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The Three-Factor Model and Skills for Employability

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Abstract

This study examines the evolving landscape of employability skills in the context of technological revolution 5.0 and the increasing integration of artificial intelligence in the workplace. Conducted in collaboration with the ADECCO Group and the Talent Research Group at San Pablo CEU University of Madrid, the research underscores the necessity for workers to develop new competencies and adapt to shifting job requirements. The study highlights the significance of both technical and soft skills, particularly socio-emotional competencies such as resilience, flexibility, and lifelong learning, in addition to cognitive and academic skills. The research methodology involved a comprehensive survey of 7,034 workers across diverse professional profiles and sectors, assessing 11 key competencies through a validated questionnaire. Data analysis was conducted using SPSS, incorporating both descriptive and multivariate statistical techniques, with a particular emphasis on exploratory factor analysis to identify latent factors that account for variations in competency profiles. The results revealed three principal factors that significantly contribute to employability: general skills, socio-emotional skills, and cognitive or academic skills. The study concludes that a systemic approach involving educational institutions, businesses, and other stakeholders is crucial to bridging the gap between the skills demanded by the labor market and those possessed by graduates. The findings emphasize the need for universities to align their curricula with the evolving demands of employers, ensuring that graduates acquire the competencies necessary for success in a dynamic job market. This research offers valuable insights for the development of targeted training programs aimed at enhancing the employability of future professionals.

Keywords: *Employability, Soft skills, Technological revolution 5.0, Socio-emotional competencies, Exploratory factor analysis.*

Introduction

Recent global events, such as the pandemic, have brought great uncertainty, volatility and complexity to organizations, society and the economy in general, and have accelerated the arrival of the technological revolution 5.0, which poses the challenge of integrating artificial intelligence with human talent in the workplace.

Automation and interconnectivity within organizations are not the only forces that will shape the future of work, as this technological revolution does not necessarily have to be linked to efficiency, nor does it necessarily imply massive job losses, but it does require workers to develop new skills and occupations (Rubi *et.al*., 2020).

According to the study carried out by the World Economic Forum by 2025, 85 million jobs could be displaced by a change in the division of labor between people and machines. Therefore, in the face of the future of jobs by 2025, 40% of workers will need to be retrained in approximately six months, both in learning for the use of new technologies, but particularly working on the development of soft skills. The socio-emotional attitudes that companies consider to be growing in importance most rapidly are curiosity and lifelong learning; resilience, flexibility and agility;

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and motivation and self-knowledge. Systems thinking, Artificial Intelligence and big data, talent management and customer service and customer service orientation complete the main growing skills. (WEF, 2023)

Therefore, the future of employment demands knowledge and a deep understanding of the knowledge and skills that companies will need in the coming years. It is companies that ultimately create jobs and play a crucial role in defining the professional skills needed to ensure the employability of young people in the future. Our society requires a high-quality education system, flexible and capable of adapting to the changing needs of both companies and society itself. The evolution of fundamental professional competences at any given time has advanced at a much faster pace than the communication and subsequent adaptation of the education system, which has led to obvious mismatches between the skills required and those offered for jobs, reflecting a global gap between education and employability, and generating a lack of success in today's workplaces (Meissner and Shmatko, 2018; Lennox & Ross, 2017).

The Inter-American Development Bank in its 2017 report (IDB, 2017) already considered that with the Fourth Industrial Revolution, marked by the convergence of digital, physical and biological technologies, permanent and rapid changes will be imposed that will bring with them new challenges, which makes it necessary to have employees in companies who master the knowledge of their field and who provide solutions to technical and scientific problems. but also know how to deal with unforeseen events that are solved with the so-called soft skills, which are part of human talent.

The transformations that have taken place in the business environment, added to the social needs linked to these changes, lead to the recognition of the need for other types of skills, which have not yet received a unanimously accepted name. Some of the names used are: participatory competencies, personal competencies, basic competencies, key competencies, generic competencies, transferable competencies, relational competencies, life skills, interpersonal competencies, transversal competencies, basic life competencies, social competencies, emotional competencies, socio-emotional competencies, etc. (Bisquerra, 2003).

These abilities, whether innate or acquired, can be developed throughout life, improve productivity across a wide range of professional profiles, and can be classified into three broad categories: general, social-emotional, and cognitive or academic skills.

For the IDB (2017), socio-emotional skills help people identify and manage their own emotions and those of others, such as the ability to work in a group and solve problems together. Cognitive skills include long-term memory, pattern recognition, and executive control, which is related to the coordination of various mental functions. Academic skills include knowledge of facts, concepts, procedures and the ability to apply strategies in disciplines such as mathematics, reading, science, and computer and digital skills, since currently it is not enough to only know how to search for and access information but also to know how to function in the technological field (Area & Guarro, 2012).

