doi.org/10.26398/IJAS.0033-003

ANALYSIS OF YOUNG PEOPLE NEITHER IN EMPLOYMENT NOR IN EDUCATION AND TRAINING: A FUZZY MCA BASED APPROACH

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Abstract *Young adults in Neither in Employment nor in Education and Training (NEET) are at high risk of adverse health outcome, in particular of mental health problems. The aim of this study is to identify the symptomatological profiles of young Italian NEETs. The data set in question consists of 150 Italian respondents to the Adult Self Report (ASR 18-59) survey for assessing the mental health problems. A two-step unsupervised learning approach that involves fuzzy multiple correspondences analysis and clustering is applied to identify different symptomatological profiles of NEETs-related problems. The obtained results are compared to a principal component analysis-based approach. Finally, clinical implications in psychological practices are discussed.*

Keywords: *NEETs, fuzzy multiple correspondence analysis, cluster analysis.*

1. INTRODUCTION

The Neither in Employment nor in Education or Training (NEET) is a labor market and social category that refers to an increasing proportion of young people aged 15 to 34 that disengage from the labor market. The rise of the NEET phenomenon is mostly due to the current economic crisis in Western Countries and the consequent fall in labor demand. As a result of the economic crisis, the school-to-work transition (SWT) is increasingly slow, for Young Italians in particular. In fact in 2019, Italy showed the highest percentage of NEETs (27.8%) across the EU-28 (Eurostat, 2020b). The largest part of young people NEET is concentrated in the age groups 20-24 (26.6%), 25-29 (31.5%), and 30-34 (29.9%), while it is lower in the age span 15-19 (11.1%) due to higher participation in the education system. Women are the most affected subgroups, and the largest part is concentrated in the age groups 30-34 (39.8%). Regional disparities are among the highest in the EU-28 and the south of the country is the most affected (36.1%).
According to Pastore (2019), the SWT being slow is the consequence of the instability of the labor market: *i.e.*, a low job-finding rate that causes unemployment

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and it prevents young people from gathering work experience. A further aspect is the lack the educational system of technical and vocational branches. The Italian context maintains one of the highest rates of school dropout from compulsory education (13.5%, Eurostat, 2020a), and from university (12.2%, AlmaLaurea, 2020).

In line with the socio-economic perspective, from a psychological point of view the Italian context is conceived as the prototype of young people condition in southern European countries. Young people in Italy (and, more generally, in southern Europe) face socio-economic difficulties that affect the chances to develop coherent and satisfying future careers and life plans (Leccardi, 2006). SWT difficulties may lead to anxiety, discouragement, and maladaptive behavior (Arnett, 2007; Reifman et al., 2007).

Unemployment in this age group has a serious effect on individuals. The consequences of unemployment on health may differ between young people and adults: the SWT plays a different role in identity development (Reine et al., 2004), as well as in the transition to adulthood (Jongbloed and Giret, 2021). A increasing body of literature suggests that NEETs are more likely to have health risks. Some studies show consequences on everyday life and well-being (Gaspani, 2018; Parola and Donsì, 2018). Several other studies show the link between unemployment among young people and mental health (Bartelink et al., 2020; McKee-Ryan et al., 2005; Paul and Moser, 2009). Youth unemployment is associated with distress (Bjarnason and Sigurdardottir, 2003; Stea et al., 2019), psychosomatic symptoms (Axelsson and Ejlertsson, 2002), increased depression and anxiety disorders (Bartelink et al., 2020). Moreover, unemployment is associated with increased risks of suicidal thoughts (Fergusson et al., 2001), crime (Atkinson and Hills, 1998; Henderson et al., 2017; Robins and Rutter, 1990), and alcohol and substance abuse (Baggio et al., 2015; Hagquist and Starrin, 1996). Strandh et al. (2014) analyze different cohorts of unemployed people found how the mental health affects young people more than adults. This evidence confirms the young age as a sensitive period where exposure to unemployment risk may lead to permanent mental health issues.

The aim of the paper is to describe NEETs mental health problems (internalizing, externalizing, and co-occurring internalizing and externalizing problems) and to identify the symptomatological profiles linked to the NEET status. In particular, a two-step unsupervised learning approach is applied that involves fuzzy multiple correspondence analysis (fuzzy MCA) and clustering: the symptomatological profiles will therefore correspond to homogeneous groups of NEETs. The data set

refers to a study of 150 Italian NEETs: the enrollment procedure has been carried out through the third sector associations involved in the Campania region in the period between 2018 and 2019. The minimum sample size required to conduct this study was computed considering the percentage of the NEET in the 25-34 age group in the Campania region before the data collection (38.8%). Participants were aged from 25 to 34 (M= 29.5, SD= 2.91), 75 males and 75 females; 68% had a masters' degree, 84% were living with parents, and 90% were financially supported by parents. They were fully informed about a complete guarantee of confidentiality and voluntary participation.
The paper is structured as follows: in Section 2 the NEETs symptomatology model is introduced, Section 3 describes a classic two-step data reduction approach: more specifically, Section 3.1 describes the data reduction approach for crisp-coded data, whereas Section 3.2 describes the modified approach for fuzzy-coded data. Section 4 illustrates the main results of the analysis and Section 5 is for discussion and conclusion.

