of the ANNs. The results obtained are very interesting. Hence, we can see that the predicted target value (DSWB) is more affected by the simple logistic prediction of the untransformed variables. In particular, the logarithm values and the differential variations (D) are either lower or generate a negative prediction

[3] Result = $DR_{n,k}$. In this case, k, a positive integer, can also be greater than or equal to n.

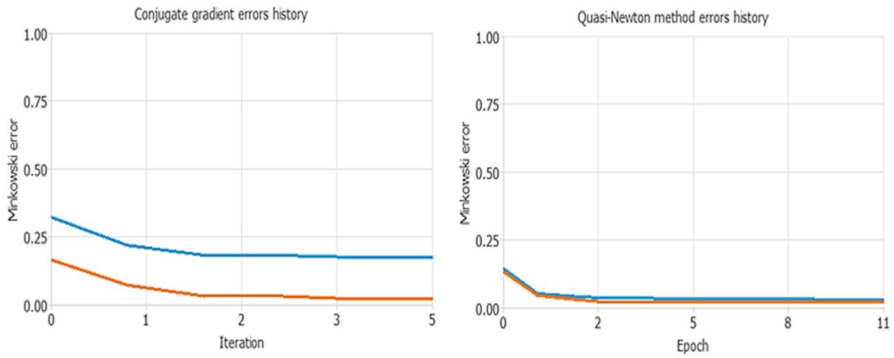


Fig. 5 Training process test. Source: our elaborations in Oryx with NN design implementation

attributable to a likely slowdown of the target. This result can be interpreted as the awareness of the future well-being variation compared to current situations. In other words, the inputs' variations represent, for the target of our NN, an event that still has to happen and is unknown. Since this scenario can be negative or positive, it has caused a process of uncertainty in predicting the change in well-being (DSWB) demonstrable by the low values obtained (DSR: 0.11, DET: 0.08, and DII: −0.17). The higher value is recorded for the prediction of income (II) and the target (DSWB). Therefore, by acting on the positive change in income, through an increase in per capita GDP, it is possible to generate a change in the prediction of output.

Finally, to check for errors in the prediction process, we test our model through two different tools: the conjugate gradient errors history and the quasi-Newton method (Fig. 5).

Both methodologies follow the belief that the best training strategy is the one that allows the best possible loss of information as interactions or epochs grow. In the left-hand figure, the conjugate gradient is used for training. In this algorithm, the search is performed along with conjugate directions, which produces generally faster convergence than gradient descent directions. The initial value of the training error (orange line) is 0.19338, and the final value after 5 ITE is 0.0475421. The initial value of the selection error (blue line) is 0.368511, and the final value after 5 ITE is 0.0432092. The analysis of this test confirms how in our prediction the error decreases as the ITE increases, and this result confirms the goodness of our model. The quasi-Newton test is based on Newton's method, although it does not require the calculation of second derivatives. Instead, the quasi-Newton method computes an approximation of the inverse Hessian at each iteration of the algorithm, by only using the gradient information. The blue line represents the training error, and the orange line represents the selection error. The initial value of the training error is 0.165464, and the final value after 11 epochs is 0.031882. The initial value of the selection error is 0.21105, and the final value after 11 epochs is 0.0386188. Again, this analysis, confirming the previous one, highlights how the whole selection and training process of our neural network presents an (almost) cancellation of errors as the eras increase.