García-Pérez *et al* (2021) conducted a systematic review of the literature defining the ten skills to work on in the future, including socio-emotional skills such as sensitization or social awareness and digital skills such as computational thinking or digital literacy.

The study by Rakowska and Juana-Espinosa (2021) identified the key skills and competencies for employability in the twenty-first century, as well as the main trends in the demand for these skills. This study not only integrates the categorization of the 'Future Work Skills 2020' report, but also adds the skills needed for the 2030 labor market, according to McKinsey (2018). These competencies are grouped into: technical and digital, social and higher cognitive (including creativity and complex information processing) and should enable new ways of thinking, working and using tools in a world transformed by technology.

The training of professionals with a high probability of employability requires a systemic vision and approach with the participation and articulation of the actions of various actors, the educational institution, the company, industry, the family, the State, etc. (Díaz, 2019).

Thus, universities must identify the knowledge, skills and abilities demanded and valued by the labour market in order to achieve a double objective. On the one hand, to be able to define the training profile required by employers (Galán, 2003) and, on the other, to make a comparison with the profiles that are currently being offered. The latter should serve to detect the existence of discrepancies between the competencies and skills possessed by graduates and those demanded by organizations. Logically, if the existence of significant differences, both positive and negative, is detected, they should be corrected in order to satisfy, in the best possible way, the needs of the organizations.

In summary, the labor market is becoming increasingly competitive, organizations are looking for profiles that, in addition to having the training and experience required for each job, have skills to work efficiently, communicate effectively, solve problems and adapt to changing situations and employers tend to select personnel who perform efficiently within changing environments and achieve objectives. that are aligned with the values and vision of the company, and for this they must develop competencies in effective communication, leadership, autonomous and teamwork with ethical values and the mastery of technical capacity (Fuentes *et al*, 2021).

From this approach, the question would be how to adjust employability within the general purpose of universities and how to do so to minimize the gap between the labor market and higher education institutions, effective communication between both agents being of vital importance.

Objectives

It is crucial to understand that the development of soft skills does not automatically make the worker a potential candidate for any company. Previously, it is necessary to identify and differentiate which are the specific soft skills demanded by each sector and professional profile. The worker can choose between two approaches: carry out a self-knowledge exercise to address the sector that is looking for profiles with their skills, or analyse the skills demanded by the desired sector and train, train and develop those specific skills to facilitate their access to that sector.

Therefore, it is essential to guide the development of training and training plans for companies and universities, to know how the different skills are associated with each occupation, which is not an easy task. First, it is necessary to have a classification that describes the skills and, subsequently, to determine how to relate them to the different profiles or business occupations. Secondly, it must be considered that it is a dynamic process that can change as new occupations or needs arise. Finally, it is a process that requires the coordination and effective communication of various actors in the educational and labor fields.

The main objective of the research is twofold: to know and predict the usual behaviour of the person evaluated in their job in this group of dimensions, as well as to determine the degree of adjustment of these behaviours with those expected for the position and the organisation through the creation of a job or client profile.

As a secondary objective, it is also sought to provide a guide for the analysis of the candidate's areas of interest (strengths and areas for improvement) that allow the evaluator to determine the complete competency profile of the subject and the educational institutions to know the training needs in competencies for each branch of knowledge.

Methodology

Sample and Data Collection

In the present research, a questionnaire was used as a tool to collect data on the work competencies of the participants. The survey was designed and validated by the Institute of Knowledge Engineering (Universidad Autónoma de Madrid) in collaboration with the company The Adecco Group, which was responsible for its implementation and subsequent data collection.

The questionnaire is generated online through the AdeccoXpert platform and is composed of items that describe common behaviors in the work environment in various areas. Through this questionnaire, the candidate indicates to what extent these descriptions reflect his or her abilities and performance at work, taking into account a scale with four possible answers: rarely (only on very exceptional occasions he behaves like this), sometimes (he does not behave like this habitually), frequently (he usually behaves in the indicated way) and very frequently (he always acts as indicated in the sentence).