2. THE NEETS SYMPTOMATOLOGY MODEL

In the psychological literature, correlation analysis is used to assess the mental health of young people in NEET condition. These studies use different measures that refer to mental health problems (*e.g.*, anxiety, depression, behavioral problems) by creating a booklet of several questionnaires. We refer to the Achenbach and Rescorla (2003) model, which makes it possible to use a single questionnaire for a pool of mental health issues and it is well suited for the identification of symptomatological profiles. To our knowledge, there are no Italian studies on symptomatological profiles related to the NEET condition. The Achenbach System of Empirically Based Assessment (ASEBA) allows a typological approach that identifies groups based on the presence/absence of problem behaviours closely related to clinical practice. Such a typological approach allows for investigating how different problem behaviours co-occur in young adults with an unemployment condition. The ASEBA model proposes a taxonomy generalizable across different populations (Bérubé, 2004). According to this model, problem behaviors are dichotomized into two empirically established syndromes reflecting internalizing and externalizing problems. A syndrome is a set of problems that consistently occur.
The present study considered the 6 Syndromic Scales of the Adult Self Report 18-59: Anxious/Depressed, Withdrawn, Somatic Complaints, Aggressive Behavior, Rule-Breaking Behavior, and Intrusive. The Syndrome Scales were used both to

document specific problems and to identify syndromes of co-occurring problems. Each syndrome title summarizes the kind of problems that form the syndrome. The higher the score, the more significant the problem. One group of scales, designated as Internalizing, consists of the three syndromes: Anxious/Depressed, Withdrawn, and Somatic Complaints; the second group of scales, defined as Externalizing, consists of three syndromes: Aggressive Behavior, Rule-Breaking Behavior, and Intrusive. Internalizing problems reflect internal distress while Externalizing consists of problems that mostly involve conflicts with other people and with social rules. The survey results have been collected with the approval from the University Research Ethics Committee of the University of Naples Federico II.
The ASR 18-59 is a rating scale and contains 77 items on problem behaviors that have occurred over the past six months from the assessment. The ASR 18-59 is a reliable and valid measure for the 18-59 general population (Achenbach and Rescorla, 2003; Ivanova et al., 2015a). This instrument was compared with other questionnaires used for assessment of general population and clinical diagnosis, such as personality inventories (*i.e.*, MMPI, MCMI, SCL-90-R), and single construct measures (*i.e.*, BDI, BAI, STAI). Each of these measures is compatible with the ASR 18-59 instruments. The model is often used for the assessment of young adults showing its accuracy (Ivanova et al., 2015a,b; Rescorla et al., 2016) also in the Italian context (Biasi et al., 2015; Cerutti et al., 2020; Parola et al., 2020). Therefore for this study, we considered the Italian validation (Ivanova et al., 2015a). Six psychometric scales refer to the following six-syndrome structure: Anxious/Depressed (18-items, *i.e.*, worries, fearful), Withdrawn (9-items, *i.e.*, rather be alone, enjoys little), Somatic Complaints (12-items, *i.e.*, tired, vomiting), Aggressive Behavior (15- items, *i.e.*, temper, threatens), Rule-Breaking Behavior (14-items, *i.e.*, steals, use drugs), and Intrusive (6-items, *i.e.*, teases, loud). Items were recorded using a three-point ordinal scale. In line with the ASR 18-59 scoring (Achenbach and Rescorla, 2003), the total score of each syndrome scale is computed by summing up the scores of the items belonging to the same scale. High scores indicate clinically important deviations from normal behaviours, and they reflect numerous problems.

3. TWO-STEP DATA REDUCTION OF SYNDROMIC SCALES

The starting data structure is a $n \times p$ matrix $\mathbf{X}$, where n is the number of respondents and p is the number of considered scales. The general aim is to identify meaningful groups of homogeneous observations; to this end we synthesize the

$\mathbf{X}$ matrix via row and column-wise data reduction. In particular, following the so-called *tandem* approach, a two-step analysis is performed: in the first step, a dimension reduction method is applied to define a reduced set of synthetic attributes that are insightful combinations of the original ones; in the second step, a distance-based cluster analysis is applied on the observations, with pairwise distances being computed with respect to the synthetic attributes obtained in the first step. The advantage of the *tandem* approach is two-fold: *i)* the dimension reduction in step 1 removes redundancies and noise from the data structure, that is of help to cluster analysis; *ii)* the scatterplot-based visualization of the dimension reduction results can be used to characterize the identified clusters and to interpret the corresponding profiles.

