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ORIGINAL RESEARCH

Multilevel Modeling of Training Needs in Artificial Intelligence

Veronica Distefano[1,2,5] · Sabrina Maggio[1] · Sandra De Iaco[1,3,4]

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Abstract

Nowadays, Artificial Intelligence (AI) is playing a rapidly increasing role in several fields of research and in almost all sectors of real life. However, few studies have assessed the effects of AI applications on training needs. This paper proposes an innovative multilevel modeling in order to investigate Awareness, Attitude and Trust towards AI and their reflections on learning needs. In particular, it is shown how a machine learning variable selection algorithm can support the definition of the optimal subset of all relevant covariates with respect to the outcome variable and improve the multilevel model performance for estimating the probability of educational needs. Thus, starting from a complex web survey to European citizens distributed in eight countries, the estimation of a multilevel binary model, defined on the basis of covariates selected through the Boruta random forest algorithm, is proposed. A discussion on the gender differences of the related estimated multilevel logit models is presented. A sensitivity analysis is also included in order to assess the prediction accuracy of the proposed multilevel logit modeling.

Keywords Multilevel logit model · Boruta random forest · Variables selection · Sensitivity analysis

✉ Sabrina Maggio
sabrina.maggio@unisalento.it

Veronica Distefano
veronica.distefano@unisalento.it

Sandra De Iaco
sandra.deiaco@unisalento.it

[1] Department of Economic Sciences, University of Salento, Ecotekne, Lecce, Italy

[2] European Centre for Living Technology (ECLT), Ca' Foscari University of Venice, Venice, Italy

[3] National Centre for HPC, Big Data and Quantum Computing, Bologna, Italy

[4] National Biodiversity Future Center, Palermo, Italy

[5] Pegaso Telematic University, Faculty of Economics and Law, Department of Management and Economics, Naples, Italy

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1 Introduction

Artificial intelligence (AI) has been introduced as a technology to improve decision-making steps involving uncertainty and complexity. It provides learning and reasoning from experience through machine learning and data mining techniques, natural language processing, image recognition (Khalid, 2020). The impact of AI and its capability has also rapidly grown in several real world applications, such as in the energy sector modeling for improving the efficiency of the energy systems and decreasing the costs (Olabi et al., 2023), in the business process for enabling making smarter and faster decisions (Sarker, 2022), in customer relationship management, where Chatterjee et al. (2021) developed and examined how AI-based customer relationship management could influence firm's performance with respect to firm size, firm age and industry type, as well as in the sector of E-Commerce, Banking and Finance (Huynh et al., 2020; Volkova et al., 2021).

In this context, although the rapid growth of AI technologies is transforming societies and economies for generating productivity gains and improving welfare, few studies have focused on assessing the ethical and social implications of AI. Indeed, many people do not trust AI for several reasons. In particular, some people do not understand the real meanings of AI, or they are afraid of it because they see AI as positively related to other problems, such as fear of becoming unemployed or fear of autonomous robots (Liang and Lee, 2017). Floridi (2019) stated that although the benefits of AI contribute to the well-being of people and the advancement of organizations and societies, in the meanwhile a number of ethical and social challenges might hinder the valuable contributions of AI if not managed appropriately. These problems are associated for instance with the risk of violating people's privacy and unintentionally tracking people on the Internet via Clearview AI. Recently, Huisman et al. (2021) investigated knowledge and attitude towards AI by radiologists in Europe highlighting how the limited AI knowledge levels among radiologists are associated with fear, while intermediate to advanced AI-specific knowledge levels are connected with a positive attitude towards AI. Moreover, among other works on this subject, it is also interesting to include those oriented to evaluate the AI-related impacts on the people, which have shown socio-demographic differences in the assessment of public perception of AI concerning gender and respondents' level of education (Carradore, 2022; Fietta et al., 2022; Zhang and Dafoe, 2019; Ahmad et al., 2023; Scantamburlo et al., 2024). Additional works have been focused on studying the impact of AI on people's social relationships (Puteri et al., 2024; Williamson, 2023) with the aim to understand its impact on inequality reduction or excessive dependence on technology (Tai, 2020). On the other hand, Kelley et al. (2021) conducted a survey to assess the public perception of AI among eight countries discovering that residents of non-Western countries (e.g. Brazil and South Korea) are more positive about AI than residents of Western countries (e.g., the United States and France).

Differently from previous works, this paper aims to provide a detailed analysis to determine the likelihood of people of taking a course on AI to improve their knowledge and then to enhance the associated decision-making process. It is worth pointing out that the field of AI is continuously evolving and will likely continue to do so. Thus, knowing people's views and investigating their awareness, attitude and trust towards AI is a key factor in supporting a trustworthy AI system. On the other hand, gain skills to use AI tools effectively and confidently apply AI in different fields of research can help to make informed decisions.

In particular, the novelty of this contribution concerns the implementation of a multilevel binary model, based on a set of optimal variables selected through a machine learning dimensionality reduction technique, in order to estimate the probability of training needs in AI, with different level of variability referred to various European countries and city-sizes. Indeed, the Boruta Random Forest (BRF) algorithm has been proposed as an explanatory machine learning methodology for variable selection. Note that, in comparison with other dimensionality reduction methods, it captures all the covariates that are relevant with respect to the outcome variable and help to improve the multilevel modeling setting as well as its accuracy (Kursa and Rudnicki, 2010). The few works associated with Boruta algorithm are limited to select the most relevant variables to improve forecasting performance or classification models in financial, environmental, medical and social context (Li et al., 2024; Masrur Ahmed et al., 2021; Manikandan et al., 2024; Anand et al., 2021). After a brief review of Boruta algorithm and multilevel modeling (Sect. 2), a description of data used in this paper has been presented (Sect. 3). Then, the variables selection based on the Boruta algorithm has been proposed (Sect. 4) and a multilevel binary model has been implemented on the basis of the selected covariates in order to determine the likelihood that European citizens take a free course on AI to improve their knowledge (Sect. 5). An interesting focus on the gender differences has been also included. In addition a discussion on the social implications of the results has been presented. A sensitivity analysis has been applied in order to assess the prediction accuracy of the multilevel logit model constructed on the basis of the selected relevant variables (Sect. 6). Finally, some concluding remarks have been presented (Sect. 7).

2 Theoretical Background

In the next two sections, a brief review of the Boruta algorithm and the multilevel binary model used in this paper, has been proposed. More specifically, starting from the available data on the opinions on AI in eight countries (Italy, Spain, France, Germany, Netherlands, Sweden, Romania, Poland) collected through a web-based survey, the multilevel modeling has been boosted by defining a subset of relevant items, from the given baseline questionnaire, on the basis of a random forest algorithm.

2.1 Variables Selection by Boruta Random Forest Optimiser

Variables selection is one of the important tasks in the applications of machine learning methods since it enhances the performance of the modeling process through the dimensionality reduction without loosing relevant information in the original dataset. As highlighted in Guyon and Elisseeff (2003) these methods provide many benefits that are shortening computational cost, understanding of the underlying process that generated the data and improving the prediction accuracy.

In this paper, variables detection is performed by using the Boruta algorithm (Kursa and Rudnicki, 2010) which is designed as a wrapper method of the features selection based on the Random Forest classifier algorithm. The choice of this variables selection algorithm is justified since it aims at finding all relevant variables (with respect to the response variable) as opposed to just the no redundant ones (Kursa and Rudnicki, 2010). This Random Forest classification algorithm is quick and it is run with tuning of parameters to give a better numerical estimate of the variables importance as pointed out in Mohtasham et al. (2024), Manhar et al. (2020) and Degenhardt et al. (2017); then it is an ensemble method in which classification is performed by voting decision trees. These trees are independently built on different bagging samples of the training set. It uses shadow variables which are copies of original variables obtained by duplicating and permuting the order of values in the original variables and embedded into the training set. In particular, these shadow variables are mixed by using bootstrap sampling with replacement to remove the correlation between the independent and the dependent variables. Thus, the final dataset, also known as extended information system, is created by combining the data of the original variables, the shadow variables and the dependent variable. Based on this new dataset, the Boruta algorithm is trained on the Random Forest algorithm and the importance measure (*zscore*) is computed for each variable by using the Mean Decrease in Accuracy (*MDA*) that is a permutation-based accuracy measurement method. The *MDA* is based on the Out-of-Bag (*OOB*) data and it is used to measure the reduction of prediction accuracy by computing the difference in prediction errors before and after the permutation of each variable (Cutler et al., 2011). More specifically, the bootstrap sampling technique is carried out to extract training samples from the original dataset, then these training samples are used to build a decision tree; while the *OOB* samples (belowing to the training samples), not considered for build a decision tree, are considered to evaluate the accuracy of decision tree (Janitza et al., 2016). Hence, the extended information system is used to train the Random Forest and the *zscore* of all variables are recorded. If an original variables has a greater *zscore* than the highest maximum *zscore* (*MZSA*) earned by shadow variables in a particular Random Forest iteration, it is considered important for that run. These shadow variables are permuted at random for each Random Forest iteration. In this way, a hit is defined as the number of time an original variable presents a higher *zscore* than the *MZSA* of the random variables. To this end, by using a statistical test, known as two-tailed equality test (Kursa and Rudnicki, 2010), a variable is deemed relevant (or not important) when it has a significantly higher (or lower) number of hits than expected. To provide statistically valid results, this procedure is performed repeatedly until all variables are classified or when the maximum number of iterations with some uncertain attributes has been reached. The flowchart of the BRF algorithm is shown in Fig. 1.

Formally, let $\mathbf{X} = \{(x_{ij}) : i = 1, \dots, n, j = 1, \dots, p\}$ be the matrix of variables where x_{ij} is the value of the jth variable for the ith individual. Given the matrix $\mathbf{Z} = \{(z_{ij}) : i = 1, \dots, n, j = 1, \dots, p\}$ obtained from the original matrix $\mathbf{X}$ by permuting the values of the variables in $\mathbf{X}$, called shadow variables, then $\mathbf{S} = (\mathbf{X}, \mathbf{Z})$ represents the extended information system.

The Boruta algorithm runs a Random Forest classifier on this extended information system $\mathbf{S}$ with the response variable $\mathbf{Y} = \{(y_i) : i = 1, \dots, n\}$ where $y_i \in \{0, 1\}$.