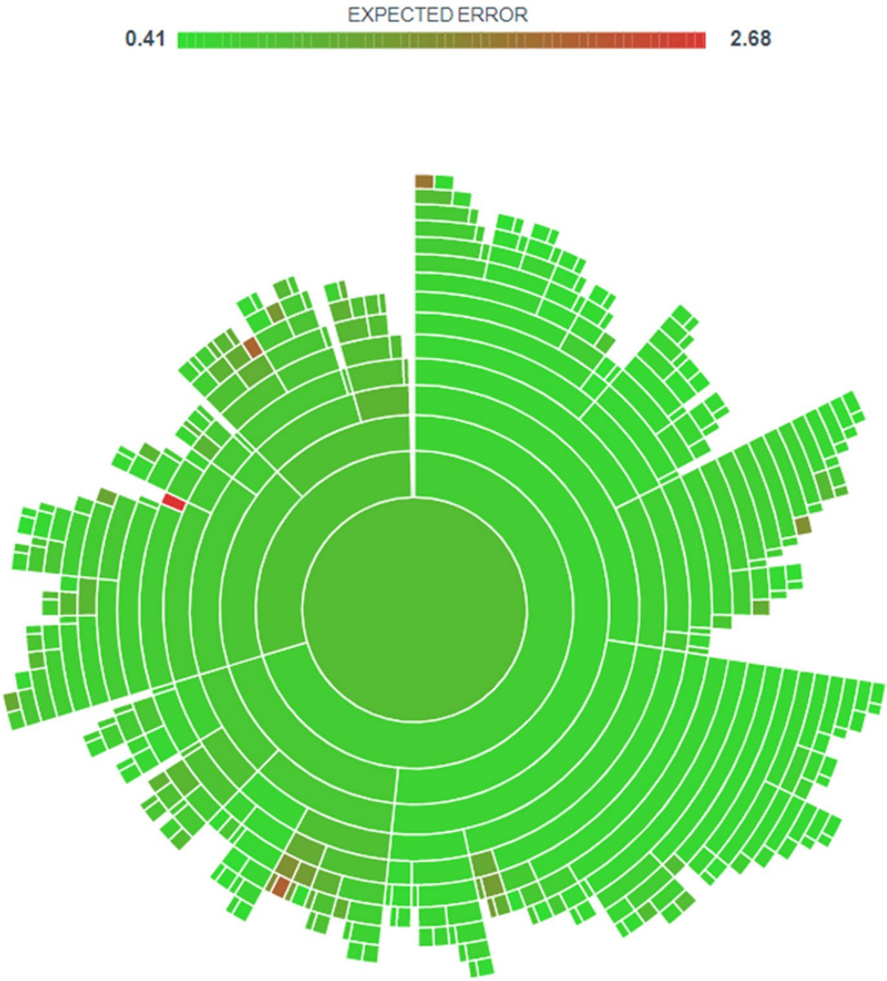


Fig. 6 Sunburst ML test. Source: our elaborations in BigML

To check the robustness of the algorithm's results, we performed the Sunburst ML test (Fig. 6). This test verifies the infinite combinations of predictions of the algorithm used concerning the dataset. This test splits the combinations into several circular areas, which symbolizes the predictive phases from the start to the conclusion of the calculations. When the predictive analysis exhibits a low value of the calculation error, then the cell relative to the algorithm appears in green. While, if the error increases, then the cell becomes darker and darker until a dark red: in that case, the predictive error assumes the maximum value.

As we can see from Fig. 6, the prediction error of our algorithm is quite low. More in detail, the cells external to the test's circular flow present shallow errors (in light green). Only six cells out of 120 show a high prediction error value.

Thus, these cells represent less than 5% of the predictive cells of the algorithm. The six cells with top predictive errors lie at the side of the test. The central cells and the last main cell have a green color, and this underlines how a low error characterizes our algorithm.

Generally speaking, the ANN results obtained can provide some useful policy recommendations. Taking Italy as an example in our paper, countries that manage to guarantee their citizens a high level of economic security could show a higher level of well-being. From our NN results, we can say that the main determinant of well-being at the regional level is not the change in income (DII). On the contrary, the critical element is the degree of security of current income (II), calculated in terms of income protection and a low level of income inequality.

Furthermore, the relationship between the neurons that generate the variation of the target (DSWB) indicates that a high level of income security also passes from the signals linked to the education and training index (SR: 94.0), as well as from the education and training index (ET: 89.7).