3.1 DATA REDUCTION OF CRISP-CODED DATA

The reference dimension reduction method for continuous attributes is the principal component analysis (PCA, see, e.g., Jolliffe and Cadima, 2016). To briefly define the PCA of the $\mathbf{X}$ matrix, let the p considered attributes be standardized; the PCA solution is obtained via the singular value decomposition (SVD) of the following matrix (see, e.g., Greenacre, 2010, Formula 6.2, page 60)

$$\mathbf{S}_{pca} = n^{-1/2}\left(\mathbf{X}-\mathbf{M}\right)p^{-1/2} = \mathbf{U}\Sigma\mathbf{V}^{\mathsf{T}} \tag{1}$$

where $\mathbf{M} = n^{-1}\mathbf{1}\mathbf{1}^{\mathsf{T}}\mathbf{X}$ is the centering operator and $\mathbf{1}$ is an n-dimensional vector of ones; $\mathbf{U}$ is a $n \times p$ matrix of left singular vectors, Σ is a diagonal matrix containing the p singular values $\sqrt{\lambda}_j$, $j = 1,\ldots,p$, and $\mathbf{V}$ is a $p \times p$ orthonormal matrix with right singular vectors on columns; λ_j is the $j^t h$ eigenvalue and $\mathbf{V}_j$ is the j^{th} eigenvector of the matrix $\mathbf{S}^{\mathsf{T}}\mathbf{S}$. Therefore, the j^{th} singular value corresponds to the standard deviation along the direction of the j^{th} singular vector, $j = 1,\ldots,p$. Selecting the first d singular vectors and values in $\hat{\mathbf{V}}, \hat{\mathbf{U}}$ and $\hat{\Sigma}$, we refer to $\hat{\mathbf{F}} = n^{1/2}\hat{\mathbf{U}}\hat{\Sigma}$ as row principal coordinates, and to $\hat{\mathbf{G}} = p^{1/2}\hat{\mathbf{V}}$ as standard column coordinates. The joint plot of $\hat{\mathbf{F}}$ and $\hat{\mathbf{G}}$ is the well-known d-dimensional biplot representation.

The d-dimensional PCA solution seeks to approximate the linear correlation structure of the attributes; therefore, non linear relations between attributes will not be captured via PCA. A variation of PCA that is capable of capturing non linear relations is correspondence analysis (CA, Greenacre, 2017). In particular, CA is suited for counts or proportions and, in general, any data table with non negative values measured on the same units. The generalization of CA to the case of more than two categorical attributes is the multiple correspondence analysis (MCA). When the p attributes are categorical, each with q_j categories, $j = 1,\dots,p$ and $Q = \sum_{j=1}^{p} q_j$, the starting data matrix $\mathbf{X}$ is recoded as the $n \times Q$ indicator matrix $\mathbf{Z} = [\mathbf{Z}_1,\dots,\mathbf{Z}_p]$, such that the general block $\mathbf{Z}_j$ represents the dummy coding for the j^{th} categorical attribute. The grand total of $\mathbf{Z}$ is nQ and the contingency matrix $\mathbf{P} = \frac{\mathbf{Z}}{nQ}$; let the margins of $\mathbf{P}$ be $\mathbf{r} = \mathbf{P1} = \frac{1}{n}\mathbf{1}$ and $\mathbf{c}^{\mathsf{T}} = \mathbf{1}^{\mathsf{T}}\mathbf{P}$; the weights matrices are $\mathbf{D_r} = diag(\mathbf{r})$ and $\mathbf{D_c} = diag(\mathbf{c})$. Just like the PCA, see Equation 1, the MCA also boils down to the SVD of the matrix $\mathbf{S}_{mca}$, as follows

$$\mathbf{S}_{mca} = \mathbf{D_r}^{-1/2}\left(\mathbf{X} - \mathbf{rc}^{\mathsf{T}}\right)\mathbf{D_c}^{-1/2} = n^{1/2}\left(\mathbf{P} - \frac{1}{n}\mathbf{1c}^{\mathsf{T}}\right)\mathbf{D_c}^{-1/2} = \mathbf{U\Sigma V}^{\mathsf{T}}. \quad (2)$$

Finally, the d-dimensional MCA solution consists of the principal coordinates of the rows $\hat{\mathbf{F}} = \mathbf{D_r}^{-1/2}\hat{\mathbf{U}}\hat{\Sigma}$ and the standard coordinates of the columns $\hat{\mathbf{G}} = \mathbf{D_c}^{-1/2}\hat{\mathbf{V}}$: the two-dimensional biplot is obtained selecting the first two columns of $\hat{\mathbf{F}}$ and $\hat{\mathbf{G}}$.

