

Ivana Kužet*, Ivana Kovačević, Gordana Savić, Jelena Anđelković Labrović, Ivona Živković
University of Belgrade, Faculty of Organizational Sciences, Serbia

Exploring DEA Personality Index Utility for Reskilling Candidate Selection

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Abstract:

Research Question: This study examines whether personality traits can be a valid criterion for candidate selection in reskilling programs and whether they can be objectively aggregated and ranked using quantitative methods. **Motivation:** Governments increasingly fund reskilling programmes to address shortages of IT competencies. Selecting the right candidates becomes critical when traditional criteria such as prior knowledge or formal qualifications are excluded. In such contexts, decision-makers need transparent and data-driven tools to differentiate among candidates with similar profiles. This study addresses that gap by combining psychological assessment with quantitative evaluation. The novelty lies in applying the Data Envelopment Analysis (DEA) method for personality-based candidate ranking. This approach enables more objective and transparent decision-making in the selection process. **Idea:** This study proposes a personality-based competence index for candidate selection in reskilling programs, integrating Cattell's 16 Personality Factor model with the DEA method. **Data:** Data were collected from 240 candidates who applied for a government-funded IT reskilling program in Serbia. Candidates had no prior IT knowledge, experience, or formal qualifications in the field. **Tools:** The study applies Cattell's 16PF questionnaire for personality assessment and DEA, a non-parametric method based on linear programming, to construct a composite personality index. DEA enables objective weight assignment for each candidate without predetermined criteria importance, allowing relative competence ranking across all candidates. **Findings:** Reasoning emerged as the strongest predictor of reskilling success, followed by self-control, independence, and extraversion. Anxiety and tough-mindedness were identified as undesirable dimensions in this context. The DEA method successfully ranked candidates, identified competence gaps, and provided measurable improvement targets, demonstrating its practical utility as a selection support tool in reskilling contexts. **Contribution:** This study introduces a novel DEA-based personality competence index as an objective, transparent decision-support tool for candidate selection in reskilling programs.

Keywords: reskilling, personality traits, Cattell 16PF, DEA method

JEL Classification: M51, M53, J24, C61, C43

1. Introduction

The market is witnessing an increase in government-funded reskilling programs, supported by European and global organizations, aimed at addressing the shortage of technical and IT competencies (Council of the European Union, 2024; OECD, 2025). These initiatives are designed to equip the workforce with the necessary skills to meet industry demands (European Commission, 2024; OECD et al., 2024) given that skills gaps represent the most significant obstacle to business transformation (WEF, 2025). The success of such reskilling programs, however, does not depend solely on the acquisition of new technical skills but also on candidates' competencies, which influence their motivation, persistence during training, and adaptability to new job roles, more precisely, their readiness for career shift (Obradovic et al., 2024). Competence refers to a set of observable and measurable attributes necessary for effective work performance. This includes knowledge, skills, abilities, values, personal traits, and motives (Boyatzis, 1982; Wong, 2020). These attributes collectively enable individuals to perform their tasks successfully and adapt to various job demands, making competence a crucial factor in workforce development and selection processes. In this study the focus is on personal traits (personal factors), as one of relatively stable personal characteristics that can be used for predictions of work behaviour and outcomes.

* Corresponding author: Ivana Kužet, e-mail: ivana.kuzet@fon.bg.ac.rs

This study explores whether personality traits can serve as factors of success in reskilling programs and whether candidates can be objectively evaluated and ranked based on these characteristics during the selection process. To achieve this, the study proposes the development of a competence index for candidates, integrating psychological assessment with quantitative evaluation methods. This approach should allow data-driven and transparent comparison of candidates' potential for success. For the assessment of personality, this study employs Cattell's personality model (Cattell, 1949), operationalized through the 16 Personality Factors (16PF) questionnaire. Data Envelopment Analysis (DEA) method is applied as a quantitative tool enabling objective aggregation and comparison of candidates' personality factors.

2. Theoretical Background

The requirements of the reskilling project targeted candidates who had neither formal education, nor prior work experience in information and technology. Consequently, knowledge and experience could not serve as selection criteria at the point of entry into the program. Specific skills are tested otherwise, and according to KSAO competence framework personality domain left to be covered. Accordingly, candidates' reasoning and personality traits were selected as the basis for determining their readiness to successfully follow the course.

This approach is consistent with established models of competence. As previously noted, competence is commonly understood to encompass knowledge, skills, abilities, and other characteristics (the KSAO model). Other characteristics domain includes personal characteristics, such as attitudes, traits, motives, values. Personal characteristics have been incorporated into competence frameworks since the earliest conceptualizations of the construct. McClelland (1973) originally defined competencies as the individual characteristics that differentiate superior from average performers, explicitly moving beyond knowledge and skills alone. Boyatzis (1982) formalized this by defining competencies as an underlying characteristic of a person, encompassing motives, traits, skills, aspects of self-image, social role, or a body of knowledge, that results in effective or superior job performance. Similarly, Spencer and Spencer's (1993) iceberg model of competence distinguishes between visible, surface-level competencies (knowledge and skills) and deeper, less visible ones (self-concept, traits, and motives), arguing that the latter are often more powerful predictors of performance. As such, they represent a meaningful element of the competence profile and are associated with successful functioning within professional and organizational contexts (Fantozzi et al., 2024).