Discussion

The impact of social relations on SWB is substantial, influencing both the emotional and cognitive aspects of an individual's life satisfaction. Positive social interactions, supportive relationships, and a sense of belonging consistently correlate with elevated levels of SWB (Helliwell et al., 2018; Kawachi & Berkman, 2001). Quality relationships, be they familial, romantic, or friendships, enhance emotional well-being by offering support during challenging times and amplifying positive experiences. Conversely, feelings of loneliness and social isolation have detrimental effects on SWB, increasing susceptibility to mental health issues (Hawkley & Cacioppo, 2010). The universal importance of social connections is evident across cultures, underscoring the crucial role of social relations in shaping individuals' subjective assessments of their lives.

In addition, education plays a crucial role in influencing an individual's SWB, significantly contributing to their overall life satisfaction and happiness. Higher levels of education are often linked to an increased sense of well-being, highlighting the positive impacts of intellectual growth, expanded opportunities, and a sense of accomplishment (Diener et al., 2018; Layard et al., 2014). Beyond imparting knowledge and skills, education fosters a sense of purpose and personal development. Pursuing meaningful goals and finding fulfillment in educational achievements are key contributors to heightened well-being. Additionally, education equips individuals with cognitive tools for navigating life's challenges, promoting resilience and adaptive coping strategies. The strength of the connection between education and SWB underscores the importance of considering not only academic attainment but also the quality of education and the emphasis on meaningful goals in shaping this relationship.

The effects of income and inequality on SWB are shaped by the complex interplay between economic factors and overall life satisfaction. Beyond a certain threshold, the relationship between income and SWB exhibits diminishing returns, as indicated by Easterlin's paradox (Easterlin, 1974). Additionally, lower levels of SWB are associated with income inequality within societies, with greater disparities resulting in decreased well-being for individuals across different socioeconomic strata (Oishi & Kesebir, 2015; Wilkinson & Pickett, 2009). The observed effects on SWB are influenced by psychosocial factors linked to income inequality, including feelings of relative deprivation and social comparison. Recognizing the nuanced dynamics between income, inequality, and well-being is considered crucial for the development of comprehensive strategies addressing economic disparities while fostering individual and societal flourishing.

Concluding Remarks and Policy Implications

This study investigates the relationship among SWB, education, income, and social relations in a panel of 19 Italian regions and two independent provinces, with data ranging from 2004 to 2021. The empirical strategy used an NN experiment. This tool, unsupervised and trained for self-learning, confirmed some previous results in the literature.

Our empirical findings show that happiness is positively related to income, education, and social relations. Policymakers can increase happiness among the population by increasing per capita GDP, reducing the Gini index, strengthening the educational systems, and developing social cohesion. Our results seem to be in contradiction with two main economic ideas: the Easterlin (1974) paradox of happiness-income relation and the Hirschman (2002) proposition of the existence of a zero-sum game between individual interests and public actions.

The positive relationship between well-being and income is coherent with the critique of Easterlin's paradox as indicated in Sacks et al. (2012) and Stevenson and Wolfers (2013). Policymakers can increase the level of well-being by augmenting per capita GDP in absolute value. Wealthier people are happier with respect to poorer people. Wealthier countries have a higher level of well-being with respect to poorer countries. The presence of a satiation point in which the positive relationship between income and well-being turns negative is rejected (Magazzino & Leogrande, 2021).

In addition, also the idea of a juxtaposition of private interests and public action does not apply to our data, since happiness increases both with per capita GDP and with social relations. Therefore, it seems that the Hirschman effect does not hold. Policymakers can improve well-being through policies able to promote a more sustainable balance between public and private life. Citizens can be happier if they increase their individual wealth by taking care of their private interests and, at the same time, participating in the social life of the community. There is no contradiction between private and public interests in the pursuit of well-being. However, policymakers can remove some obstacles in the pursuit of well-being, for example, reducing working hours for employees that require deeper social commitment and promoting a more harmonious balance between private and public life.