3.2 DATA REDUCTION OF FUZZY-CODED DATA

The MCA is designed for categorical data sets. However, upon transforming continuous attributes into categorical, MCA can be applied to mixed-type data set, or even continuous data sets. The most straightforward way to recode (transform) a continuous attribute into a categorical one (*categorization*) is to split the range of the attribute values into intervals, each labeled with a different category; observations are then labeled with the category of the interval their value belongs to. Such crisp (hard) coding determines a considerable loss of information, that can be mitigated using a fuzzy (soft) coding of the data. The fuzzy coding allows an observation to be labeled with two different categories, with associated weights that add up to one. Several *fuzzyfication* processes are proposed in the literature (see, e.g., Jang et al., 1997; Zimmermann, 2011). We refer to the coding used in Aşan and Greenacre (2011): each original attribute is re-coded into three categories, *low*, *medium* and *high*, and the weights are defined using the so-called three-point triangular membership function. In particular, for each category, a piece-wise linear function passing through three points is defined. Given a continuous attribute X_j, with knots at $min(X_j)$, $median(X_j)$ and $max(X_j)$, the piece-wise functions take 1/0 values at the knots, see Table 1 for details.
The fuzzy coding of the i^{th} observation of the j^{th} attribute is obtained by simply plugging x_{ij} into the three considered piece-wise linear functions, that is $f_{low}(x_{ij})$, $f_{medium}(x_{ij})$ and $f_{high}(x_{ij})$. In Figure 1 the coding of two values of the attribute X_1 is described, $x_{a,1} = 10$ and $x_{b,1} = 30$.

Tab. 1: The three considered knots are set at the min and max, and at the median of the $X j$ distribution. Three piece-wise linear functions are defined, $flow(xi\,j)$, $fmedium(xi\,j)$ and $fhigh(xi\,j)$, one for each category. Reported are the values of the functions at the knots.

category	$min(X_j)$	$median(X_j)$	$max(X_j)$
low	1	0	0
medium	0	1	0
high	0	0	1

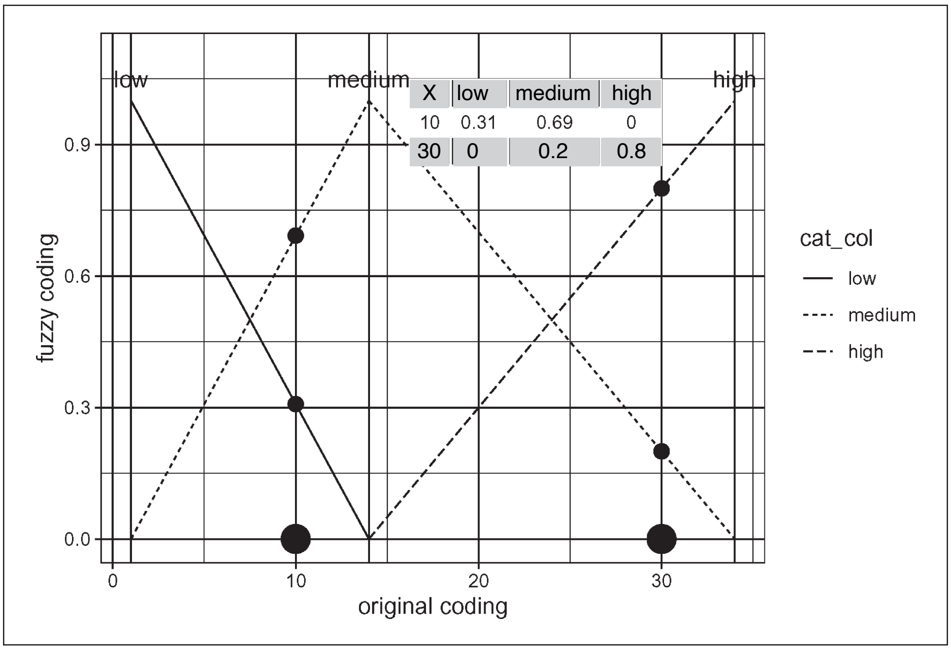

Fig. 1: Two examples of triangular membership function coding. The original coding on the horizontal axis, the fuzzy coding on the vertical axis

The fuzzyfication of the $n \times p$ matrix $\mathbf{X}$ leads to the $n \times Q$ fuzzy indicator matrix $\tilde{\mathbf{Z}}$: such matrix has the same grand total and row margins of the indicator matrix $\mathbf{Z}$, resulting from the crisp coding of $\mathbf{X}$; the column margins of $\tilde{\mathbf{Z}}$ and $\mathbf{Z}$ do differ. The fuzzy MCA solution can be obtained by applying the MCA procedure described in Section 3 on $\tilde{\mathbf{Z}}$. Also, the fuzzy MCA solution shares different properties with the standard MCA one, see Aşan and Greenacre (2011) for a thorough discussion. Finally, the fuzzy MCA is capable to approximate non linear relations between attributes, and therefore it is a suitable alternative to PCA.