The variable importance is calculated for each original variable and the respective shadow variable on the overall trees by using *MDA* based on the *OOB* data for all tree. This measure is defined for each variable as follows:

$$MDA_{X_{j.}} = \frac{1}{n_{tree}} \sum_{t=1}^{n_{tree}} \frac{\sum_{i \in oob_t} I\left[y_i = f(x_{_K})\right] - \sum_{i \in oob_t} I\left[y_i = f(x_{_{K-j}}, z_{ij})\right]}{|oob_t|} \tag{1}$$

where

- $MDA_{X_{j.}}$ is the *MDA* of $X_{j.}$ (for a subset of variables) in the tree t, $t = 1, \dots, n_{tree}$,

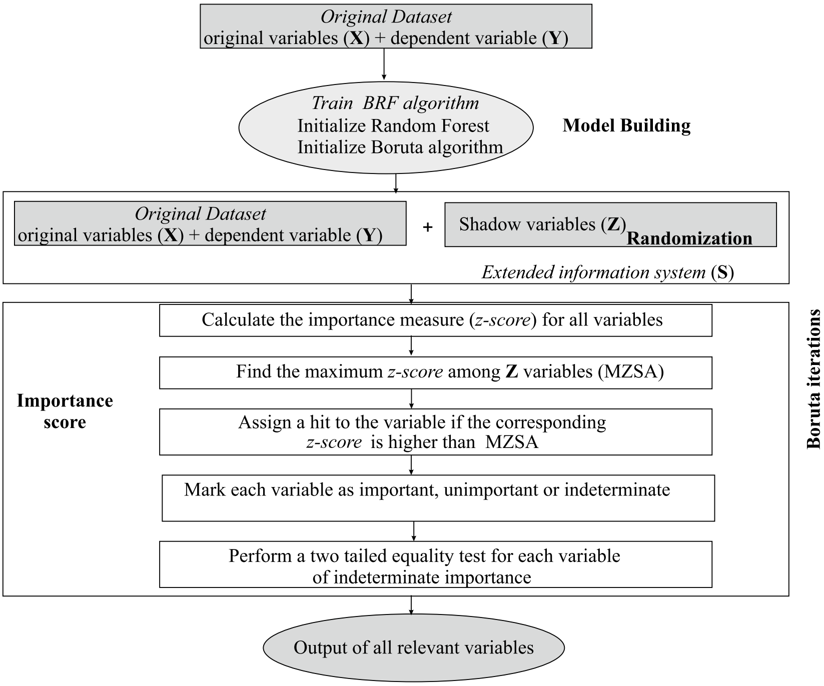

Fig. 1 Flowchart of the BRF algorithm

- $y_i = f(x_K)$ denotes the Random Forest prediction of *OOB* values before permuting, with $x_{_K} = \{(x_{il}), l = l_1, l_2, \dots, l_K, K \le p\}$,
- $y_i = f(x_{K-j}, z_{ij})$ represents the Random Forest prediction of *OOB* values after permuting, with $x_{_{K-j}} = \{(x_{il}), l = l_1, l_2, \dots, l_K, K \le p,\ l \ne j\}$,
- $I(\cdot)$ is the indicator function,
- the $|oob_t|$ is the cardinal number of the *OOB* sample for tree (i.e. the training data subsets denoted with *oob* which are not included in subtree construction).

As a result, the *MZSA* of shadow variables is used as filter indicator. In particular, if the *zscore* of the original variables is less than the *MZSA*, the variable is classified as "unimportant" and removed from the information system, otherwise, the variable is classified as "relevant". On the other hand, when the result is indeterminate, a two-tailed equality test with the *MZSA* is performed. The two-tailed test (T-test) is used to evaluate the null hypothesis that there is no difference on average between the importance of each observed variable (overall tree in RF) and the corresponding MZSA of the shadow variable.

Additionally at the end of the iterations, for each original variable a statistical test is computed using a binomial test. By fixing a significance level (α) equal to 0.05, the binomial test is used to evaluate the null hypothesis (H_0) that the given variable is relevant, that is the total number of hit is higher than $0.5N$ to consider relevant the variable. On the contrary, the variable is deemed unrelevant when the number of hit for N iterations is significantly lower than $0.5N$.

Therefore, the Boruta algorithm removes all shadow variables made at the beginning and the procedure is repeated until all variables have been assigned the importance or the algorithm has reached a predetermined number of iterations (*N*), previously defined. The Boruta algorithm used in this paper is defined as reported in the following list of instructions (Algorithm 1).

Algorithm 1 The Boruta algorithm

```
Data: Input: S, response variable, Random Forest run
Result: final Set that contains all relevant variables and rejected variables
Procedure
 for each Random Forest run do
   define S ← (X, Z, Y)
   calculate zscore ← Random Forest(S)
   identify the MZSA ← max (zscore(shadow variables))
   for each X_j. two-tailed test do
     if zscore_{X_j.} > MZSA then
       hit
   end
end
for each X_j. Binomial test do
   p-value(X_j.) ← H_0 : Nr_hit > 0.5N
   if p-value(X_j.) > α then
     confirmed original variable as relevant variable
   else if p-value(X_j.) < α then
     rejected original variable as relevant variable
end
return final Set
```

2.2 Theoretical Hints on Multilevel Binary Model

The multilevel approach is often recalled in Statistics for the study of hierarchical data structure characterized by complex patterns of variability (Goldstein, 2011; Snijders and Bosker, 2011). This structure organizes the cases into known clusters and a set of explanatory variables (covariates) associated with each group level.

The multilevel models can be considered as a natural extension of classical linear models or generalized linear models. Nevertheless, unlike traditional regression models, covariates in multilevel models can be picked for each cluster with the assessment of variability at the selected levels of aggregation, in order to measure the cluster effects on the outcome variable. Over the past years multilevel regression models have been the object of many papers and books (Distefano et al., 2025; Cappello et al., 2024; De Iaco and Maggio, 2022; De Iaco et al., 2019; Goldstein, 2011; Reise and Duan, 2004; Snijders and Bosker, 2011).

In the following, the two-level binary logit model is presented.

Let $Y_{ij} \sim Ber(\pi_{ij})$ be the binary response variable which takes values 0/1 (response categories), with the index i $(i = 1, \ldots, n_j)$ representing the level 1 unit, the index j $(j = 1, \ldots, N)$ corresponding to the level 2 unit.

Given the set of covariates $\{X_{1\cdot}, X_{2\cdot}, \ldots, X_{H\cdot}\}$, which influence the dependent response variable Y_{ij}, the two-level logit model is defined as follows:

$$\eta_{ij} = \beta_{0j} + \sum_{h=1}^{H} \beta_{hj} x_{hij} \tag{2}$$

where link between the mean π_{ij} and the linear predictor η_{ij} is given by the *logit* function (well-known as link function),

$$\eta_{ij} = \log it(\pi_{ij}) = \ln \frac{\pi_{ij}}{1-\pi_{ij}} \quad \text{and} \quad \pi_{ij} = \frac{\exp\{\eta_{ij}\}}{1+\exp\{\eta_{ij}\}} \tag{3}$$

with

- $\beta_{hj} = \beta_h + u_{hj}, \quad h = 0, 1, \ldots, H$
- $\begin{bmatrix} u_{0j} \\ u_{1j} \\ \vdots \\ u_{hj} \\ \vdots \\ u_{Hj} \end{bmatrix} \sim N\left(\mathbf{0}, \boldsymbol{\Omega}_u\right), \boldsymbol{\Omega}_u = \begin{bmatrix} \sigma^2_{u0} & & & & & \\ \sigma_{u01} & \sigma^2_{u1} & & & & \\ \vdots & \vdots & \ddots & & & \\ \sigma_{u0h} & \sigma_{u1h} & \cdots & \sigma^2_{uh} & & \\ \vdots & \vdots & \vdots & \vdots & \ddots & \\ \sigma_{u0H} & \sigma_{u1H} & \cdots & \sigma_{uhH} & \cdots & \sigma^2_{uH} \end{bmatrix}.$

The parameters of such a model can be estimated through the marginal maximum likelihood estimation, where the marginal likelihood of the observed data, obtained by integrating out the distribution of the random effects, is maximized.

The estimated regression coefficients stand for changes in the log-odds (logits) and their exponentials correspond to the odds ratios (*OR*s) which can take any value from 0 to infinity.

3 Data Description

The data used in this paper were collected during a European survey on AI and Ethics which was conducted from the 1st to the 15th of June 2021 on a sample of units from eight countries (Italy, Spain, France, Germany, Netherlands, Sweden, Romania, Poland). This survey was conducted by the market research agency Marketing Problem Solving (MPS) based in Italy (https://www.mpsresearch.it/en/). The MPS developed an *ad hoc* questionnaire and managed data collection. The data that support the findings of this study are available in Zenodo at the link: https://zenodo.org/records/13890780.

The data gathered through a questionnaire consist of 61 items grouped into two sections. The first section, titled "screening and demographics data", is composed of 7 items and it is focused on socio-demographic aspects, such as Gender, Age, country, job, Qualification level, digital skills of the sample and the number of residents in the area where they live classified by city-size (rural-small urban area and medium–large urban area); while the second section called "AI questionnaire" includes 54 items that describe three ethical and social aspects: the Awareness, the Attitude and the Trust on the citizen's approach towards AI. More specifically, the AI awareness comprises 29 items concerning the people's self-reported knowledge of AI, the perceived impact on their daily life as well as the general awareness of European Commission's initiatives such as the General Data Protection

Regulation, the Ethics Guidelines for Trustworthy AI and the recent Proposal for an AI Regulation. The Attitude comprises 12 items and is referred to citizens' attitude towards AI and its use in some specific sectors or contexts of application (e.g. job application and energy consumption). The Trust or self assessed comprises 13 items and is referred to citizens' priorities to promote a responsible development of AI which could ensure a beneficial use of AI. The assessment of the items is based on dichotomous, multi-responses or ranking responses and likert scale.

The survey was carried out by computer-assisted web interview methodology, in order to ensure quality of the dataset; contradictory answers, as well as the participants' responses that completed the survey too quickly were removed. The respondents were randomly selected by using an exhaustive sampling scheme. Indeed, the population was first divided into non-overlapping subgroups of units called strata (country), then a random sample was selected from each country stratified by age, gender and geographic regions. The sample size corresponds to 4006 respondents, out of which equal share of the sample was interviewed for each country (12.5%). After excluding missing value, the sample consists of 3992 respondents, composed of 49.4% of men and 50.6% of women and the mean age of them is 45.82 (standard deviation equal to 14.9). Moreover, with reference to the Qualification level, the descriptive analysis has highlighted that the 30.8% of the respondents has the highest level of formal education (bachelor, master or doctoral degree), while the 20.6% has short cycle tertiary education (i.e. also including trade schools and vocational education). Furthermore, 50.3% of people is employee, the 13.9% is self employed and the remaining 35.8% of people are retired (17.3%), students (5.2%), homemakers (5.7%) and unemployed (7.6%).