Finally, we can affirm that the Italian path to well-being puts together income, education, and social relations in a sort of public happiness resembling the idea of Verri (1763) and the eudaimonia defined by Aristotle. Our results show that policymakers can increase population well-being by promoting GDP growth, developing social cohesion, and strengthening the educational system.

Understanding the impact of education, inequality, and social relations on SWB holds crucial policy implications. Investing in quality education not only enhances cognitive abilities but also promotes meaningful goal pursuit, positively influencing SWB. Addressing income inequality and fostering social connections are pivotal for societal well-being, necessitating policies that ensure fair distribution of resources and promote inclusive social structures. By recognizing the interconnectedness of these factors, policymakers can formulate holistic strategies that contribute to a more equitable, supportive, and fulfilling societal environment, ultimately enhancing the overall SWB of the population.

The limitations of the study are essentially related to the peculiar nature of this topic. Indeed, it is quite difficult to condense in a vector some broad and abstract concepts such as well-being and social relations. This is another reason why we chose to rely on a unique database, conducting the empirical analysis on series that share a similar construction methodology and source.

Future research may apply alternative methods to this data or try to derive a similar dataset for different countries to compare the empirical findings.

Appendix

Table 3 Descriptive statistics

Variable	Mean	Median	SE mean	Skewness	Kurtosis	Range
SWB	96.3381	95.4500	1.0462	0.4608	3.5286	60.0000
ET	105.0870	105.9500	0.7943	−0.1743	2.5595	40.8000
II	101.3820	105.5500	1.1415	−0.5976	2.3445	54.4000
SR	100.3310	101.7500	1.0342	0.2895	2.7203	48.6000