The database resulting from this questionnaire and used in this study comprises a comprehensive collection of data. It includes a total of 7,034 workers from different professional profiles and sectors covering a total of 11 competencies: This research evaluates a group of eleven competencies distributed in 24 differentiated scales, which are considered key to success in job performance in most organizations:

1. Planning and Organization: refers to the ability to effectively manage available resources, priorities and times in order to achieve specific objectives.
2. Action and performance at work: refers to the ability to effectively carry out specific actions in adverse situations, actively, independently, responsibly and under different work environments.
3. Application, Commitment and Responsibility: refers to the ability to work constantly, meeting the established time deadlines, respecting others and ensuring the proper functioning of human and/or material resources.
4. Problem solving: ability to act effectively in problematic situations, identifying the causes of problems and applying the appropriate measures to solve them or minimise their impact, taking into account their cost .
5. Teamwork: the ability to work with other people, both colleagues and supervisors and subordinates, in a coordinated and cooperative manner in order to achieve individual and collective goals.
6. Dynamism: the ability to manifest an optimistic and confident attitude in relation to their own abilities and those of others, continuously seeking improvement and improvement through effort and continuous learning.

7. Communication: ability to express reflections, opinions or ideas to collaborators, superiors and/or clients in a clear and understandable way, selecting the appropriate messages and taking into account the objectives to be achieved and the interlocutors to whom it is addressed.
8. People management: ability to lead groups, coordinate people and resources, promote professional development and direct others in achieving clear objectives.
9. Customer orientation: it involves establishing and maintaining an adequate relationship with customers, solving problems and anticipating new needs, guaranteeing high customer satisfaction . It also assesses the ability to analyse business problems from a broad point of view that allows finding new lines of action that are beneficial to the organisation.
10. Stress Tolerance: refers to the ability to maintain performance or effectiveness in a situation of frustration or stress.
11. Learning and Innovation: involves the interest and ease of learning and putting into practice new approaches or ways of doing things, in order to improve performance in the position.

To ensure data integrity and accuracy, data cleansing and validation processes were carried out.

The results of the questionnaire are reflected in decatipos, on a scale of 1 to 10, which allow their interpretation based on the following table (Table 1):

Table 1. Score-to-dectypus conversion table

Decatype	Meaning	Level of development
1-2	Well below average	Competence to improve
3-4	Below average	Developing competence
5-6	Average	Acquired competence
7-8	Above average	Remarkable competence
9-10	Well above average	High-potential competition

Source: The Adecco Group, 2023

In addition, depending on the decatype, a classification of competencies was made into four levels of development (Table 2):

Table 2. Table of conversion of decatypes to levels of development. **Source:** The Adecco Group, 2023

Areas	Decatypes	Description
High-potential strengths	9-10	It refers to those competencies that the candidate has fully developed and that they usually show in the performance of the position.
Developing strengths	7-8	Competencies developed by the candidate, but not always shown in the development of the position.
Areas in development	4-6	Competencies that the candidate can

		sometimes show, but that are not always present.
Areas for improvement	1-3	Competencies that the candidate never or only occasionally displays. In most cases, they will need training or development actions.

Data Analysis

Data analysis was performed using SPSS, an advanced statistical analysis and exploration tool. The data previously organized in Excel was imported into SPSS, where the variables were defined and labeled according to their type. A descriptive, univariate and multivariate analysis has been carried out in order to evaluate significant differences between the variables under study. In this study, correlation and commonality analyses would stand out, providing a detailed view of the relationships between different variables and the underlying structure of competencies.

Multivariate analyses of interdependence aim to analyse the relationships that are established between a set of variables in which they all have an equal importance and are at the same level without establishing roles or hierarchies between them.

Most multivariate interdependence analysis techniques aim to reduce redundant or excessive information that may be associated with the collection of information with many variables. These techniques, known as multivariate methods of dimension reduction, operate under the logic of reduction, trying to discover a smaller number of underlying, unobservable factors that represent the original set of variables with the least possible loss of information.

There are two techniques to reduce the dimensions when the variables are quantitative: principal component analysis and factor analysis, which, according to Pérez (2008) differ fundamentally in the objective they pursue. With principal component analysis, factors are obtained that result from the combination of observable variables and whose calculation is based on mathematical aspects without taking into account their theoretical or applied interpretability, so that it may happen that the emerging factors are mathematically perfect, but conceptually useless. Factor analysis seeks to discover unobservable latent variables, whose existence is presupposed, which remain hidden waiting to be found, and which have logic within the framework of a theory or in the way of understanding the relationships between variables.

Finally, it is important to differentiate between the two types of factor analysis. Exploratory factor analysis aims to uncover the underlying structure of a quantitative dataset by defining a small number of common latent dimensions that explain most of the variance observed across a broader set of variables. On the other hand, in confirmatory factor analysis, the factors are known a priori, generally described in the theory, and the objective is to check if this previous theoretical structure fits the data through hypothesis testing.