Although personality might not be crucial predictors of success in work setting, previous research provides a solid introduction to understanding how personality traits predict success in learning, career transitions and reskilling, as well as the role of quantitative methods in the decision-making process in selection.

2.1 Personality traits as predictors of success

Research has shown that cognitive ability and conscientiousness are seen as the most valid predictors of work performance (Jex & Britt, 2008), although neuroticism, extraversion, and agreeableness are relevant too (Van Eijck & Graaf, 2004; Cubel et al., 2016). Lado and Alonso (2017) found that conscientiousness and emotional stability predict overall job performance, task performance, and contextual performance, while personality traits are especially linked to organizational citizenship behaviour (Trapmann et al., 2007). Authors generally advocate combining personality and cognitive ability tests with interviews in personnel selection. The predictive value of specific traits varies by occupational domain (Salgado, 1998; Robertson et al., 2000; Vinchur et al., 1998). Notably, conscientiousness, though generally the most pervasive predictor, was found irrelevant in managerial contexts (Robertson et al., 2000). For the IT domain, control, independence, and toughness predict dedicated work behaviour (Arora & Adhaikari, 2015), while openness, emotional stability, and lower agreeableness may be associated with lower susceptibility to digitalization (Bode et al., 2019). Regarding labour market outcomes, extraversion, conscientiousness, and low neuroticism predict occupational and economic success (Judge et al., 1999), while openness and conscientiousness correlate positively with income (Alderotti et al., 2023).

For career transitions and reskilling, conscientiousness consistently predicts training performance (Dehn & Damitz, 2022; Hurtz & Donovan, 2000), while openness predicts training participation and outcomes (Laible et al., 2020; Salgado, 1998; Barrick & Mount, 1991). In higher-autonomy contexts typical of reskilling programs, personality effects on performance are especially pronounced (Barrick et al., 2001; Barrick & Mount, 1993).

We are aware that personality characteristics might not be crucial predictors of success in work setting and not often used as the selection criteria but according to the criteria of successfully passing the training program, some of these traits might make a difference. Further, to reduce the possible bias in assessing personality traits, quantitative methods that do not post the prior weighting criteria were chosen.

2.2 Quantitative approaches in selection process

Quantitative multi-criteria decision-making methods enable objective ranking of candidates based on defined criteria, reducing subjectivity and increasing transparency in the selection process (Sarýkaya, 2025; Stanujkic et al., 2024). Methods such as AHP (Analytic Hierarchy Process), TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution), PROMETHEE (Preference Ranking Organization Method for Enrichment of Evaluations) and their fuzzy or hybrid variants are widely used across HRM domains, including performance appraisal, talent attraction, and employee selection. They enable standardization of scores and creation of composite rankings (Salehzadeh & Ziaean, 2024; Nalbant, 2024). These approaches are especially valuable when many candidates are compared across multiple criteria, which can be time-consuming and lead to overwhelming data (Johnson & Zhu, 2003).

Although the effectiveness of these methods is evident, the choice of the most appropriate approach remains context-dependent, as different methods may yield diverse recommendations (Megawaty et al., 2025; Ziemba, 2023). AHP appears to be the preferred choice in HRM decision-making due to its flexibility and data-driven criteria prioritization (Salehzadeh & Ziaean, 2024; Gelgor & Can, 2025), with recent trends moving toward hybrid approaches and decision support systems (Bahri et al., 2022; Megawaty et al., 2025).

DEA has also demonstrated effectiveness in personnel selection across various contexts, such as academic staff recruitment (Johnson & Zhu, 2003), electrical engineering selection using ANP combined with fuzzy DEA (Lin, 2010), IT candidate assessment (Mrdak & Nanusevski, 2023), and green tourism candidate selection combining AHP and DEA (Langovic et al., 2025). A key strength of DEA is its ability to assign optimal weights independently for each candidate (Warning, 2014) and to detect sources of inefficiency (Langovic et al., 2025). In this study, DEA is applied to evaluate the relative competence of reskilling candidates, providing an evidence-based framework that not only ranks individuals but also identifies areas for targeted competency development (Manoharan et al., 2009).

3. Method

The aim of this study is to develop a competence index for candidates' selection by integrating psychological assessment and quantitative evaluation methods. For the general personality factor assessment, Cattell's 16 personality factor model was used in the first phase. Research seeks to apply the DEA method as a quantitative support in the employee selection process, enabling objective aggregation and comparison of candidates' personality factors. The proposed methodology is presented in Figure 1.