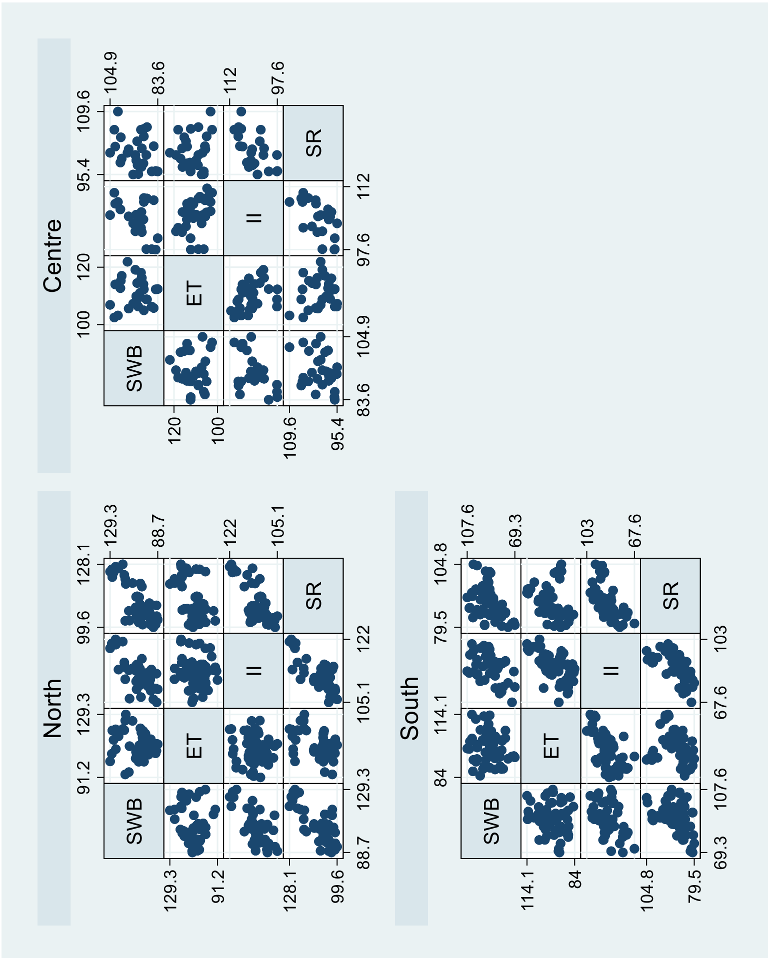


Fig. 7 Scatterplot matrices for macro-regions. Source: our elaborations in Stata

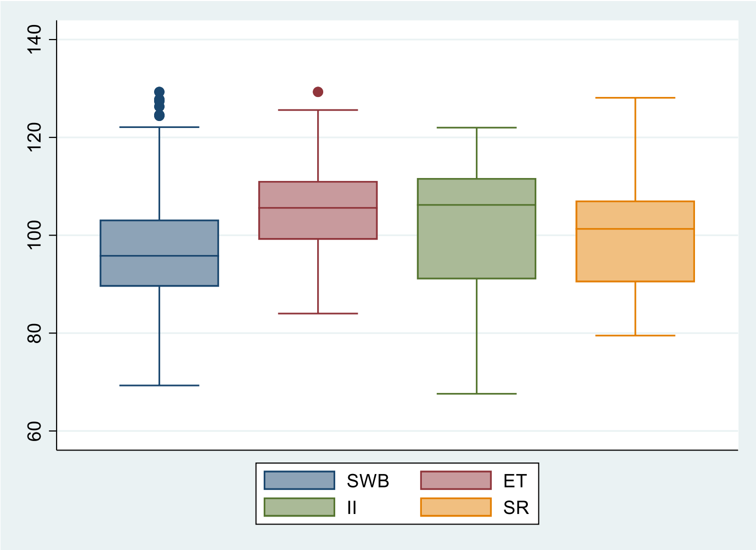
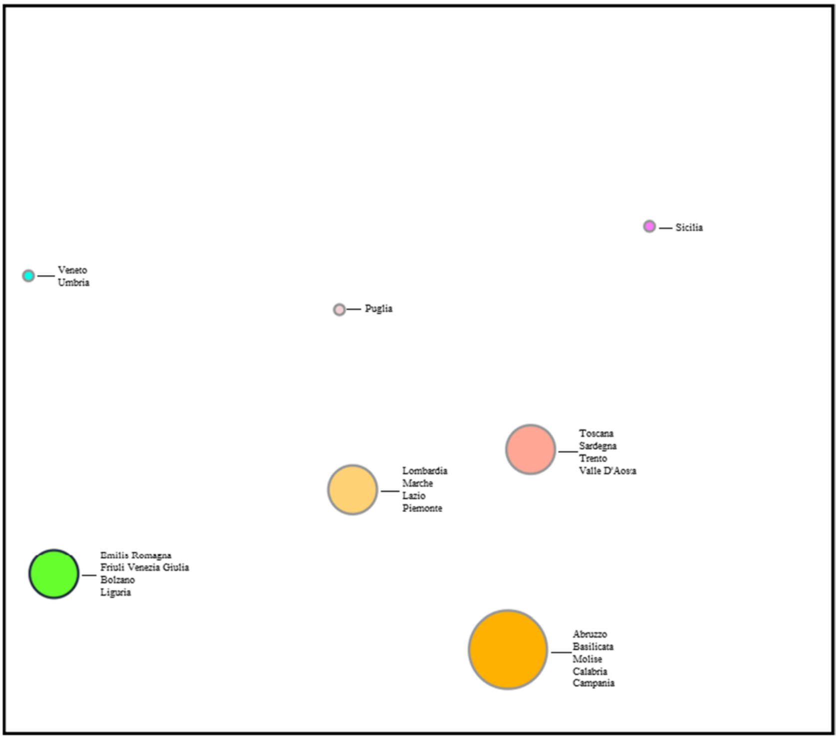