In this case, exploratory analysis will be used since we will try to define a small group of factors that explain the higher percentage of common variance.

Results

The analysis of results is divided into two sections, one purely descriptive and the second factor analysis:

Descriptive Analysis

With this initial descriptive analysis, the aim is to obtain an overview of the 11 competencies that are reflected in the questionnaire. As can be seen in Table 3, the statistics show great homogeneity, since the sample means for each of the variables range from 5.64 to 6.47, while the dispersion of the data is also moderate, with a coefficient of variation (CV) in all cases of around 0.37.

Table 3. Descriptive analysis of each competency

	N	Stocking	Desv. standard
Planning and Organization	7037	6,03	2,135
Action and Performance at Work	7037	6,06	2,109
Involvement, Commitment and Responsibility	7037	5,64	1,955
Troubleshooting	7037	6,19	2,259
Teamwork	7037	6,25	2,110
Dynamism	7037	5,99	2,170
Communication	7037	6,07	2,274
People Management	7037	6,15	2,204
Customer Orientation	7037	6,31	2,426
Stress Tolerance	7037	6,47	2,399
Learning and Innovation	7037	6,05	2,304
N valid (per list)	7037		

Source: Own elaboration

Multivariate Analysis

A multivariate exploratory factor analysis of interdependence will be carried out for the reduction of the dimension that seeks to discover latent factors in a set of quantitative variables. To this end, the following phases will be carried out:

Preliminary analyses: To do this, it will be necessary to verify the unidimensionality, the adequacy of the data to the analysis and the analysis of the correlation matrix.

Regarding one-dimensionality, it would be convenient to perform Harman's Single Factor Test to check if the matrix is affected by the common variance bias, in which case all the variables analyzed would be grouped into a single factor. There are different ways to check if the data structure is one-dimensional. If a set of items is one-dimensional, when subjected to a factor analysis, the result must be a single factor. It will be checked later, taking into account that in this research the first factor must account for at least 40% of the variance in order to be considered the one-dimensional test.

Regarding the adequacy of the data, the following sample adequacy measures will be used: the Raches test, the Bartlett sphericity test and the Kaiser-Meyer Olkin (KMO) adequacy test.

The Streak Test allows us to analyze the randomness of the answers and check the absence of biases. This contrast is based on the number of streaks a sample presents. A streak is defined as a sequence of sample values with a common characteristic preceded and followed by values that do not have that characteristic. Thus, a streak is considered to be the sequence of consecutive values greater than or equal to the sample mean (or the median or mode, or any other cut-off value) provided that they are preceded and followed by values lower than the sample mean (or the median or the mode, or any other cut-off value). A sample with an excessively large or excessively small number of streaks suggests that the sample is not random.

In this case, as shown in Table 4, the p-values obtained, all higher than a significance level of 0.05, suggest that the data exhibit a non-significant pattern. In addition, the cases that exceed the median in this research are higher than those that do not. This result shows evidence that the data are random, so there would be no bias in the analyzed sample and therefore denote the reliability of the data collected.

Table 4. Streak test

	1	2	3	4	5	6	7	8	9	10	11
Test value[a]	6	6	6	6	6	6	6	6	6	6	6
Cases < Evidence Value	2789	3039	3079	2923	2549	3233	3312	2719	2607	2569	3277
Cases >= Probative value	4248	3998	3958	4114	4488	3804	3725	4318	4430	4468	3760
Total cases	7037	7037	7037	7037	7037	7037	7037	7037	7037	7037	7037
Number of streaks	3377	3442	3396	3430	3266	3519	3475	3264	3254	3283	3475
With	0,218	-0,295	-1,662	0,277	0,352	0,544	-0,775	-1,856	-0,751	0,507	-0,669
Sig. asin. (bilateral)	0,827	0,768	0,097	0,782	0,725	0,586	0,438	0,063	0,453	0,612	0,504
to. Median											

Source: Own elaboration

Bartlett's sphericity test tests the null hypothesis that the variables analyzed are not correlated in the sample or, in other words, that the correlation matrix is identity (the intercorrelations between the variables are zero). In the study carried out (Table 5) it is verified that the correlation matrix is identity.