Dimension reduction is the first step of the data reduction approach that is used to synthesize the syndromic scales data: the second step is to identify groups of homogeneous observations. An agglomerative hierarchical clustering (see, e.g., Arabie and De Soete, 1996) is applied on the pairwise Euclidean distance matrix Δ of the fuzzy MCA observation scores (principal coordinates), with general element

$$\delta_{ii'} = \left[\left(\hat{\mathbf{f}}_i - \hat{\mathbf{f}}_{i'} \right)^{\mathsf{T}} \left(\hat{\mathbf{f}}_i - \hat{\mathbf{f}}_{i'} \right) \right]^{1/2} = \sqrt{\sum_{j=1}^{d} \left(\hat{f}_{ij} - \hat{f}_{i'j} \right)^2}.$$

It can be shown that the Euclidean distances between d principal coordinates are, in fact, low-dimensional approximations of chi-squared distances between the original observations (van de Velden, 2000). The chi-square distance is a weighted Euclidean distance, and the weights are the reciprocal of the column margins: such weights prevent the Euclidean distances to be dominated by the most occurring categories. In the context of syndromic scales data, this feature is desirable since each scale is built on a different number of items.

4. UNSUPERVISED LEARNING OF YOUNG NEETS DATA

The ASR 18-59 was used to assess the NEETs mental health problems. The six scales were categorized according to the level of intensity (low, medium and high). The dimension reduction results are shown in the fuzzy MCA map reported in Figure 2. The syndromic levels on the map are represented via short labels (see Table 2): the short label itself represents the *medium* category, whereas the short label followed by '+' and '-' represents the *high* and *low* categories, respectively.

Tab. 2: Short labels for the considered syndromic scales

syndromic level	*short label*
aggressive behavior	AB
anxious depressed	AD
intrusive	In
rules breaking	RB
somatic complains	SC
withdrawn	Wi

Figure 2 shows the fuzzy MCA results: the categories of attributes *AB* (aggressive behaviour) and *AD* (anxious depressed) follow a very same pattern, with the so-called *horse shoe effect* on the factorial map, meaning that observations present

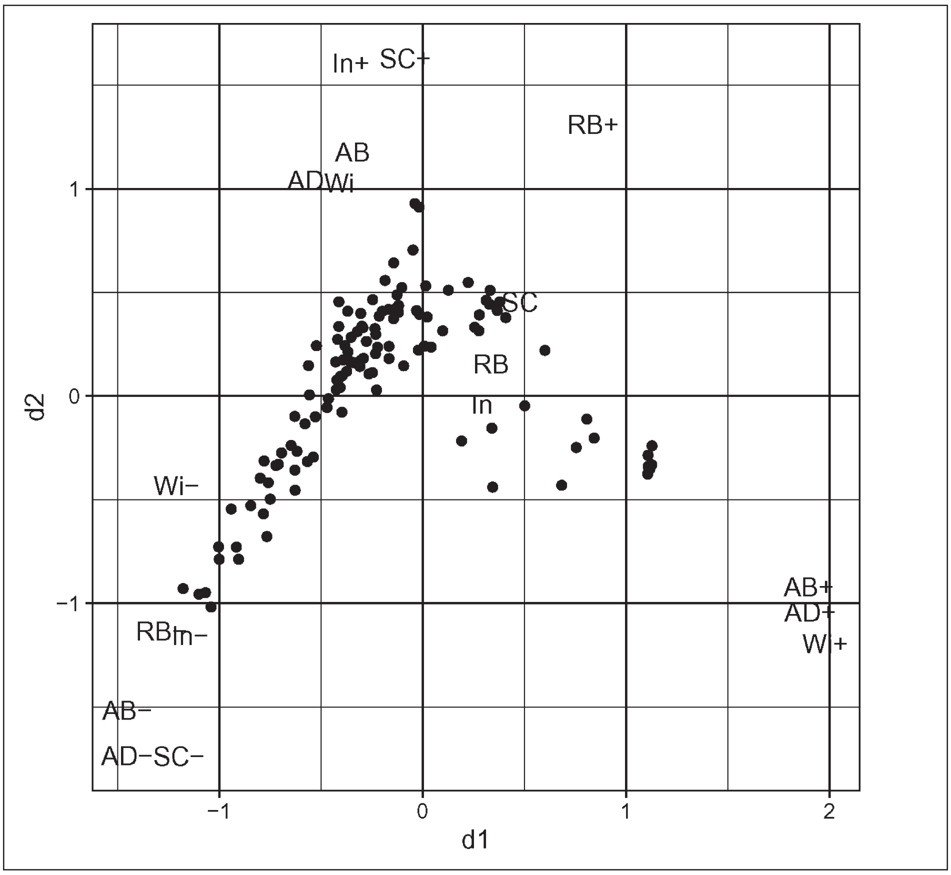

Fig. 2 FuzzyMCA biplot: *low*, *medium* and *high* categories for the six considered syndromic scales and the considered observations

similar scores for *AB* and *AD*. The *Wi* (withdrawn) attribute categories follow the same pattern as *AB* and *AD*, but for the *low* category: in fact, the category *Wi*- is closer to the center of the map than any of the other *low* categories: it means that low levels of Wi do not imply low levels of the other considered syndromic scales. The scales *In* (intrusive), *RB* (rules breaking) and *SC* (somatic complains) have a similar pattern, which differ from *AB*, *AD* and *Wi* for the *high* and *medium* categories. It is possible to conclude, based on the the fuzzy MCA solution, that, there is group of observations with low levels for all the syndromic scales, whereas for the *medium* and *high* categories, there is a difference among observations characterized by *AB*, *AD* and *Wi*, and *RB*, *In* and *SC* syndromic scales.