Fig. 8 Box plot of the variables. Source: our elaborations in Stata



- K-means vs G-means Cluster in ML (k=7) with 7 centroids
- Centroids:
- Global: Umbria: **1107**, Veneto: **1107**, Emilia-Romagna: **966**, Friuli-Venezia Giulia: **966**, Bolzano: **966**, Liguria: **966**, Veneto: **798**, Lombardia: **432**, Marche: **432**, Lazio: **432**, Piemonte: **432**, Abruzzo: **432**, Basilicata: **432**, Molise: **432**, Calabria: **432**, Campania: **432**, Toscana: **513**, Sardegna: **513**, Trento: **513**, Valle D'Aosta: **513**, Puglia: **502**, Sicilia: **301**

Fig. 9 Clustering results. Source: our elaborations in Oryx

ANN Code

```
scaled_SR = (SR-99.4819)/9.00891;
scaled_II = (II-101.896)/12.467;
scaled_ET = (ET-99.1029)/10.2632;
scaled_LSWB = (LSWB-4.60511)/0.116644;
scaled_LSR = (LSR-4.59573)/0.0932502;
scaled_LII = (LII-4.59901)/0.307843;
scaled_LET = (LET-4.59034)/0.110495;
scaled_DSR = (DSR-0.000765397)/0.0525136;
scaled_DII = (DII+0.000968022)/0.0943014;
scaled_DET = (DET-0.00188105)/0.0598945;
y_1_1 = tanh (2.5227+ (scaled_SR*-2.35779)+ (scaled_II*-3.95978)+ (scaled_ET*-3.16383)+
  (scaled_LSWB*-3.6572)+ (scaled_LSR*-2.07063)+ (scaled_LII*-1.96673)+ (scaled_LET*-
  0.762719)+ (scaled_DSR*1.67864)+ (scaled_DII*-0.333789)+ (scaled_DET*-2.96571));
y_1_2 = tanh (2.31382+ (scaled_SR*0.367563)+ (scaled_II*2.73447)+ (scaled_ET*2.37064)+
  (scaled_LSWB*-2.37189)+ (scaled_LSR*3.381)+ (scaled_LII*-1.5222)+ (scaled_LET*-2.90256)+
  (scaled_DSR*0.826758)+ (scaled_DII*-3.62487)+ (scaled_DET*3.85643));
y_1_3 = tanh (-1.51685+ (scaled_SR*0.452789)+ (scaled_II*-1.313)+ (scaled_ET*-4.01908)+
  (scaled_LSWB*-2.17948)+ (scaled_LSR*3.22022)+ (scaled_LII*0.587411)+ (scaled_LET*-
  2.88687)+ (scaled_DSR*-3.90166)+ (scaled_DII*0.381886)+ (scaled_DET*2.63883));
y_1_4 = tanh (0.700251+ (scaled_SR*1.19969)+ (scaled_II*-2.26706)+ (scaled_ET*-0.818413)+
  (scaled_LSWB*3.68029)+ (scaled_LSR*-3.23183)+ (scaled_LII*-0.816721)+ (scaled_LET*-
  0.0085531)+ (scaled_DSR*-1.07694)+ (scaled_DII*-1.27384)+ (scaled_DET*0.810821));
y_1_5 = tanh (-2.99124+ (scaled_SR*-1.88297)+ (scaled_II*-1.5236)+ (scaled_ET*0.254622)+
  (scaled_LSWB*3.06643)+ (scaled_LSR*-0.0758472)+ (scaled_LII*-1.34301)+ (scaled_
  LET*1.3535)+ (scaled_DSR*-0.0884763)+ (scaled_DII*0.548096)+ (scaled_DET*-0.41861));
y_1_6 = tanh (-2.82794+ (scaled_SR*3.36729)+ (scaled_II*-3.14703)+ (scaled_ET*1.21869)+