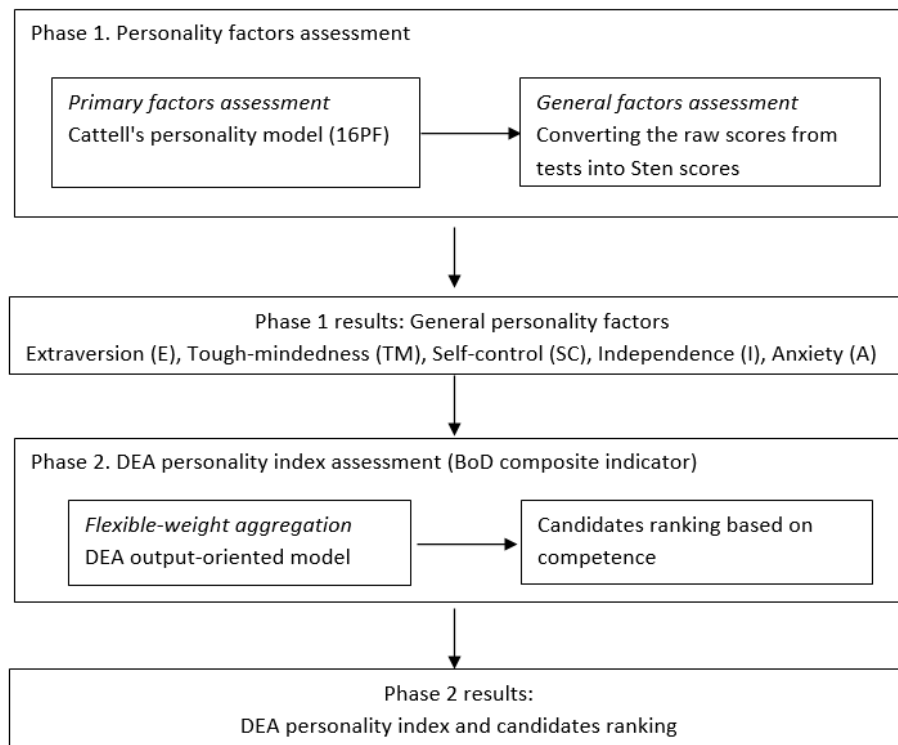


Figure 1: Candidate competence assessment – DEA personality index. (Source: Authors)

3.1 Phase 1 - Personality factors assessment

3.1.1 Personality factors model

Cattell's personality model (Cattell, 1949), operationalized through the questionnaire of 16 personality factors (16PF), represents a comprehensive measure of personality and has a wide area of application, primarily in professional selection and development, professional guidance, and psychological counselling. The model includes 16 primary personality factors from which it is possible to distinguish five general factors: extraversion (E), tough-mindedness (TM), self-control (SC), independence (I), and anxiety (A). We used the broader personality measures, not the primary factors, following the recommendations of Ones and Viswesvaran (1996) who recommend them over more narrow ones based on their superiority for selection and explanation. Only reasoning was also included in the analysis as a general factor, since we believe that in the case of reskilling, this factor is very important and can be a predictor of candidates' competence (Figure 2).

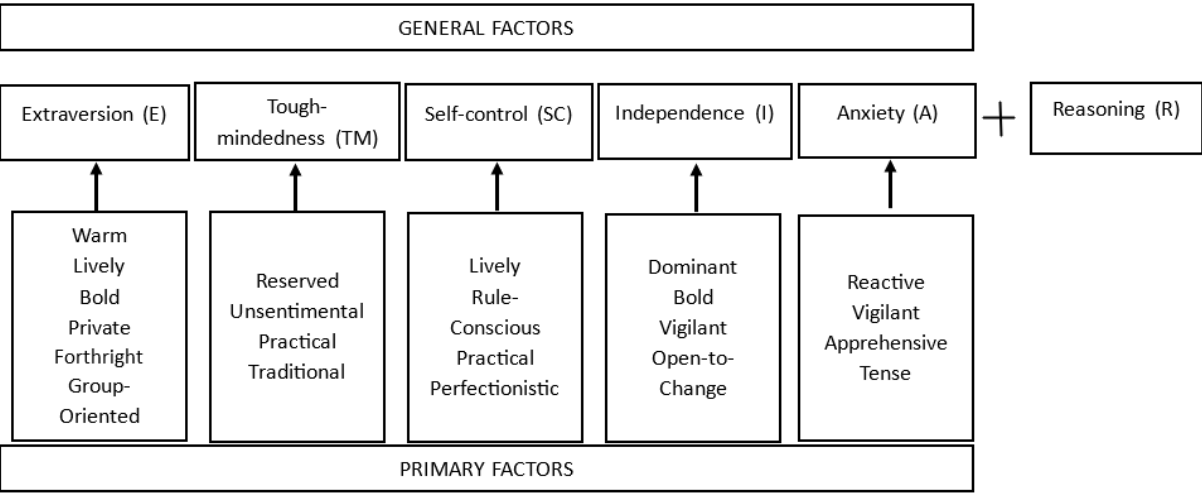


Figure 2: General and primary personality factors in 16PF model. Source: Cattell, H., & Mead, A. (2008).