Regarding the level of knowledge about digital skills, 30.3% of the respondents has an intermediate level of competence in digital skills while the remaining part has a basic (44.5%) or low degree of digital knowledge (25.2%). This aspect is considered relevant for the implications of the digital revolution in the labor market as well as because of the accelerated needs caused by the COVID-19 lockdown measures (Guitton, 2020).

In order to investigate the opinion of people concerning ethical and social aspects around AI and in particular the AI training needs, the 53 items (excluding the response variable) have been classified according to the three key factors introduced above, awareness, attitude and trust, as shown in Table 1.

Further details on descriptive statistics regarding the variables of the "AI section" can be found at the link https://zenodo.org/records/13890780. In the following the proposed two-stage procedure includes the identification of the relevant variables in the dataset through the BRF algorithm and then the implementation a two-level logit model for the estimation of the probability of people to attend a free course on AI. In particular, two hierarchical levels have been considered: the first level corresponding to the sample of European citizens (3992 respondents); the second level corresponding to the geographic units obtained through the interaction between countries (8 units) and city-sizes (2 units), that is "rural or small urban area" and "medium–large urban area". The two levels of aggregation are justified by the intrinsic hierarchical structure of the data measured with respect to the locations, in which the cultural aspects can offer different opportunities. Indeed, people living in the same country are similar to each other since the countries share similar culture, economic and social aspects; on the other hand, heterogeneity can be also assumed in the relation to the size of the city where the people live.

Before introducing the section dedicated to the multilevel binary modeling applied in the paper, it is worth focusing on the BRF algorithm used to select the optimal subset of

Table 1 Variables of the "AI section"

Factors	Questionnaire variables	Nr. of items
Awareness	$Q1$: express competency when it comes to AI and its impacts on society (likert scale from Low to High)	1
	$Q5$: express how often you are aware of interacting with a product/service based on (or including) AI (likert scale from I don't know to Always)	1
	$Q7$: express what extent AI is used in some sectors in Europe (likert scale from Low to High) from $Q7_1$ to $Q7_{10}$	10
	$Q6$: from a list of applications, select which ones you think may incorporate AI (dichotomous response Yes or No) from $Q6_1$ to $Q6_{16}$	16
Attitude	$Q2$: express how you would describe your attitude towards AI and its use (likert scale from strongly disapprove to strongly approve)	1
	$Q8$: express how you would describe your attitude towards the use of AI from a list of sectors in Europe (likert scale from strongly disapprove to strongly approve) from $Q8_1$ to $Q8_{10}$	10
	$Q9$: express how positively inclined you can be with a recruitment based on AI algorithm (likert scale from Low to High)	1
Trust	$Q3$: express what extent AI and its applications impact your daily life already (likert scale from Low to High)	1
	$Q12$: express how important the following measures to increase your trust in AI are (likert scale from Not important at all to Very important) from $Q12_1$ to $Q12_6$	6
	$Q14$: express how much you trust the following entities in ensuring that AI is in the best interest of the public (likert scale from Low to High) from $Q14_1$ to $Q14_6$	6

variables (on a total of 52 variables) to be taken into account as input to perform the multilevel binary modeling for prediction purposes.

The related computational aspect associated to the fitting process of the multilevel analysis and the variables selection have been faced by employing two distinct software packages. This choice has been motived on the basis of the following pratical reasons: the multilevel binary regression model has been fitted by using the MLwiN software since it can fit models with up to five levels, it includes several estimators and it has an easy point-and-click based user interface (Rasbash et al., 2009). On the other hand, the BRF algorithm has been fitted by using the Boruta package in the *R* environment where this procedure outlined above has been easily implemented (Kursa and Rudnicki, 2010).

4 Variables Selection using Boruta Algorithm for the Interest in AI Course

In this section, the BRF algorithm has been applied to the dependent variable "interest of people to attend a free course on AI" in order to select the most relevant variables.

4.1 BRF Selection Process

To perform the BRF algorithm on the observed dataset the steps which need to be tackled regard:

- the shadow variables obtained by duplicating the original variables in the dataset and shuffling values of each column,
- the comparison between the *zscore* of the original variable with respect to the shadow variable.

As regards the second step, it can be pointed out that the Boruta algorithm trains a Random Forest classifier on this new dataset (n_{tree} = 500 for this study) with values for the original and shadow variables and it compares whether one original variable has higher importance (*zscore*) as compared to its shadow variable. Hence, if the importance of the original variable is found to be much higher than its shadow implies that the variable is confirmed to be relevant, otherwise it is classified as unimportant. This procedure has been repeated 100 times and the average importance from 100 runs has been used as the estimate of the variables importance.

Figure 2 shows the *zscore* evolution at different Boruta runs for all the questionnaire variables (original variables). In particular, the green lines indicate the behaviour of the original variables that affect more significantly the response variable, the red lines indicate the behaviour of the original variables that affect less significantly the response variable, while the blue lines denote the minimal, average and maximum shadow variable importance.

Figure 3 shows the boxplots of the *zscore* for the variables over the Boruta algorithm runs, where they are sorted by increasing importance.

The boxplots in green represent the *zscore* distributions of the variables with high importance, the boxplots in red correspond to the datasets' rejected variables, while the boxplots in blue resemble the performance of the shadow variables. More specifically, the shadow variables with the highest and lowest importance are called "ShadowMax"

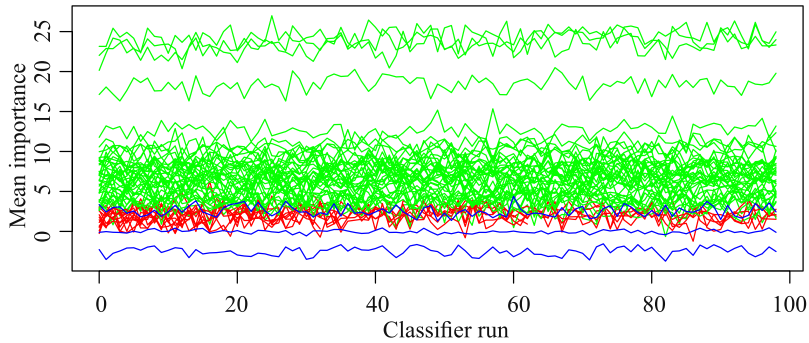

Fig. 2 *zscore* variability among variables based on the Boruta algorithm, where the green lines correspond to confirmed attributes, red to rejected ones and blue to respectively minimal, average and maximal shadow attribute importance. (Color figure online)

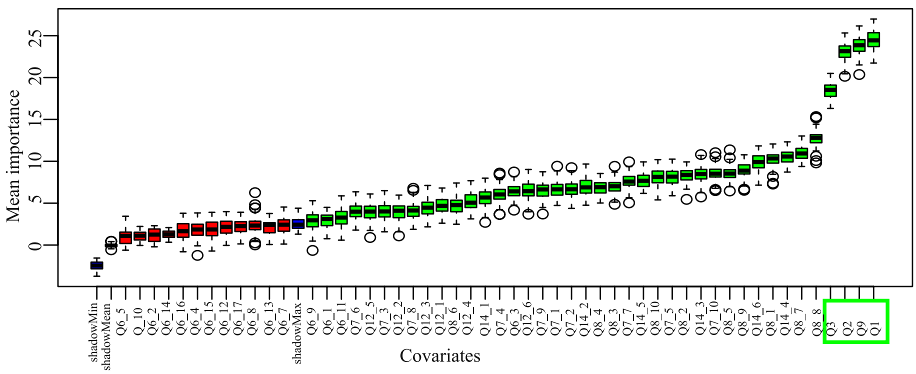

Fig. 3 Boxplots of the *zscores* obtained by the Boruta algorithm, where the variables are sorted by increasing importance. Blue boxplots correspond to the minimum, maximum and average value of shadow variables. Red and green boxplots correspond to the *zscore* of variables respectively eliminated or confirmed important by the BRF algorithm. (Color figure online)

or "ShadowMin", respectively; on the other hand, the mean performance of the shadow variables is called "ShadowMean". It is worth pointing out that in this case, the result achieved by using the Boruta algorithm, through several iterations, can be considered reasonably more stable than those obtained by using other variable selection methods based on a single Random Forest run (Kursa and Rudnicki, 2010). Therefore, the variables with mean importance greater than 15 have been selected and used as the input covariates to apply the proposed multilevel model. For this aim, the relevant variables taken into account have been the following: Knowledge of AI ($Q1$), Attitude towards AI ($Q9$, $Q2$) and Trust towards AI ($Q3$) as shown in Table 1.

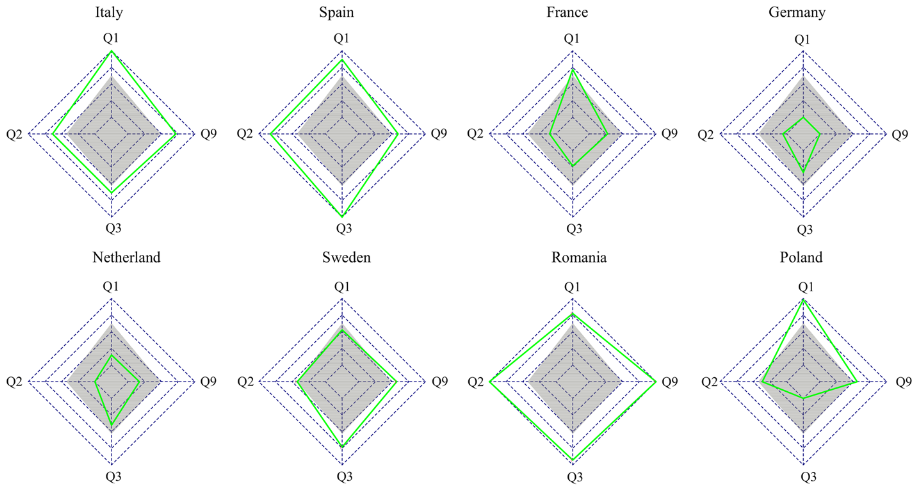

Fig. 4 Radar plots giving the estimated likert scores of all relevant variables selected by Boruta algorithm for each country

Table 2 Variables of the "AI section"

Selected Variables	Kruskal–Wallis statistic	df	*p value*
Knowledge of AI ($Q1$)	130.792	7	0.000
Attitude towards AI ($Q9$)	280.124	7	0.000
Trust towards AI ($Q3$)	280.124	7	0.000
Attitude towards AI ($Q2$)	164.220	7	0.000

4.2 Descriptive Results on BRF Selection

In this section, the variables selected by using BRF algorithm have been described. In particular, it is worth focusing on the descriptive results coming from the eight radar plots (one for each analyzed country) of the relevant variables selected by the Boruta algorithm (Saary, 2008; Duan et al., 2023).