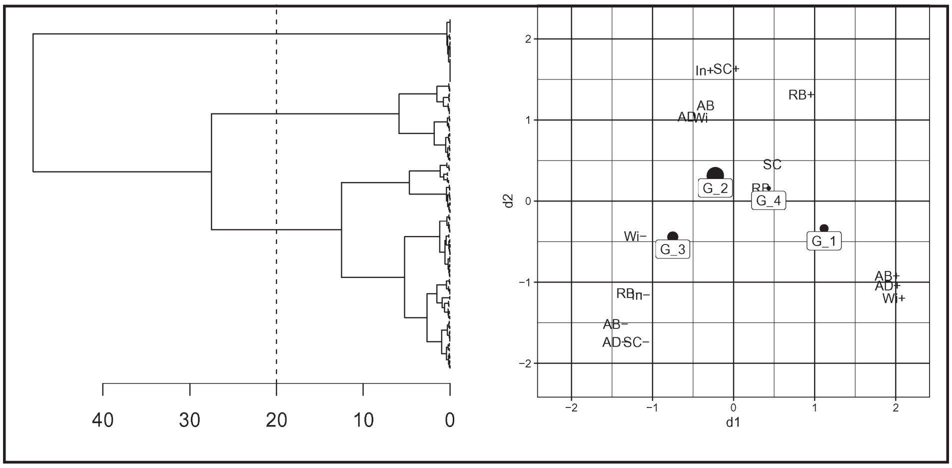

Fig. 3: Fuzzy MCA-based solution: clustering dendrogram (left); attributes and centroids map

The cluster analysis on observation scores leads to the identification of four clusters (see the dendrogram in the left-hand side of Figure 3; the fuzzy MCA map with cluster centroids is represented in the right-hand side of figure 3).

Since the natural alternative to fuzzy MCA is the PCA applied to the original (non-*fuzzyfied*) attributes, we compared the attribute maps resulting from fuzzy MCA and PCA. Figure 4 shows how both fuzzy MCA and PCA depict the relation among *AD*, *Wi* and *AB*, and between In and RB; the solutions differ when it comes to SC: according to the PCA map, the attribute in question is uncorrelated from the others, and it is poorly represented on the map; according to fuzzy MCA, instead, the *SC* attribute follows the same pattern of *In* (and, less so, of *RB*). Such disagreement of the solution may depend on the non-linear relation between *SC* and *In*, that is missed by PCA.

The observed discrepancies in the fuzzy MCA and PCA attribute maps, are confirmed by the clustering results. The parallel plots in Figure 5 report a visual characterization of the obtained clusters: each vertical axis corresponds to an attribute, the lines refer to cluster centroids and the thickness of the lines is proportional to the cluster size; finally, the horizontal line refers to the general mean (global centroid). The top display in Figure 5 shows the PCA-based cluster centroids, whereas the bottom display shows the fuzzy MCA-based centroids. It is evident that the centroids from clusters 1 and 4 show similar behavior in the two plots, yet with different size. Differences in the PCA-based or fuzzy MCA-based