The connection between these personality factors and candidates' success in acquiring new knowledge and skills, as well as adapting to a new field of work in the area of information systems and technologies, have been demonstrated in numerous studies (McCrae & Costa, 2003; Lee et al., 1995; Lounsbury et al., 2014; Baumeister, 2018; Lounsbury et al., 2007; Lounsbury et al., 2003; Proost et al., 2008; McCarthy and Goffin 2004; Hembree, 1988).

All personality factors were measured using an adapted version of Cattell's 16PF personality test, fifth edition (Cattell & Cattell, 1994). This questionnaire has good internal consistency reliability, on average 0,74 (Cronbach's alpha ranged between 0.64 and 0.83) (Russell & Karol, 1994). The questionnaire was translated into Serbian and standardized for the Serbian population (504 respondents aged 15 to 59 from all regions of Serbia) (Cattell et al., 1994/2015). The questionnaire contained 185 questions, and all candidates were informed that they would take 30–60 minutes to complete the test. They were expected to evaluate statements related to everyday situations, behaviours, interests, and opinions. Candidate tests were evaluated electronically. As the output of the test, 16 primary personality factors were combined to obtain scores for the five general personality factors as it is presented in Figure 2. The examination and interpretation of the results were carried out by an authorized person.

3.1.2 Sample

The research was conducted on 240 candidates who applied for the reskilling program. Among the candidates there were 163 men and 77 were women, aged 21 to 59 years. Regarding education, 85 candidates had high school diplomas, 132 had bachelor's degrees, 16 had master's degrees, one candidate had a PhD, and six of them did not give information about their education. The previous occupations of the candidates were diverse: students, military personnel, economists, sociologists, law graduates, engineers, pharmacists, journalists, and unemployed candidates. All participants completed the electronic version of the test under the same conditions, in specially equipped rooms, and under the supervision of a professional team.

No process-sensitive personal data were collected. Specifically, no information was gathered regarding physical, genetic, mental, or health condition; sexual lifestyle; race; ethnicity; economic or political opinion; religious or philosophical conviction; or cultural or social identity. Only gender and education were recorded, and this information was used exclusively to describe the sample, not for identification purposes; it does not allow individual respondents to be identified. All respondents were clearly informed about (i) why the data were being collected, (ii) how the data would be used, (iii) what type of information was being collected, and (iv) the fact that data would be stored securely and fully anonymized, with no possibility of individual identification. Informed oral consent was obtained from all participants, and the study was approved by the Ethics Committee of the Faculty of Organizational Sciences, University of Belgrade (approval no. 04-04 br. 7/15-2023/2).

3.3 Phase 2 - DEA personality index assessment and candidates ranking

The personality index (PI) of candidates was calculated using Data Envelopment Analysis (DEA), a non-parametric method based on linear programming (Charnes et al., 1978), which enabled the creation of a composite index, a set of sub-indicators for measuring multidimensional concepts that cannot be captured by a single indicator (Savic & Martić, 2017). This approach combines individual performance indicators without an a priori weight determination, allowing each candidate to define their own optimal set of weights while being evaluated relative to all other candidates (Cherchye et al., 2007).

To create a DEA personality composite index by aggregating the candidate's personality factors (which represent sub-indicators), the model for constructing the "Benefit of the doubt" (Cherchye et al., 2007) composite index was used. According to this model, when creating a composite index, m sub-indicators are observed for n candidates, and the value y_{ij} of the sub-indicators (personality factor) for candidate j . Each sub-indicator i have the following interpretation: if $y_{ij} > y_{ik}$, candidate j shows better results than candidate k for the specific personality factor. The goal is to combine all individual sub-indicators with a composite indicator referring to personality index. PI is defined as the weighted sum of m sub-indicators (w_i represents the weight of the i -th sub-indicator). The weights are not determined a priori but are chosen to maximize the PI value for the candidate considered. The following basic output-oriented DEA model with a dummy input indicator is used to assess the DEA personality index for each candidate j :

$$PI_k = \max_{w_i} \sum_{i=1}^m y_{ik} * w_i$$

subject to

$$\sum_{i=1}^m y_{ij} * w_i \leq 1 \quad j = 1, \dots, n, \quad (1)$$

$$w_i \geq 0 \quad \forall i = 1, \dots, m$$

When solving the model, the weights w_i are optimized to maximize the resulting value of the personality index PI_k for the k -th candidate under consideration. The highest relative weights are assigned to the sub-indicators for which candidate j achieves the best results (in relative terms) compared to the other candidates in the sample. Therefore, the candidates can be ranked according to the value of the DEA personality index PI_j , and the higher the value, the better the relative performance. The proportion of necessary improvement of the personal factors for an unsuitable candidate for reskilling program to become suitable compared to others, based on the PI_k value can be represented as $(1 - PI_k)$. This value indicates the difference between the candidate's current level of competence and the level required for competency, as measured by their personality traits. So, the lower the PI_k value, the more development is needed for the candidate to reach competency relative to others.