As illustrated in Fig. 4, each relevant variable has been represented on a different radius based on its score and the grey area has been obtained by considering the mean scores computed on the overall sample for the four items.

It is worth highlighting that people in Germany, France and Netherland have declared a low level of knowledge of AI ($Q1$), a general negative attitude towards AI ($Q2$) as well as a negative attitude to apply AI to job recruitment ($Q9$). In addition, in relation to the impact of AI in their daily lives ($Q3$), the corresponding perception is greater in Spain and lower in Poland with respect to the other countries.

Finally, the averages associated to these variables have been compared with respect to the ones related to the eight countries under study by using the Kruskal–Wallis test (Kruskal and Wallis, 1952). By fixing a significance level of 1%, this test checks for the validity of the null hypothesis that there is no difference among the countries. The results in Table 2 show statistically significant differences according to the three factors concerning Awareness ($Q1$), Attitude ($Q9$ and $Q2$) and Trust ($Q3$) towards AI among countries.

Moreover, as regards the $Q2$ and $Q9$ variables (Attitude towards AI), both represent the same ethical and social aspect referred to the factor attitude. Indeed, this can be justified since the Boruta algorithm tends to find all variables that are relevant for the response variable without considering the collinearity among variables. Thus, the variable Attitude towards AI ($Q2$) has been discarded, while the variables Knowledge of AI ($Q1$), Attitude towards AI ($Q9$), Trust towards AI ($Q3$), used to measure the degree of awareness, attitude and trust of the people concerning ethical and social aspects of AI, have been included as the input covariates of a multilevel binary model, jointly with Gender, Age and Qualification level that describe the "socio-demographic data" (Table 3).

Note that the variable Gender has been also chosen as stratification variable in order to evaluate the different attitude with respect to the propensity of attending a free course on AI.

5 A Two-Level Binary Model for the Probability of Training Needs in AI

In the following, the two-level binary logit model (4), characterized by the intercept and the slope that vary across the level 2, has been adopted to assess the probability of educational needs in AI, by focusing, first of all, on the whole sample of European citizens belonging to the eight countries under study and then by classifying them on the basis of the gender.

5.1 Modeling and Results for the Sample of European Citizens

Let $Y_{ij} \sim Ber(\pi_{ij})$ be the binary response variable which takes values 0 for "not interested in attending a free training course on AI" with probability $(1 - \pi_{ij})$ and 1 for "interested in attending a free training course on AI" with probability π_{ij}, where:

- the index $j \, (j = 1, \dots, N)$, with $N = 16$, corresponds to the country per city-size (which represents the units of level 2), constructed by considering both the 8 countries and the 2 city-sizes ("rural or small areas" and "medium–large urban areas");
- the index $i \, (i = 1, \dots, n_j)$ represents the units of level 1;
- $\sum_{j=1}^{N} n_j = 3992$ is the size of the total sample of European citizens.

Given the relevant set of covariates $\{X_{1\cdot}, X_{2\cdot}, \dots, X_{7\cdot}\}$ listed in Table 4, which can influence the dependent variable Y_{ij}, the two-level binary logit model has been defined as follows:

Table 3 The relevant variables selected for the study

Variables	Modality or derived modality
Gender	"0"= man, "1"= woman
Age	"0"= between 18 and 34 (young), "1"= between 34 and 55 (middle), "2"= more than 55 (senior)
Qualification level	"0"= until tertiary education, "1"= bachelor's degree or higher
Knowledge of AI ($Q1$)	"0" = low, "1"= medium–high
Attitude towards AI ($Q9$)	"0" = low, "1"= medium–high
Trust towards AI ($Q3$)	"0" = low, "1"= medium–high

Table 4 Estimates of fixed and random parameters, together with the standard errors (*SE*), the Wald statistic, the *p-value* and the *OR*s of the model (4) concerning the sample of European citizens

Covariate's category and estimates for fixed parameters	$\hat{\beta}$	$SE(\hat{\beta})$	Wald statistic	*p-value*	$OR = \exp(\hat{\beta})$
constant	− 0.445	0.152	− 2.928	0.003***	0.641
Knowledge of AI-$Q1$ ($x_{1\,ij}$)	0.213	0.082	2.598	0.009***	1.237
Attitude towards AI-$Q9$ ($x_{2\,ij}$)	0.894	0.082	10.902	0.000***	2.445
Trust towards AI-$Q3$ ($x_{3\,ij}$)	0.681	0.110	6.191	0.000***	1.976
Qualification level ($x_{4\,ij}$)	0.255	0.106	2.406	0.016**	1.290
Age between 35 and 55 years old ($x_{5\,ij}$)	0.017	0.091	0.187	0.852	1.017
Age between 55 and 75 years old ($x_{6\,ij}$)	− 0.258	0.095	− 2.716	0.007***	0.773
Gender ($x_{7\,ij}$)	0.358	0.074	4.837	0.000***	1.430
Random parameters					

$$\boldsymbol{\Omega}_u = \begin{bmatrix} 0.2087(0.1013) & & & & \\ -0.0313(0.0451) & 0.0114(0.0354) & & & \\ -0.0236(0.0599) & -0.0005(0.0347) & 0.0956(0.0663) & & \\ 0.0773(0.0572) & -0.0241(0.0342) & 0.0141(0.0457) & 0.0483(0.0580) & \\ -0.0629(0.0467) & 0.0067(0.0227) & 0.0107(0.0314) & 0.0014(0.0304) & 0.0065(0.0292) \end{bmatrix}$$

*p value<0.1 **p value<0.05 ***p value<0.01

$$\eta_{ij} = \beta_{0j} + \beta_1 x_{1ij} + \beta_{2j} x_{2ij} + \beta_{3j} x_{3ij} + \beta_{4j} x_{4ij} + \beta_5 x_{5ij} + \beta_6 x_{6ij} + \beta_{7j} x_{7ij} \tag{4}$$

where:

- $\beta_{0j} = \beta_0 + u_{0j}$
- $\beta_{2j} = \beta_2 + u_{2j}$
- $\beta_{3j} = \beta_3 + u_{3j}$
- $\beta_{4j} = \beta_4 + u_{4j}$
- $\beta_{7j} = \beta_7 + u_{7j}$

with

- $\begin{bmatrix} u_{0j} \\ u_{2j} \\ u_{3j} \\ u_{4j} \\ u_{7j} \end{bmatrix} \sim N\left(\mathbf{0}, \mathbf{\Omega}_u\right), \mathbf{\Omega}_u = \begin{bmatrix} \sigma^2_{u0} & & & & \\ \sigma_{u02} & \sigma^2_{u2} & & & \\ \sigma_{u03} & \sigma_{u23} & \sigma^2_{u3} & & \\ \sigma_{u04} & \sigma_{u24} & \sigma_{u34} & \sigma^2_{u4} & \\ \sigma_{u07} & \sigma_{u27} & \sigma_{u37} & \sigma_{u47} & \sigma^2_{u7} \end{bmatrix}.$

It is worth pointing out that the model in (4) allows the slopes concerning Knowledge of AI-$Q1$ ($X_{1.}$), Age between 35 and 55 years old ($X_{5.}$) and Age between 55 and 75 years old ($X_{6.}$) to be constant; on the other hand, the intercept and the other covariates' coefficients are assumed to vary across the 2nd level.

On the basis of the model (4), Table 4 reports the estimates of the significant covariates' coefficients obtained by using the iterative generalised least squares (IGLS) algorithm, with the predictive (or penalized) quasi-likelihood (PQL) approximation.

The *OR*s have been also computed (last column of Table 4) in order to evaluate the covariates' effect on the probability of training needs in AI, as discussed in the following.

- Having a medium–high level of Trust regarding the impact of AI and its applications on daily life (compared to having a very low Trust towards AI) increases the probability to attend a course in AI by +98%; in addition, feeling fairly comfortable with recruitment based on an AI algorithm (with respect to not being very comfortable and then showing a medium–high level of attitude towards AI) enhances the likelihood of requiring upgrading of their skills by +144%. The positive effect of these two covariates, Trust towards AI ($Q3$) and Attitude towards AI ($Q9$), respectively, on the probability of training needs in AI is even higher for the citizens who feel that its applications have a larger impact on real life (+144%) than for those who trust on AI as a driver to improve the efficiency of daily tasks (+98%).
- Declaring to have a medium–high level of competence in AI and a medium–high degree of awareness of its impact on society, compared with having low skill and consciousness in AI, increases the probability of being interested in attending a free course on AI by +24%. Although the effect of this covariate (Knowledge of AI-$Q1$) is positive, the OR is lower than the ones associated to the covariates Attitude towards AI ($Q9$) and Trust towards AI ($Q3$). This can be justified by considering that the citizens with a medium–high level of knowledge of AI are informed about new opportunities provided by AI in terms of economic and social development: this might reasonably produce a dampening impact on the probability to attend a course on this topic.

- Having a bachelor's degree or higher Qualification level (compared to a tertiary education level) increases the likelihood of attending a course in AI by +29%; indeed, the positive effect of this covariate on the probability of taking a course in AI could be plausibly justified by taking into consideration that citizens with advanced levels of education are more aware of the specific uses of AI in daily life than those with lower levels of education.
- Belonging to the senior age group (more than 55 years old) with respect to the young age (18–34 years old) decreases the probability to attend a course on AI by −23%. On the other hand, the probability of taking a course increases by only +1.7% (not significant) for the working-age citizens (middle age group). This could be explained by considering that the citizens belonging to the middle age group might be interested in a course of AI only for retraining and skill enhancement; on the other hand, young people might presumably have a greater interest in enrolling in an AI course not only to improve their knowledge and proficiency on the subject, but also to gain new job opportunities. In this context, as stated by Siau and Wang (2018), the role of higher education is becoming necessary to improve the citizens knowledge and skills.
- Being a woman increases the probability of taking a course on AI by +43%; this might be allegedly due to the gender difference in the attitude towards AI, as discussed in many contributions in the literature (Cai et al., 2017).