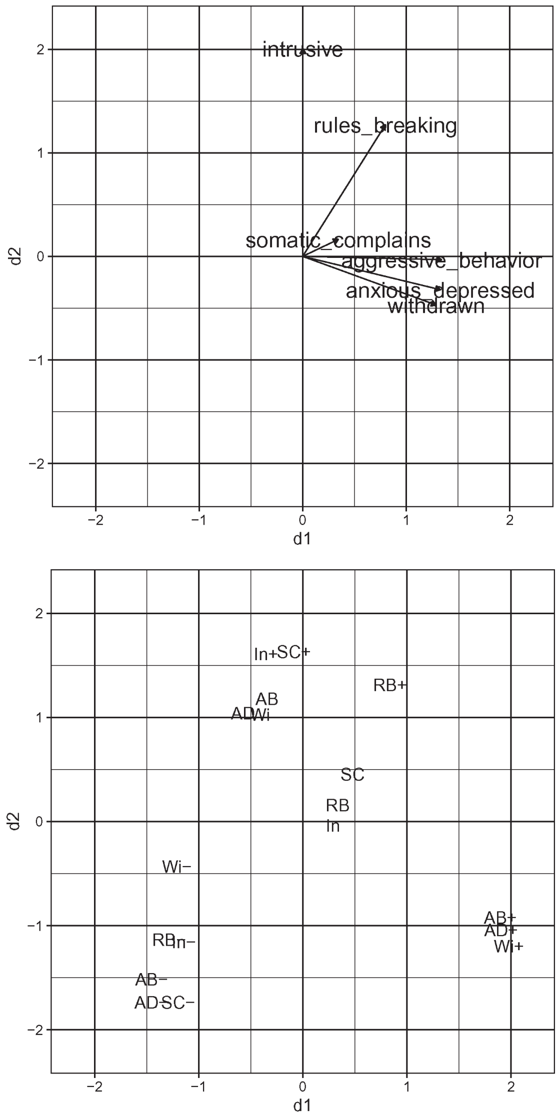

Fig. 4: Comparison of attribute maps: PCA on the continuous scales (top) vs MCA on the fuzzy coded scales

clustering solutions are observed with respect to clusters 2 and 3 from both size and conditional means perspectives. In fact, the largest cluster differs from one solution to the other, cluster 3 for PCA and cluster 2 for fuzzy MCA: with respect to the latter solution, it is worth to note that the centroid 2 has values closer to the global centroid, indicating that the largest cluster indeed contains the observations

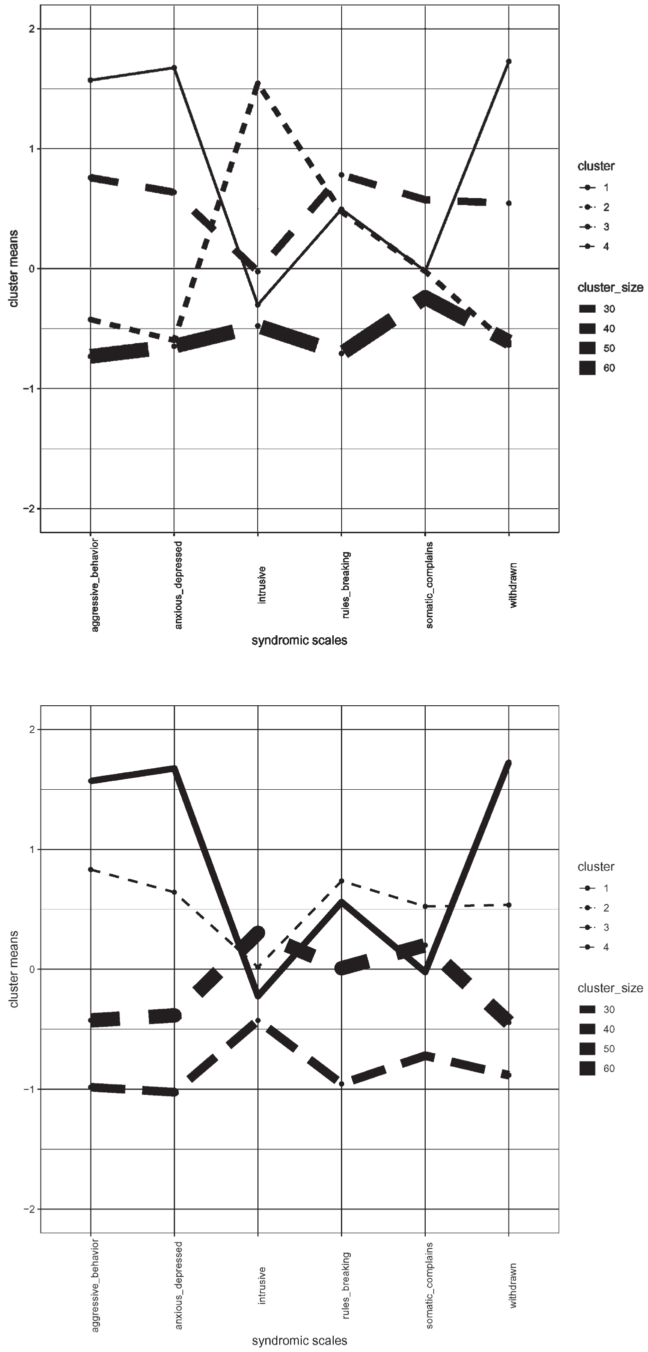

Fig. 5: Parallel coordinates plot for cluster characterization: cluster centroids and the general mean; PCA (top) vs. fuzzy MCA based clustering solutions.

with no peculiar characterization; this is not the case for the PCA-based solution, as the centroid 3 is below the global centroid for all the considered attributes. The discrepancy between the two solutions is not limited to the cluster sizes, but refers to the centroids, too: the cluster 2 centroid for the PCA-based solution is characterized by high values of *intrusive*, which is the attribute characterising most the second axis in the PCA map (Figure 4); in the fuzzy MCA map, high values of *somatic complains* scale characterises the second axis together with high values of *intrusive* scale, and this makes the cluster 2 not characterised by just one scale and therefore less peculiar.