DEA is an objective method, in which the optimal weights are derived from the data for each comparing unit separately. The only restriction is that the weights should not be negative, and the other extreme is excluded, which refers to the fact that one sub-indicator can be assigned all relative weights, which would then completely determine the overall performance (personality) index (Cherchye et al., 2008). Running the above presented basic DEA model as it stands could result in a zero-weight phenomenon (Cherchye et al., 2008) meaning that the impact of some less competitive factors is ignored when assessing the personality index. The impact of factors can be calculated as the product of its measure and assigned weight, called the virtual factor ($y_{ij} * w_i$). Therefore, several candidates could be assessed as equally suitable, with a personality index of 1.00. To rank all candidates, we used a super-efficiency-based DEA model (Andersen & Petersen, 1993). This model assumes that the first constraint is changed to the following form:

$$\sum_{i=1}^m y_{ij} * w_i \leq 1 \quad j = 1, \dots, n, \quad j \neq k \quad (2)$$

4. Results

The results are presented and discussed as descriptive statistics for individual personality factors (4.1.), an explanation of the composite index obtained by applying the DEA method (4.2.), and candidate rankings using a super-efficiency-based DEA model (4.3.).

4.1 Descriptive statistics of individual personality factors

During data analysis, personality factors were observed individually using descriptive statistics. The values of the factors for each candidate were obtained by converting the raw scores from tests into Sten scores (Russell & Karol, 1994), using the ePONS electronic scoring system (Sinapsa edicije: <https://www.sinapsaedicije.rs>). Raw scores were converted to Sten scores by applying the norms provided in the 16PF manual (Russell & Karol, 1994; Cattell et al., 1994/2015). Table 1 shows the mean values of the general personality factors (scale from 1 to 10) and standard deviations (SD) as a measure of dispersion.

Table 1: Mean and standard deviation of STEN personality factors value

	Reasoning (R)	Tough-minded (TM)	Self-control (SC)	Independence (I)	Anxiety (A)	Extraversion (E)
Mean	7.841	6.700	5.719	5.642	4.032	5.335
SD	1.627	1.826	1.683	1.570	1.711	2.161

Candidates showed the best results in reasoning, which indicates the ability to acquire new knowledge and ideas, particularly relevant for reskilling. All other factors averaged above five, except anxiety, which scored slightly lower. In the context of reskilling, lower anxiety is desirable as it reflects greater emotional stability and readiness for intellectually demanding tasks. Extraversion showed the largest standard deviation, indicating the widest variability among candidates, while Independence showed the smallest, suggesting the most consistent behavioural pattern.

4.2 DEA personality index

The DEA method was applied to create a composite index based on individual personal factors. The data weighting of all factors as sub-indicators was performed automatically when solving the output-oriented DEA method. The data were analyzed using the DEA solver software package (Cooper et al., 2006), and the CCR-O radial method with a constant return to scale was applied.

According to the results obtained, it can be concluded that 76 of the 240 candidates whose personality factors were analyzed were suitable for reskilling program ($PI=1.00$), while 164 were relatively unsuitable candidates for the program ($PI<1.00$). The candidate with the lowest PI value (0.643) exhibits below-average values across all personality factors. Table 2 displays descriptive statistics of personality factors for two groups: relatively suitable ($PI=1$) and relatively unsuitable ($PI<1$) candidates for reskilling program.

Table 2: Mean and standard deviation of personality factors values across suitable and unsuitable categories

		Reasoning (R)	Tough-minded (TM)	Self-control (SC)	Independence (I)	Anxiety (A)	Extraversion (E)
$\overline{x}$	Mean	8.750	7.126	5.839	5.754	4.200	5.528
	SD	1.782	1.978	1.791	1.944	2.021	2.353
$\overline{s}$	Mean	7.421	6.503	5.663	5.590	3.954	5.246
	SD	1.370	1.728	1.639	1.372	1.553	2.075

In the suitable group, candidates exhibit superior values across all personal factors. This disparity is particularly pronounced in Reasoning, where the difference in average values is especially notable, i.e. the difference between two groups is equal to 1.329. Furthermore, it is interesting to note that 25 candidates have one personality dimension with a virtual factor value of 1.0, while all other dimensions have a value of 0, and in 25 cases that is reasoning. Descriptive statistics of the personality factors for those 25 candidates are shown in Table 3.

Table 3: Descriptive statistics of suitable candidates based on one personality dimension

	R	TM	SC	I	A	E
Virtual factor values	1.000	0.000	0.000	0.000	0.000	0.000
Mean	10.000	6.396	5.148	5.364	3.952	4.720
SD	0.000	1.454	1.491	1.430	1.424	1.652

This result indicates that reasoning, with maximal values of 10 for all 25 candidates, is singled out as their most important factor. Other personality dimensions with below-average values were marked as irrelevant for a given candidate, as their relative weights were equal to 0. Examples are listed in Table 4.