Moreover, by focusing on the random part of the model, it is evident that the variation in the probability to attend a course in AI occuring in the second level, concerns the covariates Attitude towards AI ($Q9$), Trust towards AI ($Q3$), Qualification level and Gender, with an influence of the 2nd level-group effect (country per city-size) which is slightly higher on the Trust towards AI ($Q3$) and Qualification level covariates than for the two others. This is also confirmed by the estimated intra-class correlation coefficient corresponding to 3 and 2%, for Trust towards AI ($Q3$) and Qualification level, respectively.

5.2 Modeling and Results for the Sample of European Citizens, by Gender

Let $Y_{ij}^{(k)},\ k = 1, 2$, be two binary response variables for the sub-sample of women and men, respectively, which take values 0 for "not interested" or 1 for "interested" into attending a free training course on AI, where:

- the index $j\,(j = 1, \dots, N)$, with $N = 16$, corresponds to the country per city-size (which represents the units of level 2), constructed by considering both the 8 countries and the 2 city-sizes ("rural or small areas" and "medium–large urban areas");
- the index $i\,(i = 1, \dots, n_j^{(k)})$ represents the subset of women for $k = 1$ or the subset of men for $k = 2$;
- $\sum_{j=1}^{N} n_j^{(1)} = 1974$ and $\sum_{j=1}^{N} n_j^{(2)} = 2018$ are the sub-sample sizes for women and for men, respectively.

Given the set of covariates $\{X_{1\cdot}, X_{2\cdot}, \dots, X_{6\cdot}\}$, which influence the dependent variables $Y_{ij}^{(1)} \sim Ber(\pi_{ij}^{(1)})$ and $Y_{ij}^{(2)} \sim Ber(\pi_{ij}^{(2)})$ (Table 5), the corresponding two-level binary logit models are expressed as follows:

$$\eta_{ij}^{(1)} = \beta_{0j} + \beta_1\, x_{1ij} + \beta_2\, x_{2ij} + \beta_{3j}\, x_{3ij} + \beta_{4j}\, x_{4ij} + \beta_5\, x_{5ij} + \beta_6\, x_{6ij} \tag{5}$$

$$\eta_{ij}^{(2)} = \beta_{0j} + \beta_1\, x_{1ij} + \beta_{2j}\, x_{2ij} + \beta_{3j}\, x_{3ij} + \beta_4\, x_{4ij} + \beta_5\, x_{5ij} + \beta_6\, x_{6ij} \tag{6}$$

where the model in (5) presents:

- $\beta_{0j} = \beta_0 + u_{0j}$
- $\beta_{3j} = \beta_3 + u_{3j}$
- $\beta_{4j} = \beta_4 + u_{4j}$

Table 5 Estimates of fixed and random parameters, together with the standard errors (*SE*), the Wald statistic, the *p-value* and the *OR*s of the binary model referred to binary model classified on the basis the gender

Covariate's category and estimates for fixed parameters	$\hat{\beta}$	$SE(\hat{\beta})$	Wald statistic	*p value*	$OR = \exp(\hat{\beta})$
Gender: woman					
Individual-level covariates					
constant	− 0.365	0.166	− 2.199	0.028**	0.694
Knowledge of AI-*Q*1 ($x_{1\,ij}$)	0.600	0.147	4.082	0.000***	1.822
Attitude towards AI-*Q*9 ($x_{2\,ij}$)	0.970	0.115	8.435	0.000***	2.638
Trust towards AI-*Q*3 ($x_{3\,ij}$)	0.591	0.142	4.162	0.000***	1.806
Qualification level ($x_{4\,ij}$)	0.329	0.129	2.550	0.011***	1.390
Age between 35 and 55 years old ($x_{5\,ij}$)	0.243	0.136	1.787	0.074*	1.275
Age between 55 and 75 years old ($x_{6\,ij}$)	0.017	0.142	0.120	0.905	1.017
Random parameters					
$\mathbf{\Omega}_u = \begin{bmatrix} 0.106(0.081) & & \\ -0.029(0.071) & 0.0113(0.105) & \\ 0.056(0.060) & 0.016(0.069) & 0.067(0.091) \end{bmatrix}$					
Gender: man					
Individual-level covariates					
constant	−0.430	0.192	−2.240	0.025**	0.651
Knowledge of AI-*Q*1 ($x_{1\,ij}$)	0.508	0.148	3.432	0.001***	1.662
Attitude towards AI-*Q*9 ($x_{2\,ij}$)	0.765	0.111	6.892	0.000***	2.149
Trust towards AI-*Q*3 ($x_{3\,ij}$)	0.653	0.164	3.982	0.000***	1.921
Qualification level ($x_{4\,ij}$)	0.357	0.108	3.305	0.001***	1.429
Age between 35–55 years old ($x_{5\,ij}$)	−0.084	0.127	−0.661	0.508	0.919
Age between 55–75 years old ($x_{6\,ij}$)	−0.375	0.132	−2.841	0.004***	0.687
Random parameters					
$\mathbf{\Omega}_u = \begin{bmatrix} 0.283(0.135) & & \\ 0.004(0.068) & 0.009(0.064) & \\ -0.086(0.108) & 0.0059(0.070) & 0.241(0.148) \end{bmatrix}$					

**p-value*<0.1 ***p-value*<0.05 ****p value* < 0.01

with

- $\begin{bmatrix} u_{0j} \\ u_{3j} \\ u_{4j} \end{bmatrix} \sim N(\mathbf{0}, \mathbf{\Omega}_u), \mathbf{\Omega}_u = \begin{bmatrix} \sigma^2_{u0} & & \\ \sigma_{u03} & \sigma^2_{u3} & \\ \sigma_{u04} & \sigma_{u34} & \sigma^2_{u4} \end{bmatrix}$.

On the other hand, the model (6) shows:

- $\beta_{0j} = \beta_0 + u_{0j}$
- $\beta_{2j} = \beta_2 + u_{2j}$
- $\beta_{3j} = \beta_3 + u_{3j}$

with

- $\begin{bmatrix} u_{0j} \\ u_{2j} \\ u_{3j} \end{bmatrix} \sim N(\mathbf{0}, \mathbf{\Omega}_u), \mathbf{\Omega}_u = \begin{bmatrix} \sigma^2_{u0} & & \\ \sigma_{u02} & \sigma^2_{u2} & \\ \sigma_{u03} & \sigma_{u23} & \sigma^2_{u3} \end{bmatrix}$.

The models (5) and (6) are denoted as random multilevel intercept and random slope models (De Iaco and Maggio, 2022). In particular, there is a variability across the second level (countries per city-size) for:

- the constant and the Trust towards AI ($X_{3.}$), in both models (5) and (6),
- the Qualification level ($X_{4.}$) in model (5),
- the Attitude towards AI ($X_{2.}$) in model (6).

On the other hand, the slopes are assumed to be constant for all the remaining covariates. Thus, Table 5 shows the estimates of fixed and random parameters of the logit models for women and men, obtained by using the IGLS algorithm, with the PQL approximation. The *OR*s given in the last column of Table 5 highlight the following aspects.

- For what concerns the sub-sample of women, having a medium–high level of knowledge ($Q1$), a medium–high Attitude towards AI ($Q9$) and a medium–high level Trust towards AI ($Q3$) increases the probability of training needs in this field by +82, +164 and +81%, respectively. In addition, having at least a bachelor's degree or a higher education degree increases by +39% the probability of taking a course in AI. Moreover, it can be observed that belonging to the middle age group (35–55 years old) with respect to the young age (18–34 years old) enlarges by +28% the probability to attend a course on AI; on the contrary, the probability of taking a course increases by only +1.7% for the senior age group (more than 55 years old) with respect to the young age.
- With reference to the sub-sample of men, having a medium–high level of knowledge ($Q1$), a medium–high Attitude towards AI ($Q9$) and a medium–high level Trust towards AI ($Q3$) increases the probability of training needs in this field by +66, +115 and +92%, respectively. Moreover, having at least a bachelor's degree or a higher education degree increases by +43% the probability of taking a course in AI. It can be also pointed out that belonging to the senior age group (more than 55 years old) with respect to the young age decreases the probability to attend a course on AI by −31%; conversely, belonging to the middle age group (35–55 years old) with respect to the young age decreases the probability to attend a course on AI by only −8%.

The *OR*s' results show a different behaviour of women with respect to men in relation to the choice to take a course to improve their skills in AI. This might depend both on the different job opportunities for women compared to men, due to their higher risk of displacement, as well as to a distinct attitude towards technological aspects, as clarified in some contributions in the literature (Cai et al., 2017; Goswami and Dutta, 2016). In particular, as discussed in Erickson et al. (2017), the women are more critical about their skills than men even if they have the same positions. This kind of gender stereotypes can lead to different levels of self-motivation and create structural barriers that perpetuate workplace gender inequality (European Commission, 2021).

On the other hand, the positive effect on the training needs in AI given by a medium–high level of Trust towards AI ($Q3$) is attenuated for women with respect to men.

With reference to the level of knowledge ($Q1$) and of Awareness of AI applications in everyday life ($Q9$), the positive effect on the probability to attend a course in AI is stronger for women than for men. This could be explained by considering that the presence of women in education, in research and, more generally, in activities connected with computer science is lower compared to men, as well as fewer women achieve leadership positions in these fields. In this context, an educational need could help to overcome this gender disparity.

Finally, by focusing on the random part of the model, it is important to pointing out that the variation in the probability to attend a course in AI regarding the second level, is related to:

- the covariates Trust towards AI ($Q3$) and Qualification level, with an incidence of the 2nd level-effect which is slightly greater on the Qualification level (with the estimated intra-class correlation coefficient equal to 2%) compared to Trust towards AI ($Q3$), in the case of the sub-sample of women;
- the covariates Attitude towards AI ($Q9$) and Trust towards AI ($Q3$), with an influence of the 2nd-level which is moderately larger for Trust towards AI ($Q3$) (with the estimated intra-class correlation coefficient equal to 3%) compared to Attitude towards AI ($Q9$), in the case of the sub-sample of men.