  (scaled_LSWB*-2.74081)+ (scaled_LSR*-2.00181)+ (scaled_LII*-3.13384)+ (scaled_LET*-
  3.25173)+ (scaled_DSR*1.44092)+ (scaled_DII*2.73366)+ (scaled_DET*-0.114697));
y_1_7 = tanh (1.91232+ (scaled_SR*-0.411502)+ (scaled_II*1.19699)+ (scaled_ET*-0.619507)+
  (scaled_LSWB*1.05066)+ (scaled_LSR*-3.24083)+ (scaled_LII*2.61552)+ (scaled_LET*-
  1.01679)+ (scaled_DSR*2.94336)+ (scaled_DII*0.287161)+ (scaled_DET*3.75045));
y_1_8 = tanh (-0.632517+ (scaled_SR*-0.808647)+ (scaled_II*1.93835)+ (scaled_ET*1.34502)+
  (scaled_LSWB*-0.866388)+ (scaled_LSR*2.52413)+ (scaled_LII*2.87843)+ (scaled_LET*-
  3.15507)+ (scaled_DSR*1.91677)+ (scaled_DII*-1.08043)+ (scaled_DET*-2.24451));
y_2_1 = tanh (0.600175+ (y_1_1*-1.75213)+ (y_1_2*-2.57439)+ (y_1_3*0.00413019)+ (y_1_4*-
  1.93339)+ (y_1_5*-1.2824)+ (y_1_6*-2.92872)+ (y_1_7*1.20603)+ (y_1_8*1.40688));
y_2_2 = tanh (-1.45333+ (y_1_1*1.09237)+ (y_1_2*1.43032)+ (y_1_3*-3.44763)+ (y_1_4*-
  1.52533)+ (y_1_5*3.55707)+ (y_1_6*-1.65615)+ (y_1_7*-1.26352)+ (y_1_8*-2.63343));
y_2_3 = tanh (0.552755+ (y_1_1*-0.799638)+ (y_1_2*-2.04757)+ (y_1_3*3.87826)+ (y_1_4*-
  1.89651)+ (y_1_5*-1.59486)+ (y_1_6*1.25606)+ (y_1_7*1.80827)+ (y_1_8*0.499858));
y_2_4 = tanh (2.26479+ (y_1_1*-1.59744)+ (y_1_2*1.62012)+ (y_1_3*-1.26624)+ (y_1_4*1.70945)+
  (y_1_5*-3.98406)+ (y_1_6*1.57587)+ (y_1_7*1.06065)+ (y_1_8*-2.8572));
y_2_5 = tanh (-3.77386+ (y_1_1*1.67232)+ (y_1_2*-1.03243)+ (y_1_3*0.0909528)+
  (y_1_4*2.99135)+ (y_1_5*0.810197)+ (y_1_6*-0.221132)+ (y_1_7*-3.71405)+ (y_1_8*1.29275));
y_3_1 = tanh (1.38565+ (y_2_1*-3.82559)+ (y_2_2*-0.144568)+ (y_2_3*2.13774)+ (y_2_4*-
  1.67046)+ (y_2_5*2.16204));
```

y_3_2 = tanh (1.35202+ (y_2_1*3.37379)+ (y_2_2*1.3652)+ (y_2_3*-1.45767)+ (y_2_4*0.398747)+ (y_2_5*-1.25719));

y_3_3 = tanh (2.03561+ (y_2_1*-3.18534)+ (y_2_2*-1.21879)+ (y_2_3*-2.97095)+ (y_2_4*1.59164)+ (y_2_5*-2.62134));

scaled_DSWB = (-0.69842+ (y_3_1*2.2052)+ (y_3_2*2.18417)+ (y_3_3*0.473009));

DSWB = (0.5*(scaled_DSWB+1.0)*(0.803487+0.485608)-0.485608);

Abbreviations *AI*: Adaption Inputs; *ANNs*: Artificial neural networks; *GDP*: Gross domestic product; *ML*: Machine learning; *SWB*: Subjective well-beingFunding Open access funding provided by Università degli Studi Roma Tre within the CRUI-CARE Agreement.

Data Availability Data are available upon reasonable request.

Declarations

Conflict of Interest The authors declare no competing interests.

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