Table 4: Examples of suitable candidates based on one personality dimension

			Virtual factor values					
Candidate	PI	Rank	R	TM	SC	I	A	E
1	1	1	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000
15	1	1	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000
16	1	1	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000
17	1	1	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000

This result indicates that reasoning is singled out as the most important factor for those candidates (relative to the observed group), a factor that completely determines their suitability for reskilling program. Other personality dimensions were marked as irrelevant for a given candidate, as their relative weights were equal to 0.

In case of other candidates, there is not one personality dimension that constitutes their comparative advantage (weight that has a value equal to 1.0) and suitability for program, but rather a combination of several personality dimensions (Table 5).

Table 5: Examples of suitable candidates based on multiple personality dimensions

			Virtual factor values					
Candidate	PI	Rank	R	TM	SC	I	A	E
21	1	1	0.0160	0.0195	0.0000	0.0000	0.0000	0.9645
22	1	1	0.2397	0.0000	0.0000	0.7297	0.0000	0.0305
39	1	1	0.0000	0.1902	0.2285	0.1939	0.0820	0.3054
45	1	1	0.2436	0.3698	0.0000	0.2156	0.0000	0.1711

The most significant personality factors associated with candidate suitability were reasoning, self-control, independence, and extraversion. Candidates whose current suitability score was driven primarily by tough-mindedness and anxiety were flagged by HR experts as less promising candidates for the reskilling program at this stage, as these dimensions are commonly associated with difficulties in adapting to change and novel situations. Rather than being excluded outright, such candidates may benefit from preparatory interventions targeting adaptability and stress management before entering the program, while candidates with stronger current scores on reasoning, self-control, independence, and/or extraversion are better positioned to develop the required competencies through training in the short term.

For example, Candidate 164 (Table 6) qualifies as suitable based on a single personality dimension, anxiety, and would therefore not be recommended for the reskilling program at this point in time, though this reflects the candidate's current profile rather than a fixed limitation.

Table 6: An example of a suitable candidate with a pronounced anxiety dimension

			Virtual factor values					
Candidate	PI	Rank	R	TM	SC	I	A	E
164	1.000	1	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000

It would be advisable to replace such a candidate with one who shows a more pronounced level on one of the “desirable” personality dimensions, such as reasoning or self-control, even if that candidate was not classified as suitable at the time of selection (see Candidate 19, Table 7).

Table 7: An example of an unsuitable candidate with a pronounced dimension of self-control

			Virtual factor values					
Candidate	PI	Rank	R	TM	SC	I	A	E
19	0.996	79	0.0219	0.0000	0.8732	0.0604	0.0000	0.0445

A key advantage of the DEA method is that it allows assessment of the extent to which specific personality-related behaviours need to be improved for a candidate to become more suitable for the reskilling program, providing a basis for targeted development. It is important to emphasize that the aim is not to change candidates' personality traits themselves, but rather to influence and develop the behaviours grounded in those traits, and to monitor the candidate's overall developmental trajectory over time. Candidates initially assessed as unsuitable may subsequently replace suitable ones if experts evaluate that they possess better scores on key factors and that the necessary behavioural improvement is feasible through training (Lajcin et al., 2023). This value projection, generated during the selection process, can thus serve as a basis for later candidate development, particularly for improving the behaviours and competencies identified as lacking at the point of selection.

The DEA method also allows decision-makers to adjust weights in line with expert preferences (Martić, 1999). PI is calculated as a weighted sum of personality factors, where each factor's influence equals the product of its assigned weight and factor value. Weight restrictions can be incorporated by setting upper and lower limits on each factor's influence on PI; for example, if self-control prevails with a weight of 0.873, a restriction limiting its influence on 0.500 can be applied, redistributing influence across other factors. Objectively derived limits based on statistical methods are also applicable (Radojičić, Savić & Jeremić, 2018).

4.3 Candidates ranking

To rank 76 equally suitable candidates, a super-efficiency-based DEA model is employed in the subsequent step. Similarly to the “benefit-of-doubt” DEA-based model, the super-efficiency-based DEA categorizes candidates into two groups: unsuitable and suitable. In the case of unsuitable candidates, the Performance Index (PI) remains below 1, indicating the extent to which (1-PI) proportionally highlights factors for improvement needed to achieve suitability for the reskilling program. The values of PI and below-average personality factors for the bottom five candidates are presented in Table 8.

Table 8: Personality factors of bottom five candidates

			Personality factor values					
Candidate	PI	Rank	R	TM	SC	I	A	E
95	0.719	236	7.0	5.2	4.5	5.4	2.6	3.8
133	0.706	237	7.0	2.7	4.2	4.8	4.6	0.4
240	0.693	238	5.0	5.1	1.4	3.8	5.2	4.5
197	0.673	239	5.0	6.3	5.2	4.5	1.1	3.8

Conversely, for suitable candidates, PI values can exceed 1, allowing for the ranking of candidates. For instance, among the top five candidates presented in table 6, candidate no. 238 stands out with a PI of 1.149, indicating a balanced structure of above-average Personality factor values. These values could be lowered by 14.9% while still maintaining suitable status, resulting in a lower PI value and rank. Several candidates achieve top rankings due to exceptionally high values in certain Personality factors, which compensate for others. For example, the extreme values of reasoning (R) and Thought-Mindedness (TM) elevate candidate 101 into the top five group (Table 9).