5.3 Estimated Probability of attending AI Courses

In order to clarify the modeling findings, the predicted probabilities of attending an AI course have been calculated for a sample of European citizens in eight countries, also stratified by gender, as reported in Table 6. More specifically, from what concerns the whole sample of citizens (third column of Table 6), it is evident that the countries with the highest estimated probability of training needs in AI (greater than 0.60) are Romania, Spain, Italy and Sweden differently from the other four countries (Netherland, Germany, Poland, France). These results suggest that the Trust and Awareness in human-AI interactions is perceived in the most disparate manner among countries, where moral and ethical issues might differ. This can be justified by taking into account that the strategies of the European Union, are oriented to a regulation on the development and use of AI. In particular, the European Commission proposed on April 21, 2021, a legal framework, known as AI Act, where policy options to enable a trustworthy and secure development of AI in Europe, in full respect of the values, transparency and accountability of European citizens are described. As highlighted in European Commission (2021), this document also provides some measures about new risks or negative consequences for individuals or the society posed by the development and use of AI.

In this context, since 2021 the member states have developed an action plan to follow up the implementation of their national AI strategies. By considering the information regarding the policy approaches across member states, the above mentioned empirical evidences might be reasonably due to peculiar AI policies adopted by each country. Indeed, Romania, Italy, Spain and Sweden have stated as priority target the development of education and skills in AI in the public and private sector as well as the improvement of AI education at all levels and the introduction of reskilling opportunities the working age. The remaining countries are focused not only on actions to support on education and skills in AI, but also to increase the use of AI for public service (i.e. including climate change, health, Finance, and Agriculture) and develop an ethical framework for a transparent use of AI applications. According to the country per city-size (2nd level), the Table 6 highlights that people who live in medium–large urban areas of Spain and Romania reveal a greater likelihood to attend a course on AI than people residents in rural or small areas. On the other hand, from the estimated probabilities in Table 6 it is highlighted that people who live in rural or small areas of Netherland and Sweden reveal a greater likelihood to attend a course on AI than people residents in medium–large areas. In addition, by focusing on the the sample of European citizens classified with respect to gender, the results in Table 6 show a higher probability to continue learning in order to improve their skills for the women living in Romania (with predicted values ranging from 0.719 to 0.734) compared to the men (with predicted values spanning from 0.648 to 0.655). On the other hand, it is evident that the lowest estimated probability for the European citizens to enhance their education level in AI are observed in the Netherland with predicted values spanning from 0.601 to 0.614 for women and 0.530 to 0.532 for men.

Table 6 Estimated probabilities for the evaluation of the interest in AI courses, classified with respect to the country per city-size for the whole sample of citizens ($\hat{\pi}_{ij}$), the subset of women ($\hat{\pi}_{ij}^{(1)}$) and the subset of men ($\hat{\pi}_{ij}^{(2)}$)

Country	City-size	$\hat{\pi}_{ij}$	$\hat{\pi}_{ij}^{(1)}$	$\hat{\pi}_{ij}^{(2)}$
	Rural or small area	0.625	0.684	0.599
Italy	Medium–large urban area	0.620	0.695	0.583
	Rural or small area	0.629	0.701	0.594
Spain	Medium–large urban area	0.653	0.709	0.616
	Rural or small area	0.557	0.649	0.540
France	Medium–large urban area	0.565	0.674	0.531
	Rural or small area	0.548	0.614	0.532
Netherland	Medium–large urban area	0.536	0.601	0.530
	Rural or small area	0.557	0.645	0.531
Germany	Medium–large urban area	0.553	0.661	0.521
	Rural or small area	0.600	0.703	0.555
Sweden	Medium–large urban area	0.581	0.685	0.560
	Rural or small area	0.667	0.719	0.648
Romania	Medium–large urban area	0.678	0.734	0.655
	Rural or small area	0.556	0.650	0.582
Poland	Medium–large urban area	0.590	0.692	0.596

5.4 Discussion on Social Implications

This work has developed an innovative two stage analysis to assess the effects of Awareness, Attitude and Trust of people towards on AI training needs which can have a social impact. Indeed, this paper has focused on the evaluation of the variability among different countries of AI education and has also estimated the probability of the consequent training needs. It has contributed to the knowledge of this field highlighting the importance of AI education and the predisposition of citizens to acquire digital skills. The multilevel analysis revealed the presence of relevant disparities among country-size and gender gaps in the attitude to attend training courses in order to be ready to face new digital challenges of labor market.

In this context, the European Union has adopted strategies and addressed the national policies for member countries in digital skills, supporting workforce and education system and train ICT experts.

Eurostat as part of the European Commission's Digital Decade program has noticed in 2021 a level of basic digital skills that is not yet aligned with the EU's targets, which established as a goal that at least 80% of citizens aged 16–74 should have basic skills by 2030. The indicator, used to measure this skill level, is called "Digital Skills Indicator" and can be considered as proxy of individual's skills and it identifies in skill levels in terms of basic or high skills. Based on the published results for the year 2021, 54% of people in the Europe aged 16–74 has at least basic overall digital skills. More specifically, it can be seen from the Eurostat report that Netherlands (79%) has the highest share of general basic digital skills followed by Sweden (67%), Spain (64%) and France (62%). In contrast, Germany (49%), Italy (46%), Romania (28%) and Poland (43%) have the lowest shares of digital skills. This confirms the difference among the estimated probabilities of training needs of the first group of countries (Netherland, Sweden, Spain and France) with respect to the second one (Italy, Germany, Poland and Romania), as shown in Table 6.

Furthermore, among the nations analysed in the multilevel study, the Women in Digital Scoreboard (WiD), which takes values ranging from 0 to 100, showed in 2022 that there is a gender gap in specialist digital skills (European Commission, 2022). Indeed, women living in the Netherlands (WiD equal to 71.9), Sweden (WiD equal to 71.2), France (WiD equal to 64.4) and Spain (WiD equal to 64.2) have the highest level of digital skills with respect to the European medium value (WiD equal to 54.9). On the other hand, women living in Italy (WiD equal to 49.7), Germany (WiD equal to 47.8), Poland (WiD equal to 45.5) and Romania (WiD equal to 35.8), present the lowest score on participation in the digital economy and society compared to the European medium value (WiD equal to 54.9).

The empirical findings concerning the WiD are in accordance to the results of the procedure proposed and applied in this paper. More specifically, the estimated probabilities to attend a free course on AI have been classified by gender and country-size, coming to identify differences among the two groups of countries (already defined) on the basis of the level (basic/high) of the digital skills, as reported in Fig. 5. In particular, the three radar plots in Fig. 5 illustrate the mean, the minimum and the maximum to estimated probabilities of attending an AI course, respectively. The estimated probabilities to attend a course of AI have been represented on different radius associated with the adopted classification in terms of gender and country-size for the two groups.

It is worth pointing out that, on average, the probability of countries sharing a basic level of digital skills is always higher than the probability of the group of countries with high digital skills. However, in all countries the probability of attending an AI course is

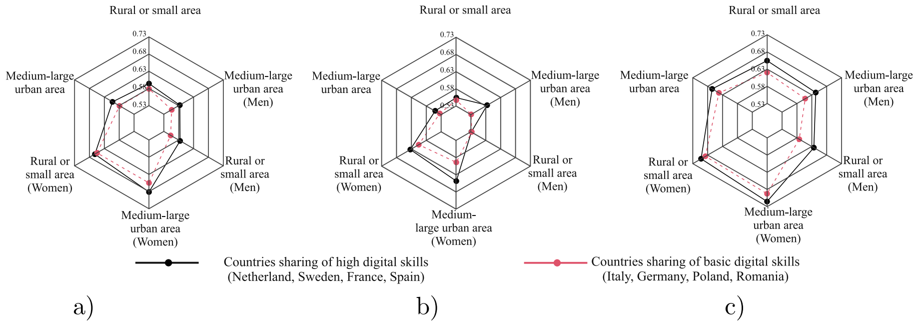

Fig. 5 Radar plots of **a** the mean, **b** the minimum and **c** the maximum estimated probabilities of attending an AI course

always higher for women than for men. This can be justified since women compared to men may not have enough knowledge and digital skills to use technology. Note that the same remark can be confirmed for the plots built on the basis of the extreme values (minimum and maximum) of the estimated probabilities.

In addition, it is possible to note some patterns based on geographical location: countries of Northern Europe as Sweden and Netherland do overall well, compared with other countries; on the other hand, Eastern and Southern European countries, such as Poland and Romania, performed less well. The performance of Italy was more moderate, along with other developed Western European countries, such as Germany. As a consequence of the results obtained there is a strong need for a public AI literacy program to strengthen public trust in AI. This aspect is more important if the institutions want to avoid issues and an aversion of people bias toward algorithmic decision making (Lukyanenko et al., 2022).

6 Sensitivity Analysis of Multilevel Models based on Variable Selection

Nowadays, the available variables selection methods are mainly aimed at reducing the high dimension motived by the massive availability of data within of a variety of research fields. In this context, the selection of variable is important for improving the prediction accuracy of a model as well as the interpretation of results. Therefore, a further aim of this study has been to evaluate the pattern of dependence related to the most relevant variables, obtained by training the Boruta algorithm, and the prediction accuracy of multilevel binary models constructed using a different number of variables.

In order to assess the benefits of the optimal choice of variables, also in terms of prediction accuracy, a comparison among various multilevel binary models associated with different subsets of covariates has been performed. More specifically, six binary multilevel models have been compared: the first model is the one defined in Eq. 4, while the other five models are implemented by including additional variables from the Boruta algorithm with the lower *zscore* values.

The covariates for each multilevel model have been selected by fixing the condition that the mean importance level is greater than a threshold which changes from one model to another. The maximum value of the threshold has been set equal to 18, in such way that the selected variables are the ones in the optimal model, and the minimum value of the threshold has been set equal to 7, since for even lower values the multilevel model is very unstable or the estimation procedure of the parameters does not converge. In other terms, the threshold value for the *zscore* has been used to define the variables to be selected as input in the multilevel model, as shown in Fig. 3.