Table 5. Correlation Matrix[a]

Correl.[a]	1	2	3	4	5	6	7	8	9	10	11
1	1,00	0,67	0,51	0,69	0,71	0,65	0,66	0,74	0,68	0,62	0,64

	0	8	4	8	3	9	4	3	9	8	7
2	0,678	1,000	0,623	0,758	0,645	0,731	0,659	0,637	0,659	0,723	0,702
3	0,514	0,623	1,000	0,585	0,523	0,573	0,526	0,473	0,515	0,623	0,502
4	0,698	0,758	0,585	1,000	0,705	0,738	0,713	0,690	0,698	0,805	0,736
5	0,713	0,645	0,523	0,705	1,000	0,672	0,694	0,755	0,683	0,639	0,670
6	0,659	0,731	0,573	0,738	0,672	1,000	0,657	0,661	0,677	0,702	0,743
7	0,664	0,659	0,526	0,713	0,694	0,657	1,000	0,661	0,691	0,662	0,676
8	0,743	0,637	0,473	0,690	0,755	0,661	0,661	1,000	0,723	0,608	0,684
9	0,689	0,659	0,515	0,698	0,683	0,677	0,691	0,723	1,000	0,629	0,703
10	0,628	0,723	0,623	0,805	0,639	0,702	0,662	0,608	0,629	1,000	0,668
11	0,647	0,702	0,502	0,736	0,670	0,743	0,676	0,684	0,703	0,668	1,000

the. Determinant = 6.47E-005

Source: Own elaboration

Regarding the determinant of the correlation matrix, a very low determinant indicates high intercorrelations between the variables, but it should not be zero (non-singular matrix), as this would indicate that some of the variables are linearly dependent and certain calculations necessary in the Factor Analysis could not be performed. Here the determinant is low, 6.47, which confirms the high intercorrelations.

Bartlett's test, in Table 6, also confirms this with the p-value, since a p-value less than 0.05 indicates that there is a significant difference in the variations. High values of the statistic, associated with small values of significance, will allow us to conclude that the variables of the sample are sufficiently correlated with each other to perform the factor analysis.

According to the results obtained by the Kaiser-Meyer Olkin test (KMO index), being greater than 0.9, the correlations between the variables are high enough to justify factor analysis. This statistic allows us to assess the degree to which each of the variables is predictable from the others. It is distributed in values between 0 and 1, and the higher the value, the more related the variables are to each other. It is recommended to consider the appropriate matrix to perform factorization when the value of this indicator is greater than or equal to 0.80.

Table 6. KMO and Bartlett test.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0,963
Bartlett's sphericity test	Approx. Chi-square	67821,558
	Gl	55

	Mr.	<,001

Source: Own elaboration

In the anti-image correlation matrix are the sample adequacy measures for each variable. To do this, the diagonal elements must be close to zero and the rest must be small, as shown in this matrix (table /).

Table 7. Anti-image correlation matrix

Anti-image	1	2	3	4	5	6	7	8	9	10	11
1	,966a	-0,144	-0,028	-0,08	-0,158	-0,05	-0,086	-0,281	-0,114	-0	0,021
2	-0,144	,966a	-0,21	-0,17	0,012	-0,18	-0,045	0,004	-0,039	-0,13	-0,129
3	-0,028	-0,21	,963a	-0	-0,065	-0,09	-0,043	0,052	-0,048	-0,21	0,066
4	<-,079	-0,169	-0,001	,952a	-0,082	-0,09	-0,113	-0,059	-0,062	-0,41	-0,137
5	-0,158	0,012	-0,065	-0,08	,964a	-0,08	-0,171	-0,306	-0,053	-0,03	-0,047
6	-0,045	-0,18	-0,094	-0,09	-0,076	,970a	-0,022	-0,043	-0,074	-0,11	-0,262
7	-0,086	-0,045	-0,043	-0,11	-0,171	-0,02	,977a	-0,031	-0,169	-0,09	-0,104
8	-0,281	0,004	0,052	-0,06	-0,306	-0,04	-0,031	,949a	-0,216	0,024	-0,114
9	-0,114	-0,039	-0,048	-0,06	-0,053	-0,07	-0,169	-0,216	,972a	0,006	-0,163
10	-0,001	-0,127	-0,212	-0,41	-0,025	-0,11	-0,085	0,024	0,006	,947a	-0,036
11	0,021	-0,129	0,066	-0,14	-0,047	-0,26	-0,104	-0,114	-0,163	-0,04	,966a

Source: Own elaboration

Analysis of the correlation structure: in this stage, it is necessary to extract the factors, determine their number, and rotate the factors.

There are several methods for the extraction of factors, in this case a factor analysis by principal components will be performed, with data extraction by **the** Kaiser method, which determines factors and eigenvalues greater than 1. This means that only factors with eigenvalues greater than 1 should be retained, defining eigenvalues as the amount of variance obtained by each factor. If the variance is greater than 1, it means that the factor contributes more variance than that of a standard individual variable, so these factors are considered relevant and should be conserved.