Table 9: Personality factors of top five candidates

			Personality factor values					
Candidate	PI	Rank	R	TM	SC	I	A	E
238	1.149	1	8.0	6.4	7.1	8.4	7.6	5.7
164	1.144	2	10.0	4.4	3.7	5.9	9.5	5.7
134	1.140	3	10.0	7.9	7.1	2.5	9.0	3.1
101	1.088	4	9.0	7.6	9.2	1.6	4.5	1.3
99	1.085	5	9.0	10.3	7.5	1.6	6.7	1.0

The descriptive crosstab analytics of the DEA results and demographic characteristics of the candidates are shown in Table 10.

Table 10: Descriptive analytics of Super-efficiency based DEA model results

DEA Personality Index (PI)		Suitable candidates		Unsuitable candidates				Total
		Super-suitable	Suitable	Up-and-comer	Promising	Emerging	Developing	
		>1	1	(0.9 – 1]	(0.8 -0.9]	(0.7 -0.8]	(0.6-0.7]	
Candidates	Number	51	25	98	57	6	3	240
	Percentage	21.25%	10.42%	40.83%	23.75%	2.50%	1.25%	
Education	High school (3Y)	1	1	2	1	0	0	5
	High school (4Y)	9	6	34	27	2	2	80
	University (3Y)	5	0	8	8	0	1	22
	University (4Y)	29	16	45	17	3	0	110
	Master	5	1	7	3	0	0	16
	PhD	0	0	0	1	0	0	1
	Unknown	2	1	2	0	1	0	6
Gender	Female	16	8	29	20	3	1	77
	Male	35	17	69	37	3	2	163

The suitable candidates are classified into two groups of “Super-suitable” (PI>1.0) and “Suitable candidates” (PI=1.0). The main feature of 21.5% of super-suitable candidates is their ability to maintain competence even with lower personality factor values (PI-1) which is not the case with the suitable group (10.42% of candidates).

Furthermore, candidates categorized as unsuitable are divided into four groups based on their PI level. The largest “Up-and-comer” group, comprising 40.83% of candidates, required a slight improvement of up to 10% in their personality traits. The next group, representing 23.75% of “Promising” candidates, must put effort into enhancing their personality factors by 10 to 20%. The “Emerging” and “Developing” groups, collectively accounting for 3.75% of candidates, constitute the smallest groups, whose members need to significantly improve their personality factors by 20 to 40% to attain competence and eligibility for selection in the reskilling program.

From an educational standpoint, 62.08% of all candidates hold university degrees, indicating a greater inclination towards curiosity and readiness for reskilling and lifelong learning. Conversely, 32.45% have completed high school. This example suggests that university-educated candidates may be more inclined to undergo reskilling compared to those with only a high school education. Cross-evaluation with PI values reveal that candidates with master’s degrees are the most successful, with 26.36% classified in the “Super-suitable” group. Following closely are candidates with 4-year undergraduate diplomas with 26.36% and 3-year undergraduate diplomas with 22.73% also classified in the “Super-suitable” group. There is no difference in the success between gender groups: 21.47% of males and 20.78 of females are classified into “Super-suitable” group.

By analyzing the rank of candidates according to competence based on personality factors and their demographic characteristics, HR experts could gain a better insight into the candidate’s readiness to successfully attend and complete the reskilling course and acquire the necessary knowledge and skills to perform the job.

Conclusion

The present study addressed two key questions: whether personality traits are relevant competencies for reskilling selection, and whether the DEA method is an appropriate quantitative approach to support this process.

Regarding personality traits, the literature consistently shows their correlation with work performance across industries (Bode et al., 2019; Lado & Alonso, 2017; Cubel et al., 2016; Hurtz & Donovan, 2000; Barrick & Mount, 1993), learning outcomes (Laible et al., 2020; Hurtz & Donovan, 2000; Barrick & Mount, 1991), and employability (Neneh, 2020; Fletcher, 2013; Semeijn et al., 2005). Our results identified reasoning as the most important predictor of reskilling success, followed by self-control, independence, and extraversion. Findings are consistent with previous research on skill acquisition and job performance (Oakes et al., 2001), training excellence (Barrick & Mount, 1991), and dedication in IT occupations (Arora & Adhikari, 2015). Although personality traits are relatively stable, specific behaviours based on these traits can be modified during the reskilling process (Sanghi, 2016), which further supports their relevance for candidate development, not only selection.