In order to support the above mentioned results, the prediction accuracy of the models has been evaluated by using an adaptation of the Brier score (Gneiting and Raftery, 2007) and the concordance probability index for the two level binary multilevel model proposed by Steyerberg et al. (2010) and Van Oirbeek and Lesaffre (2012) within the context of survival analysis. These measures summarise the ability of model to predict accurately and are usually known as validation measures. More specifically, the Brier score is a measure of predictive accuracy for probabilistic predictions while the concordance probability index quantifies the concordance between the ranking of the predicted and observed responses, namely, how well the model discriminates between individuals with different outcome. Formally:

- the sample Brier score ($\widehat{BS}$) as index of predictive ability is defined as follows:

$$\widehat{BS} = \frac{1}{n}\sum_{j=1}^{N}\sum_{i=1}^{n_j}\left(y_{ij} - \hat{\pi}_{ij}\right)^2 \tag{7}$$

  where n is the number of observations, y_{ij} is the response variable and $\hat{\pi}_{ij}$ is the predicted probability that the observation i belongs to response category. The Brier score takes values in the range [0−1], where values close to 0 indicate high prediction accuracy; in particular, when $BS = 0$ the observations are all correctly classified with probability one. Thus, it is computed as the mean squared difference between the true response categories and the predicted probabilities;
- the sample index of concordance probability ($\widehat{C}$-index) takes the following form:

$$\widehat{C}\text{-index} = \frac{\sum_{j=1}^{N}\sum_{i=1}^{n_j}\sum_{q=1}^{N}\sum_{p=1}^{n_q} I(\hat{\pi}_{ij} > \hat{\pi}_{pq};\, y_{ij} = 1;\, y_{pq} = 0,\ \ i \neq q)}{\sum_{j=1}^{N}\sum_{i=1}^{n_j}\sum_{q=1}^{N}\sum_{p=1}^{n_q} I(y_{ij} = 1; y_{pq} = 0,\ \ i \neq q)} \tag{8}$$

  where $I(\cdot)$ represents the indicator function which can be equal to either 0 or 1. The $\widehat{C}$ -index takes values in the range [0.5−1], where values close to 1 indicate that model fit well the capacity to predict individuals with different response variable. In particular, this index, also known as "concordance probability", estimates the probability that for a randomly selected pair with different responses, the model predicts that response category $y_{ij} = 1$ has a higher predicted probability than the one with the response category $y_{ij} = 0$.

Hence, Table 7 shows for each model the threshold value *zscore*, the corresponding mean importance, the number and the name of covariates, the measures to assess the predictive ability of the multilevel binary models and then the number of iterations.

All comparison models have been computed on the dataset regarding the sample of European citizens.

Table 7 Measures of predictive ability of the multilevel model referred to the sample of European citizens (Model 1) and for the 5 multilevel models obtained by adding other variables with a decreasing level of relevance on the basis of the Boruta algorithm

Model	*zscore*	*MDA*	Nr. Cov	Covariates$^{(*)}$	$\widehat{BS}$	$\hat{C}$-index	Nr. Iterations
Model 1	$z > 18$	22.43	6	$Q3$; $Q9$; $Q1$	0.20	0.72	11
Model 2	$z > 12$	20.46	7	$Q3$; $Q9$; $Q1$; $Q8_8$	0.20	0.72	12
Model 3	$z > 10$	16.74	10	$Q3$; $Q9$; $Q1$; $Q8_8$; $Q8_7$; $Q14_4$; $Q8_1$	0.21	0.71	11
Model 4	$z > 9$	15.98	11	$Q3$; $Q9$; $Q1$; $Q8_8$; $Q8_7$; $Q14_4$; $Q8_1$; $Q14_6$	0.21	0.71	13
Model 5	$z > 8$	12.6	18	$Q3$; $Q9$; $Q1$; $Q8_8$; $Q8_7$; $Q14_4$; $Q8_1$; $Q14_6$; $Q8_9$; $Q8_5$; $Q7_{10}$; $Q14_3$; $Q8_2$; $Q8_{10}$; $Q7_5$	0.35	0.54	12
Model 6	$z > 7$	11.8	21	$Q3$; $Q9$; $Q1$; $Q8_8$; $Q8_7$; $Q14_4$; $Q8_1$; $Q14_6$; $Q8_9$; $Q8_5$; $Q7_{10}$; $Q14_3$;$Q8_2$; $Q8_{10}$; $Q7_5$; $Q14_5$; $Q7_7$; $Q8_3$	0.35	0.53	18

(∗) Each multilevel binary model comprises also variables regarding socio-demographic aspects (Gender, Age and Qualification level)

By analysing the values of the $\widehat{C}$-index computed for the six multilevel models, one can observe that the first four listed in the Table 7 (from Model 1 to Model 4) show a better performance than the last two models (Models 5 and 6); in addition, the highest prediction accuracy has been highlighted for the first two models (Model 1 and Model 2). Moreover, the number of iterations has been also considered to evaluate the runtime efficiently of each model. On the basis of the results obtained, the runtime are similar for each model up fixing as condition *zscore* greater than 7. For values below 7, the optimization algorithm fails to converge since the corresponding estimated covariance matrix for the multilevel models is not positive definite. Thus, these findings suggest that the first model outperforms in terms of prediction accuracy the other models.

As already specified, the novelty of this analysis has been to evaluate the effects of AI applications on people by investigating Awareness, Attitude and Trust towards AI and the performance of multilevel model based on the Boruta variables selection method. This results indicate that the use of the variables selection algorithm contributes to define an optimal multilevel model more stable; the multilevel binary model based on the selected variables represents a suitable choice for the study. Therefore, the results are noteworthy because the Boruta algorithm jointly with the multilevel model have allowed to reduce the dimensionality of the data and the complexity of the model improving the model's performance. However, according to the findings, some upgrades might regard the metric that it uses to rank a variable's importance. Further developments will evaluate an enhanced Boruta approach by using alternative classifiers, such as genetic algorithm since that it is entired based on a specific algorithm (RF).

7 Concluding Remarks

The continuous and potential development of AI is receiving constant attention for the economic and political implications associated with it. These aspects have brought all European Member States to promote policies and national strategies to seize the benefits of AI for the economy and society, as reported by European Commission (2021). Thus, it is clear that there is a pressing need to foster policy strategies aimed at monitoring the above mentioned aspects and supporting citizens' confidence in these innovative technologies. In this regard, it would be advisable to plan dedicated courses, aimed at improving the skills and way of working of citizens, in order to avoid the adverse effects of AI on human capital, ranging from the job unsatisfaction, the influence of worker freedom, the cognitive overload, the insecurity, the stress and, eventually, the burnout. Indeed, as reported in some contributions (Nazareno and Schiff, 2021; Kong et al., 2021), AI could represent a threat to human resources since people who have a high awareness of AI are worried of losing their job because of AI.

The purpose of this paper was to propose an innovative analysis to investigate Awareness, Attitude and Trust of people towards AI, as well as their reflections on learning needs. In particular, a multilevel binary model for estimating the probability of training needs in AI was defined on the basis of an optimal variables selection obtained through the implementation of the Boruta Random Forest algorithm. Indeed, this algorithm was able to define the optimal subset of all relevant variables instead of only the non-redundant ones from the dataset. It is also worth pointing out that the multilevel model was applied in order to assess the probability of educational needs in AI, by considering, firstly, all the sample of European citizens belonging to the eight countries under study and then by classifying them with respect to gender. Finally, a sensitivity analysis was carried out to evaluate the prediction accuracy of the multilevel logit model compared to other five models obtained by adding other variables with a decreasing level of relevance on the basis of the Boruta algorithm.

After identifying as the most relevant variables Awareness of AI ($Q1$), Attitude towards AI ($Q9$), Trust towards AI ($Q3$), as well as Gender, Age and Qualification level, the fitted multilevel binary logit model underlined that, except for the Age, all the other covariates produce a positive effect on the probability to attend a course in AI. In particular, it was highlighted that there is a different behaviour of women with respect to men concerning the choice of attending a course to improve their skills. Indeed, being woman increases the probability of taking a course on AI with respect to man, however, men reveal a greater Trust towards AI than women. This could be explained by considering that the presence of women in education, in research and, more generally, in activities connected with computer science is lower compared to men, as well as fewer women with respect to men achieve leadership positions in these fields. In this context, an educational need could help to overcome this gender disparity. Moreover, the estimated probability of attending an AI course for the whole sample of citizens highlighted that the countries with highest estimated probability of training needs in AI (greater than 0.60) are Romania, Spain, Italy and Sweden differently from the other four countries (Netherland, Germany, Poland, France).

By focusing on the sample of citizens classified with respect to gender, it emerged a higher probability for the people who live in Romania to continue learning (i.e. AI training for the workforce or students) in order to improve their skills, with predicted values ranging from 0.719 to 0.734 for women and predicted values spanning from 0.648 to 0.655 for men. On the contrary, the lowest estimated probability for people to enhance their education level in AI was observed in the Netherland with predicted values spanning from 0.601 to 0.614 for women and 0.530 to 0.532 for men. Thus, the empirical evidences also pointed out that the rise of AI applications implies new learning needs aimed at supporting new skill sets and reskilling working force for increasingly automated economies and societies.

As reported in European Commission (2021), it is important to define legislative actions to ensure a development of AI in secure, trustworthy and ethical way and to regulate the effects of AI on the social context.

In perspective, it would be interesting to apply the multilevel approach to analyse the changes over time of people's behaviour about the "literacy on AI", as well as to introduce a bayesian structural equation modeling (Zachary and Holger, 2023), with the goal to determine the factors which influence public trust towards AI. This is consistent with the guidance of the European Commission (2021) where are listed, among others, the following targets:

- "ensuring that existing AI systems are safe and respect fundamental rights and Union values";
- "fostering the development and uptake across the single market of safe and lawful AI that respects fundamental rights".

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Data Availability The data that support the findings of this study are openly available in Zenodo at the link: https://zenodo.org/records/13890780. It comprehends: (1) the dataset "Data_Boruta_Random_Forest" used to estimate the variables importance. (2) the dataset "Data_Multilevel" to perform the comparison among different multilevel binary models proposed in the paper.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Ahmad, S. F., Han, H., Alam, M. M., Rehmat, M. K., Irshad, M., Arraño-Muñoz, M., & Ariza-Montes, A. (2023). Impact of artificial intelligence on human loss in decision making, laziness and safety in education. *Humanities and Social Sciences Communications, 10*(1), 1–14.

Anand, N., Sehgal, R., Anand, S., & Kaushik, A. (2021). Feature selection on educational data using Boruta algorithm. *International Journal of Computational Intelligence Studies, 10*, 27.

Cai, Z., Fan, X., & Du, J. (2017). Gender and attitudes toward technology use: A meta-analysis. *Computer and Education, 105*, 1–13.

Cappello, C., De Iaco, S., Maggio, S. (2024). A new approach for assessing the probability of museum opening choices and its spatial continuity. *Socio-Economic Planning Sciences, 95*, 102011, https://doi.org/10.1016/j.seps.2024.102011.

Carradore, M. (2022). People's attitudes towards the use of robots in the social services: A multilevel analysis using eurobarometer data. *International Journal of Social Robotics, 14*, 845–858.