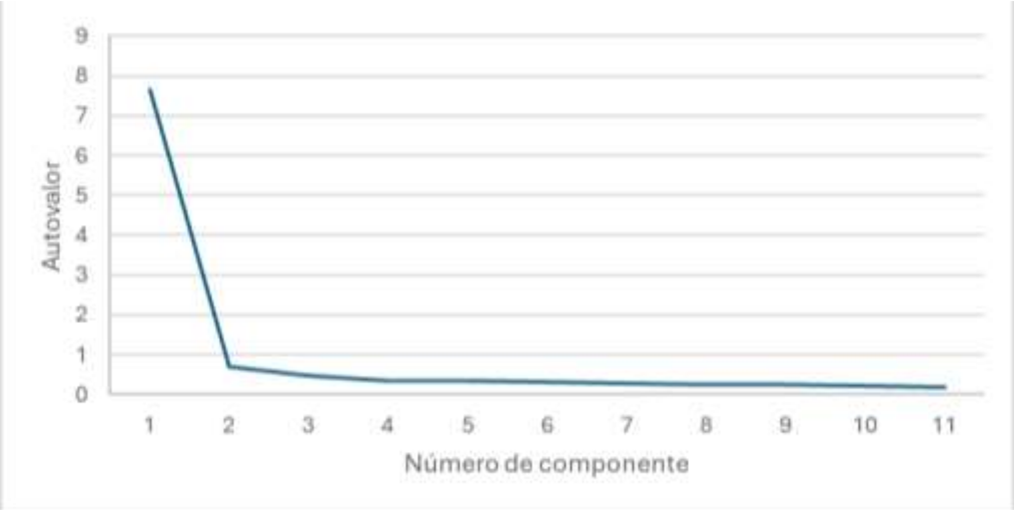
In the research, as can be seen in Table 8, there is only one factor with an eigenvalue greater than one, so only this can be extracted, with the rest remaining. The analysis detects the only latent factor that explains 69.50% of the common variance.

Table 8. Total variance explained.

Component	Initial eigenvalues			Sums of charges squared from extraction		
	Total	% variance	Cumulative %	Total	% variance	Cumulative %
1	7,646	69,505	69,505	7,646	69,505	69,505
2	0,693	6,303	75,808			
3	0,462	4,199	80,007			
4	0,363	3,299	83,306			
5	0,354	3,214	86,520			
6	0,308	2,796	89,316			
7	0,292	2,657	91,973			
8	0,247	2,247	94,220			
9	0,242	2,199	96,419			
10	0,218	1,984	98,403			
11	0,176	1,597	100,000			
Extraction method: principal component analysis.						

Source: Own elaboration

The sedimentation criterion or graph is also used as a complementary method to make an optimal extraction of factors. It is a simple graphical representation of the size of the eigenvalues, which in this case (Graph 1) also demonstrates that it is feasible to reduce the results of the questionnaire to a final factor.



Graph 1. Sedimentation graph.

Source: Authors.

However, we will choose to extract three factors, since as can be seen in tables 8 and 9, one final factor explains 69.50% of the candidate's profile, however, three final factors are capable of explaining 80% of the competence profile of each of them.

Table 9. Total variance explained

Component	Initial eigenvalues			Sums of charges squared from extraction		
	Total	% variance	Cumulative %	Total	% variance	Cumulative %
1	7,646	69,505	69,505	7,646	69,505	69,505
2	0,693	6,303	75,808	0,693	6,303	75,808
3	0,462	4,199	80,007	0,462	4,199	80,007
4	0,363	3,299	83,306			
5	0,354	3,214	86,52			
6	0,308	2,796	89,316			
7	0,292	2,657	91,973			
8	0,247	2,247	94,22			
9	0,242	2,199	96,419			
10	0,218	1,984	98,403			
11	0,176	1,597	100			
Extraction method: principal component analysis.						

Source: Own elaboration

After the analysis of eigenvalues, the analysis of the commonalities is carried out to compare a single final factor against three final factors.

Table 10. Extraction of communalities considering 1 factor

	Initial	Extraction
Planning and Organization	1	,696
Action and Performance at Work	1	,728
Involvement, Commitment and Responsibility	1	,484
Troubleshooting	1	,791
Teamwork	1	,708
Dynamism	1	,729
Communication	1	,690
People Management	1	,698
Customer Orientation	1	,702
Stress Tolerance	1	,704
Learning and Innovation	1	,716

Extraction method: principal component analysis.