Regarding the DEA method, the study confirms its suitability for personnel selection tasks (Wen et al., 2020; Taylan et al., 2014; Lin, 2010). Compared to other quantitative approaches (Deehr, 2018; Afshari et al., 2014; Samanlioglu et al., 2018), DEA offers an objective way to weigh personality criteria without imposing predetermined importance, as each candidate's weights are optimized individually based on their own strongest relative attributes. Since "optimal competence" is generally unknown in advance (Sowlati & Paradi, 2004), DEA reframes candidate assessment not as an absolute pass/fail judgement but as a relative comparison among peers, a more realistic basis for real-world selection decision.

Beyond producing a ranking, the DEA-based approach generates process-relevant information for each candidate: it identifies the specific personality-related factors that are comparatively weak and estimates the magnitude of improvement needed to reach the performance frontier defined by top-performing peers. In this sense, the model's output functions not as an endpoint but as a developmental pathway, specifying what needs to change and by how much. This establishes a direct link between the two HR processes examined in this study: selection informs what needs to be developed and for whom, while relatively suitable candidates additionally serve as reference profiles for the rest (Manoharan et al., 2009).

A key limitation of this study is that only personality traits were included as inputs. Future research should incorporate skills, knowledge, abilities, and other qualifications, given that personality traits yield the highest predictive value when combined with other selection tools (Kumar, 2019). Further research should also track candidate outcomes after reskilling, including test results, acquired skills, and employment, to validate the selection criteria used in this study.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

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About the Authors

Ivana Kužet

University of Belgrade, Faculty of Organizational Sciences
ivana.kuzet@fon.bg.ac.rs



Ivana Kužet is a doctoral candidate in Quantitative Management at the Faculty of Organizational Sciences, University of Belgrade, where her research has focus on competency assessment and development. For 10 years, she has been teaching at the Faculty of Organizational Sciences in the fields of Business Psychology, Employee Competency Planning and Development, Group dynamics and interpersonal relations, while also applying this expertise professionally through projects in employee selection, motivation, and professional development. She is the author of several scientific papers and a monograph on motivation and leadership.

Ivana Kovačević

University of Belgrade, Faculty of Organizational Sciences
ivana.kovacevic@fon.bg.ac.rs



Ivana Kovačević is a full professor at the University of Belgrade, Faculty of Organizational Sciences, Chair of Human Resource Management, with over 20 years of experience in teaching academic courses in the field of psychology in human resource management.

She graduated in Psychology and obtained a PhD in Psychology at the Faculty of Philosophy (University of Belgrade). Her area of scientific interest is in experimental and survey-based research covering cognitive ergonomics and psychological topics in HRM. She is the author and co-author of numerous research and conference papers covering a wide range of personal side of organization and management topics.

Gordana Savić

University of Belgrade, Faculty of Organizational Sciences
gordana.savic@fon.bg.ac.rs



Gordana Savić is a full professor in the Operational Research, Performance and Business Analytics at the University of Belgrade, Faculty of Organizational Sciences. She received a PhD degree in Operations Research from the University of Belgrade, Faculty of Organizational Sciences in 2012. She has been head of Laboratory for Operational Research and Centre for Efficiency Analysis and head of undergraduate module on Business Analytics. Currently she holds a position of Vice dean for postgraduate studies.

Her research interests include Analytics with a focus on business analytics, performance analytics, efficiency analysis, mathematical modelling and optimization. Gordana is an author or co-author of more than 150 scientific and research papers. Among them, more than 37 are monograph chapters and papers in leading scientific journals including European Journal of Operational Research, Expert Systems with Application, Higher Education and Scientometrics. Gordana serves as a reviewer, editor and guest editor in several leading international and national journals. She also was a participant, coordinator, or leader of a wide range of practical projects and training courses in the fields of Analytics, ICT consulting, business and performance analytics, mathematical modelling and optimization.

Jelena Anđelković Labrović

University of Belgrade, Faculty of Organizational Sciences
jelena.andjelkovic.labrovic@fon.bg.ac.rs



Jelena Anđelković Labrović is an Assistant Professor at the University of Belgrade, Faculty of Organizational Sciences, Department of Human Resources Management. She teaches the following subjects: Training and Development, E-learning, Human Resource Management and International Human Resource Management. She has a Practitioner Diploma in Executive Coaching, Academy of Executive Coaching (AoEC), recognized by International Coaching Federation (ICF) and European Mentoring and Coaching Council (EMCC). For more than 15 years she worked as a consultant, trainer, business coach and mentor in the field of employee development. As an academic researcher she has authored or co-authored more than 60 research papers and participated in the implementation of several academic projects in the field of human resources. She is co-author of the book Employee Training and Development.

Ivona Živković

University of Belgrade, Faculty of Organizational Sciences
ivona.zivkovic@fon.bg.ac.rs



Ivona Živković is a teaching assistant and PhD candidate in Sociology. She has been employed at the Faculty of Organizational Sciences, University of Belgrade, since 2019.

Her area of expertise is the sociology of work and technology, with a focus on the impact of artificial intelligence on professional work. In her doctoral research, she specializes in the professions of law, architecture, human resource management, and higher education.