Chatterjee, S., Rana, N. P., Tamilmani, K., & Sharma, A. (2021). The effect of AI-based CRM on organization performance and competitive advantage: an empirical analysis in the B2B context. *Industrial Marketing Management, 97*, 205–219.

Cutler, A., Cutler, D., & Stevens, J. (2011). Random forests. *Machine Learning, 45*(1), 157–176.

Degenhardt, F., Seifert, S., & Szymczak, S. (2017). Evaluation of variable selection methods for random forests and omics data sets. *Briefings in Bioinformatics, 20*(2), 492–503.

De Iaco, S., & Maggio, S. (2022). Using multilevel models to evaluate the attitude of separate waste collection in young people. *Metron, 80*, 77–95.

De Iaco, S., Maggio, S., & Posa, D. (2019). A multilevel multinomial model for the dynamics of graduates employment in Italy. *Social Indicators Research, 146*(1–2), 149–168.

Distefano, V., De Iaco, S. & Maggio, S. (2025). Improving spatial clustering through a weight system on multilevel permanent museum attraction probability. *Quality & Quantity*. https://doi.org/10.1007/s11135-024-01987-7.

Duan, R., Tong, J., Sutton, A. J., Asch, D. A., Chu, H., Schmid, C. H., & Chen, Y. (2023). Origami plot: A novel multivariate data visualization tool that improves radar chart. *Journal of Clinical Epidemiology*. https://doi.org/10.1016/j.jclinepi.2023.02.020

Erickson, B. J., Korfiatis, P., Akkus, Z., Kline, T., & Philbrick, K. (2017). Deep learning at chest radiography: Automated classification of pulmonary tuberculosis by using convolutional neural networks. *Radiology, 284*, 574–582.

European Commission (2021). Proposal for a regulation of the European parliament and of the council laying down harmonised rules on artificial intelligence (artificial intelligence act) and amending certain union legislative acts. Pub. L. No. COM. 206 final.

European Commission (2022). Women in Digital Scoreboard 2022 Country profiles. https://digital-strategy.ec.europa.eu/en/policies/desi.

Fietta, V., Zecchinato, F., Stasi, B. D., Polato, M., & Monaro, M. (2022). Dissociation between users' explicit and implicit attitudes toward artificial intelligence: An experimental study. *IEEE Transactions on Human–Machine Systems, 52*, 481–489.

Floridi, L. (2019). Establishing the rules for building trustworthy AI. *Nature Machine Intelligence, 1*(6), 261–262. https://doi.org/10.1038/s42256-019-0055-y

Gneiting, T., & Raftery, A. (2007). Strictly proper scoring rules, prediction, and estimation. *Journal of the American Statistical Association, 102*(477), 359–378.

Goldstein, H. (2011). *Multilevel Statistical Models* (4th ed.). New York: Oxford University Press Inc.

Goswami, A., & Dutta, S. (2016). Gender differences in technology usage—A literature review. *Open Journal Business and Management, 4*, 51–59. https://doi.org/10.4236/ojbm.2016.41006

Guitton, M. J. (2020). Cyberpsychology research and covid-19. *Computers in Human Behavior*. https://doi.org/10.1016/j.chb.2020.106357

Guyon, I., & Elisseeff, A. (2003). An introduction to variable and feature selection. *Journal of Machine Learning Research, 3*, 1157–1182.

Huisman, M., Ranschaert, E., Parker, W., Mastrodicasa, D., Koci, M., Pinto de Santos, D., Coppola, F., Morozov, S., Zins, M., Bohyn, C., Koç, U., Wu, J., Veean, S., Fleischmann, D., Leiner, T., & Willemink, M. J. (2021). An international survey on AI in radiology in 1,041 radiologists and radiology residents part 1: Fear of replacement, knowledge, and attitude. *European Radiology, 31*(9), 7058–7066.

Huynh, T. L. D., Hille, E., & Nasir, M. A. (2020). Diversification in the age of the 4th industrial revolution: The role of artificial intelligence, green bonds and cryptocurrencies. *Technological Forecasting and Social Change, 159*, 120188.

Janitza, S., Celik, E., & Boulesteix, A. L. (2016). A computationally fast variable importance test for random forests for high-dimensional data. *Advances in Data Analysis and Classification, 12*(4), 1–31.

Kelley, P. G., Yang, Y., Heldreth, C., Moessner, C., Sedley, A., Kramm, A., Newman, D. T., & Woodruff, A. (2021). Exciting, Useful, Worrying, Futuristic: Public Perception of Artificial Intelligence in 8 Countries. In: Krol, M., Mitra, S., & Lee, D. J., editors, *AIES '21: Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society*, pp. 627–637. ACM: New York. https://doi.org/10.1145/3461702.3462605.

Khalid, N. (2020). Artificial intelligence learning and entrepreneurial performance among university students: Evidence from Malaysian higher educational institutions. *Journal of Intelligent and Fuzzy Systems, 39*, 5417–5435.

Kong, H., Yuan, Y., Baruch, Y., Bu, N., Jiang, X., & Wang, K. (2021). Influences of artificial intelligence (AI) awareness on career competency and job burnout. *International Journal of Contemporary Hospitality Management, 33*(2), 717–734.

Kruskal, W. H., & Wallis, W. A. (1952). Use of ranks in one-criterion variance analysis. *Journal of the American Statistical Association, 47*, 583–621.

Kursa, M. B., & Rudnicki, W. R. (2010). Feature selection with the Boruta package. *Journal of Statistical Software, 36*(11), 1–13.

Li, J., Liu, Y., Gong, H., & Huang, X. (2024). Stock price series forecasting using multi-scale modeling with Boruta feature selection and adaptive denoising. *Applied Soft Computing, 154*, 111365.

Liang, Y., & Lee, S. A. (2017). Fear of autonomous robots and artificial intelligence: Evidence from national representative data with probability sampling. *International Journal of Social Robotics, 9*, 379–384.

Lukyanenko, R., Maass, W., & Storey, V. C. (2022). Trust in artificial intelligence: From a foundational trust framework to emerging research opportunities. *Electron Markets, 32*(4), 1–31.

Manhar, M. A., Soesanti, I., & Setiawan, N. A. (2020). Improving feature selection on heart disease dataset with boruta approach. *Journal FORTEI-JEERI, 1*, 41–48.

Manikandan, G., Pragadeesh, B., Manojkumar, V., Karthikeyan, A., Manikandan, R., & Gandomi, A. H. (2024). Classification models combined with Boruta feature selection for heart disease prediction. *Informatics in Medicine Unlocked, 44*, 101442.

Masrur Ahmed, A. A., Ravinesh, C. D., Qi, F., Afshin, G., Nawin, R., Zhenliang, Y., & Linshan, Y. (2021). Deep learning hybrid model with boruta-random forest optimiser algorithm for streamflow forecasting with climate mode indices, rainfall, and periodicity. *Journal of Hydrology, 599*, 126350.

Mohtasham, F., Pourhoseingholi, M. A., Hashemi-Nazari, S. S., Kavousi, K., & Zali, M. (2024). Comparative analysis of feature selection techniques for covid-19 dataset. *Scientific Reports, 14*, 18627.

Nazareno, L., & Schiff, D. S. (2021). The impact of automation and artificial intelligence on worker well-being. *Technology in Society, 67*, 101679.

Olabi, A. G., Abdelghafar, A. A., Maghrabie, H. M., Sayed, E. T., Rezk, H., Radi, M. A., Obaideen, K., & Abdelkareem, M. A. (2023). Application of artificial intelligence for prediction optimization and control of thermal energy storage systems. *Thermal Science and Engineering Progress*. https://doi.org/10.1016/j.tsep.2023.101730

Puteri, S., Saputri, Y., & Kurniati, Y. (2024). The impact of artificial intelligence (AI) technology on students' social relations. *BICC Proceedings, 2*, 153–158.

Rasbash, J., Steele, F., Browne, W. J., & Goldstein, H. (2009). *A User's Guide to MLwiN Version 2.10* (3rd ed.). Centre for Multilevel Modeling, University of Bristol, Bristol.

Reise, S. P., & Duan, N. (2004). *Multilevel Modeling: Methodological Advances, Issues, and Applications. Multivariate Applications Series* (1st ed.). Lawrence Erlbaum Associate, Inc.

Saary, M. J. (2008). Radar plots: A useful way for presenting multivariate health care data. *Journal of Clinical Epidemiology, 61*, 311–317.

Sarker, I. H. (2022). AI-based modeling: Techniques, applications and research issues towards automation, intelligent and smart systems. *SN Computer Sciences, 3*(158), 011003.

Scantamburlo, T., Cortés, A., Foffano, F., Barrué, C., Distefano, V., Pham, L., & Fabris, A. (2024). Artificial intelligence across Europe: A study on awareness, attitude and trust. *IEEE Transactions on Artificial Intelligence*. https://doi.org/10.1109/TAI.2024.3461633

Siau, K., & Wang, W. (2018). Building trust in artificial intelligence, machine learning, and robotics. *Cutter Business Technology Journal, 31*(2), 47–53.

Snijders, T. A. B., & Bosker, R. J. (2011). *Multilevel Analysis. An introduction to basic and advanced multilevel modeling* (2nd ed.). SAGE Publications Ltd, London.

Steyerberg, E. W., Vickers, A. J., Cook, N. R., Gerds, T. A., Gönen, M., Obuchowski, N., Pencina, M. J., & Kattan, M. W. (2010). Assessing the performance on prediction models: A framework for traditional and novel measures. *Epidemiology, 21*, 128–138.

Tai, M. (2020). The impact of artificial intelligence on human society and bioethics. *Tzu Chi Medical Journal, 32*, 339–343.

Van Oirbeek, R., & Lesaffre, E. (2012). Assessing the predictive ability of a multilevel binary regression model. *Computational Statistics and Data Analysis, 56*(6), 1966–1980.

Volkova, N., Kuzmuk, I., Oliinyk, N., Klymenko, I., & Dankanych, A. (2021). Development trends of the digital economy: E-business, e-commerce. *International Journal of Computer Science and Network Security, 21*, 186–198.

Williamson, B. (2023). The social life of AI in education. *International Journal of Artificial Intelligence in Education, 34*, 97–104.

Zachary, J. R., & Holger, B. (2023). A latent auto-regressive approach for Bayesian structural equation modeling of spatially or socially dependent data. *Multivariate Behavioral Research, 58*(1), 90–114. https://doi.org/10.1080/00273171.2021.1957663

Zhang, B., & Dafoe, A. (2019). Artificial intelligence: American attitudes and trends. *SSRN Electronic Journal*.