Source: Own elaboration

Table 10 shows that the variable *involvement, commitment and responsibility* (3) should be considered with special attention, since their commonality is significantly less than 0.7. Therefore, according to the interpretation of communality, for values significantly less than 1, the variable is not well represented by the factors and therefore may be less relevant in the factor model.

Table 11 of communalities shows that in this new situation of three-factor extraction, all estimated communalities improve.

Table 11. Extraction of communalities considering 3 factors

	Initial	Extraction
Troubleshooting	1	,785
Dynamism	1	,778
Action and Performance at Work	1	,955
Learning and Innovation	1	,827
Teamwork	1	,793
Stress Tolerance	1	,777
Customer Orientation	1	,698
People Management	1	,837
Planning and Organization	1	,741
Communication	1	,804
Involvement, Commitment and Responsibility	1	,806
Extraction method: principal component analysis.		

Source: Own elaboration

As far as Factor Rotation is concerned, rotation procedures try to obtain more interpretable factors by transforming the initial solution. Their objective is to search for factorial solutions in which each factor has high correlations with a group of variables and low correlations with the rest.

One of the rotation methods is the Varimax, which minimizes the number of variables that have high loads on each factor. Simplify the interpretation of factors. When a single component is removed, the solution cannot be rotated, so only the solution with three-component extraction will be rotated.

Determination of the model: involves the selection of variables, the calculation of factor scores and the evaluation of the model.

The data from the study allow us to affirm that the objective of the factor analysis has been achieved since three latent factors have emerged that clearly group the total of original variables. In order to be able to carry out subsequent analyses with these new factors, it is necessary to calculate the scores achieved in each of them.

Therefore, to conclude the analysis, a multivariable linear model is proposed based on the final factors derived from the factor analysis. By definition, a regression model allows you to analyze the relationship between a dependent variable and several independent variables. In this case, the coefficients of this regression are calculated to see how 1 factor (table 12) and three factors (table 13) affect a specific response.

Table 12. Matrix of component scoring coefficients for 1 factor.

	Component
	1
Planning and Organization	,109
Action and Performance at Work	,112
Involvement, Commitment and Responsibility	,091
Troubleshooting	,116
Teamwork	,110
Dynamism	,112
Communication	,109
People Management	,109
Customer Orientation	,110
Stress Tolerance	,110
Learning and Innovation	,111
Extraction method: principal component analysis.	
a. 1 extracted components.	

Source: Own elaboration

And therefore the associated regression model considering one factor is as follows:

C1= 0.109 Planning+0.112 Accion+0.091 Implic+0.116 Soluc+ 0.110 Trab+ 0.112 Dinamis+ 0.109 Comuni+0.109 Management+ 0.110 Orientac + 0.110 Toler + 0.111 Aprise

	Component		
	1	2	3
Planning and Organization	,450	-,332	,081
Action and Performance at Work	-,205	,292	,132
Involvement, Commitment and Responsibility	-,136	-,431	1,093
Troubleshooting	-,153	,365	-,048
Teamwork	,442	-,300	,046
Dynamism	-,174	,421	-,115
Communication	,154	,045	-,046

People Management	,530	-,290	-,107
Customer Orientation	,284	-,037	-,117
Stress Tolerance	-,325	,400	,146
Learning and Innovation	-,104	,519	-,375
Extraction method: principal component analysis.			
a. 1 extracted components.			

Source: Own elaboration

And the associated regression model considering three factors will be:

C1= 0.450 Planif -0.205 Accion-0.136 Implic-0.153 Soluc+ 0.442 Trab- 0.174 Dinamis+ 0.154 Comuni+0.530 Management+ 0.284 Orientac - 0.325 Toler - 0.104 Aprise

C2= -0.332 Planning+0.292 Accion-0.431 Implic+0.365 Soluc- 0.300 Trab+ 0.421 Dinamis+ 0.045 Comuni-0.290 Management- 0.37 Orientac + 0.400 Toler + 0.519 Aprise

C3= 0.81 Planning+0.132 Accion+1.093 Implic-0.48 Soluc+ 0.46 Trab-0.115 Dinamis- 0.46 Comuni-0.107 Management- 0.117 Orientac + 0.146 Toler - 0.375 Aprise

To complete the analysis, the rotated space component graph (Graph 2) has been created. It is observed that in the 3D space generated by the final factors, the Engagement, Commitment and Responsibility competence is distanced from the rest, which, on the contrary, tend to be grouped together.