5. DISCUSSIONS AND CONCLUSION

The fuzzy MCA proved to be capable of capturing relations that may be missed by the PCA because of their non-linearity. While the linear approximation is usually a fair approximation of more complex structures, at times it may lead to biased results and cause a poor interpretation of the results. Of course, the categorization of continuous attributes involves a loss of information that can hardly be justified by the need to apply MCA instead of PCA. When it's possible to choose from MCA and PCA there is a trade-off: the use MCA provides a more flexible synthesis at the cost of information loss (because of the crisp coding); the use of PCA preserves all the information, but it is more rigid as it only detects linear relations among variables. In this sense, the application of fuzzy MCA on soft coded data represents a sweet spot in the trade-off between keeping the coding informative (continuous) and the capability to capture non-linear relations (MCA).
There are in the literature fuzzy MCA alternatives for non linear data reduction, an example is nonlinear PCA (also known as catPCA, Linting et al., 2007): it is a versatile dimension reduction method based on different types of transformations, depending on the considered variables and on the analysis goal. A comparison of fuzzy MCA and catPCA is beyond the scope of this paper but will be further investigated in future research.
The NEETs two-step data reduction led to four different profiles of the NEET symptomatology. Among the possible configurations, the first profile is characterized by high levels of anxiety, depression, social withdrawal, and aggressive behavior. From a clinical perspective, this configuration is in line with the typical ambivalence of anxious-depressive symptomatology characterized by the oscillation between acting-out tendencies and withdrawal in adolescents (APA, 2013; Deardorff et al., 2007; Townsend, 2013; Winsor and Mueller, 2020) and young adults (van Tilburg et al., 2019). In the second profile, the medium categories of

aggressive behaviors, anxiety, depression, and social withdrawal are associated with high intrusive behavior and somatic complaints. The profile links anxious-depressive problems to the young NEETs ambivalent attitudes in the relationship with the other and to discharge in the body. The third profile presents a less malaise NEET condition. The fourth profile links high levels of rule-breaking behaviors to medium levels of somatic complaints. This configuration shows a link between externalizing problems related to the transgression of social norms and a tendency to discharge in the body. The profiles show that internalizing tendencies characterized by anxiety, depression, and withdrawal are associated with aggression problems (discharge outside the body), while externalized tendencies characterized by rule-breaking and intrusive behaviors are related to psychosomatic problems (discharge into the body).

More generally, the results show that young people NEET are vulnerable to mental health conditions. Young people struggle to find suitable employment when entering the labor market. In case of an economic crisis, the newcomers are more likely to experience a job mismatch and suffer from underemployment (Kahn, 2010). This condition can lead to internalizing and externalizing emotions-related problems. As expected, our results highlight the negative consequences of youth unemployment on mental health, in line with previous studies (*e.g.,* Bartelink et al., 2020). To our knowledge, no studies are providing mental health profiles of NEETs in Italy. For this reason, our study should also be a first attempt to bridge this gap shedding light upon the mental health of Italian NEET. However, some limitations must be acknowledged. First of all, the ASR 18-59 tests a single a-priori specified syndrome model. This questionnaire does not include all the behavioral, emotional, and social problems that may be clinically relevant for the specific NEET population. Along with this, the ASR 18-59 contains a large number of items that could cause a lower response rate, lower accuracy, and lower compliance (Revilla and Ochoa, 2017; Rolstad et al., 2011). Furthermore, the study does not consider possible protective factors that could play a moderating role in mental health. For example, the resilience levels, as well as other relational protective factors (*e.g.*, the role of the family) could explain the profile of NEETs with low distress. Future studies might consider other assessment methods. Finally, our results need to be replicated in other Italian geographical areas with different neighborhood characteristics to determine their generalizability. Sampling was purposive and cannot be seen as representative of the general population. However, this data set is effective in providing a picture of the kinds of problems of NEETs. Despite these limitations, the current findings have important conceptual and practical implications. First of all, this study confirms that the lack of educational and employment opportunities for youth in a difficult economic climate is increasingly becoming an urgent problem. The NEET mental health condition appears even more serious in light of the results on the long-term risk of youth unemployment (Strandh et al., 2014). Therefore, the instability of the current labor market might be seriously harmful. About the public policy implications, strategies to facilitate the SWT are essential. This latter should be also focused on the mental health needs of those who are NEET.

In conclusion, psychological interventions aimed to support young people in SWT are needed (Fusco et al., 2021, 2020; Parola and Marcionetti, 2020). The identification of different symptom profiles appears useful for planning career guidance interventions. Our results could be useful to guide the University Counselling Services for screening their activities. In this sense, this approach can help psychologists and career development practitioners in the assessment of NEET-related problems. Future works will tackle a comparison with other suitable approaches (catPCA, latent profile analysis) and will consider also individual variables, such as sex and duration of unemployment which could affect the mental health of NEETs.

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