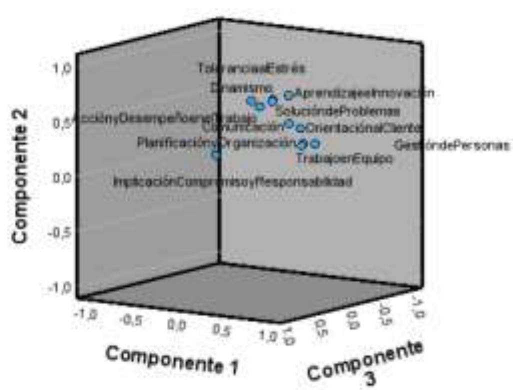


Figure 2. Component plot in rotated space.

Source: Own elaboration

If we choose a summary of 10 from among all the more than 7,000 candidates analysed, we can see (table 14), after applying the associated regression model, that with the study of three factors, conclusions can be drawn from the candidate's profile. Factorial scores appear in the table in differential format, so a score of 0 corresponds to a factorial score equal to the mean, positive scores are higher than the mean and negative scores lower than the mean.

Thus, for example, the candidate Miguel is above the average in all the competencies analyzed, with his highest score being that of component 3, which gave greater weight to involvement, commitment and responsibility. In this way, it is easier to know the degree of adjustment of this candidate's behavior with the expected behaviors for the position and to know in which skills the candidate has weaknesses and strengths based on those required for the position.

Table 14. Summary of 10 cases assessed with 3 factors.

			REGR factor score 1 for analysis 1	REGR factor score 2 for analysis 1	REGR factor score 3 for analysis 1
Candidate	Adrian	1	0,12997	1,25642	-0,51178
	Ana	1	-2,69040	2,25638	1,64977
	Carla	1	1,12977	-0,61537	-0,79256
	Gem	1	-1,52948	0,86948	0,32410
	José Luis	1	-0,43957	-0,51912	-0,45944
	Leandro	1	-1,39183	2,80031	0,07615
	Marten	1	0,26431	-1,57250	0,48630
	Miguel	1	1,27624	0,65113	1,75446
	Nativity	1	0,83359	-0,33872	-0,60508
	Noelia	1	0,94137	-0,99267	0,95168
to. Limited to the first 10 cases.					

Source: Own elaboration

Conclusions

Exploratory factor analysis is a data analysis technique widely used in social science research, especially in studies whose objective is to analyze and validate a test or other type of tests that evaluate dimensional constructs. However, there are several authors who have highlighted the incorrect use of this technique. One of the most recent analyses is that of Izquierdo *et al* . (2014), who analysed 117 studies (published between 2011 and 2012 in three Spanish impact journals) that used the technique of factor analysis, finding significant rates of erroneous or incorrectly justified decisions.

Therefore, it is necessary to carry out an exhaustive analysis of the decisions to be made in order to carry out an efficient exploratory factor analysis, depending on the starting theory, the objectives of the study and the type of variables and the relationships established between them. In the same way, it is of special interest to describe each of these decisions and the reasons that determine them, so that the analysis carried out is duly justified and, therefore, the validity of the results.

After having detailed all these aspects in this research, the use of an exploratory factor analysis is justified, since we will try to define a small group of latent factors that explain the higher percentage of common variance by analyzing the performance levels of various profiles using quantitative and data visualization techniques.

To this end, the objective has been, firstly, to be able to classify the profiles analysed, which are based on heterogeneous groups of positions among themselves, but internally homogeneous in terms of the skills requested in order to establish a classification based on the performance of each individual. Secondly, the variables considered in the questionnaire have been analysed in order to establish whether there are redundancies in the assessment of the facets evaluated in the performance of the profiles analysed.

On the other hand, the three-factor model used in this analysis offers solid evidence on how there can be competencies, such as Involvement that does not significantly correlate with the results in the other competencies evaluated. This lack of correlation would indicate either that these competencies do not contribute significantly to the overall performance of the candidates, at least in the context of this specific study, or they could suggest, due to their homogeneity and high values, that there is an underlying phenomenon of social and/or occupational desirability among the profiles analyzed. However, it should not be ruled out that these competencies are totally independent of other skills evaluated, suggesting that their development does not necessarily affect or is affected by the development of other competencies.

In conclusion, the multiple regression model obtained indicates that while some competencies are correlated and jointly affect the results of the profiles, others denote their independence. These findings are critical, as well as relevant, to better understand how different competencies contribute to the success of the individuals analyzed, while they can guide future efforts in training and assessment for specific competencies that have a greater and more direct impact on performance.

On a practical level, this form of competency assessment facilitates the work of recruiting companies and university institutions, and allows establishing a guide to the most in-demand competencies by position or professional profile, helping competency training in universities.

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