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Burnout risk profiles among French psychologists☆

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ABSTRACT

The aims of this study were 1) to show that the use of different cut-off scores available in the literature can lead to erroneous conclusions, adding to the emerging literature highlighting the problems associated with its use, and 2) to propose an alternative technique – Cluster Analysis – to assess the risk of burnout as well as to identify profiles at risk of burnout.

Burnout was measured among 664 French psychologists using the French-Canadian version of the Maslach Burnout Inventory (Dion & Tessier, 1994). Our participants were classified as high on each dimension of the MBI using different cut-off scores available in the literature and using the Cluster Analysis method.

The study showed that the use of cut-off scores can indeed be misleading as conclusions may be very different according to the cut-off used. Cluster analysis allowed us to highlight four distinct burnout risk profiles: "High risk of burnout", "Risk of burnout through high emotional exhaustion", "Risk of burnout through low personal accomplishment", and "No risk of burnout". Several variables appeared as predictors of occupational burnout such as working in a company or having several different types of contracts, showing the discriminative power of clusters. Finally, a discussion is proposed on the meaning of the identified clusters and the use of this analysis in research and practice.

1. Introduction

Burnout is an important problem for many workers as it is associated with numerous consequences (Schaufeli & Buunk, 2003; Schaufeli & Enzmann, 1998), even though it is often difficult not to confuse these with its manifestations. These consequences can be observed at various levels, whether affective (e.g., depressed mood, chronic fatigue, sadness, anxiety, see Hakanen & Schaufeli, 2012), cognitive (e.g., lower personal control, deteriorated cognitive processes, see Deligkaris, Panagopoulou, Montgomery, & Masoura, 2014; Schaufeli & Buunk, 2003), physical (e.g., poorer health, illnesses, see Kahill, 1988; Shirom & Melamed, 2005), behavioral (e.g., absenteeism, turnover, see Halbesleben & Buckley, 2004; Schaufeli, Leiter, & Maslach, 2009) or motivational (e.g., low levels of organizational commitment and mental withdrawal from others (see Maslach & Pines, 1977; Taris, van Horn, Schaufeli, & Schreurs, 2004)).

Initially described by Freudenberger (1974, 1975) and Maslach (1976), burnout is characterized by three dimensions: 1) emotional exhaustion, a feeling of fatigue, of being reduced or emotionally "emptied", 2) depersonalization, a negative attitude characterized by detachment and indifference toward recipients – colleagues, patients, or clients – in a workplace (Maslach, Schaufeli, & Leiter, 2001), and 3) reduced sense of personal accomplishment, a negative evaluation of one's work accompanied by a decline of feelings of competence and poor professional self-esteem. According to the authors, a high level of emotional exhaustion associated with a high level of depersonalization and a low sense of personal accomplishment is synonymous with burnout.

If this definition seems quite clear, its assessment and in particular the assessment of its prevalence among workers using cut-off scores seems problematic and subject to some controversy, as has already been mentioned by some authors (Bianchi, 2015; Bianchi, Schonfeld, & Laurent, 2015; Leiter & Maslach, 2016; Schaufeli & Buunk, 2003; Schaufeli et al., 1993). Indeed, Maslach herself advised not to diagnose burnout using the Maslach Burnout Inventory scale (MBI, Maslach, Jackson, & Leiter, 1996, p. 9), and warned authors and

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practitioners about the misuse of the proposed cut-off (especially hers, based on tertiles), as these are only *indicators* of a degree of burnout and as such must be complemented, in daily practice, with clinical interviews and observations. Given the importance and the prevalence of burnout in our modern societies, as well as its consequences for workers and organizations (Shirom, 2005), it is important to establish means of assessing the prevalence of burnout that are less arbitrary than is currently the case. The aims of this study are thus 1) to highlight that the use of means or cut-off – available in different literatures – for categorizing workers into groups can be misleading, and 2) to propose Cluster Analysis as an alternative technique, so as to categorize individuals according to their pattern of response to the dimensions of the Maslach Burnout Inventory (MBI). We will do this by studying a large sample of French psychologists, whose burnout has never been assessed in France, but who, given the specificities of this profession, are no doubt at risk of suffering from burnout.

1.1. Assessment of burnout

The initial Maslach Burnout Inventory (MBI-HSS) and its different versions (e.g., MBI-GS (General Survey), MBI-ES (Educator Survey)) were first developed as research tools (Maslach, Leiter, & Schaufeli, 2009, p. 97). While it is no longer especially problematic for researchers to separately use all three components in their research (especially since very powerful statistical tools make it possible to study them simultaneously in relation to other variables), this poses a problem to the general public and to practitioners, who would prefer a single score and clear-cut criteria to classify people and decide if they are suffering from burnout or not. Thus, numerous attempts at classification have been proposed and used both by researchers and practitioners.

In their manual, Maslach et al. (1996) proposed to classify people according to the distribution of their score on each dimension of the MBI. Participants scoring in the upper third of the distribution are classified as being high on the dimension, while participants who *simultaneously* score in the upper third of the emotional exhaustion, depersonalization, *and* personal accomplishment subscales (the lower third for this last subscale) are classified as having a “high degree of burnout” (Maslach et al., 1996, p. 5).[1] Even though the authors warned that this method should not be used for diagnostic purposes, it has become the norm. Clearly, as stated by Schaufeli and Buunk (2003), this way of classifying a population is inappropriate inasmuch as “the cut-off points are based on arbitrary statistical norms, but also because they are computed from a composite convenience sample that is not representative” (Schaufeli & Buunk, 2003, p. 392; see also Schaufeli and Taris (2005), and Bianchi (2015), for a recent discussion of the implication of such misuse). Thus, except in the Netherlands (Schaufeli, Bakker, Hoogduin, Schaap, & Kladler, 2001), no validated cut-off scores exist for the Maslach Burnout Inventory (MBI-HSS and other versions). When authors do not use the tertile method, they often instead use means and standard deviations found in the literature (often considering a score above 1 standard deviation as being high). However, many different scores are available in the literature and can be used to assess the prevalence of burnout (Adriaenssens, De Gucht, & Maes, 2014), each presenting specific drawbacks.

This is the case of means and standard deviations found in another profession. The burnout syndrome is specific to the working context and is the result of transactions between a worker and their professional context. This includes the culture, norms, and values associated with the profession, which directly impact how workers perceive and appraise their working environment and experience burnout (Maslach et al., 2001). Thus, a given score will not refer to the same professional experience across all professions. For example, while some medical professions such as forensic surgeons traditionally cultivate cynicism, others try to cultivate altruism and encourage altruistic behaviors. While some professional cultures discourage personal complaints about workload and fatigue (e.g., doctors), others (e.g., psychologists), do encourage verbalizations about personal feelings (at least among themselves).

Other drawbacks can arise from using scales (and the associated cut-off) developed and validated in another culture. In addition to slight differences due to translations (Vallerand, 1989), people from different cultures can vary in the way they respond to scales in general (Maslach et al., 2001; Tobi & Kampen, 2013), or in the way they appraise specific organizational settings (Schaufeli & Van Dierendonck, 1995).

So, if the MBI and its different cultural versions have good psychometric properties and mostly confirm the three dimensions of the syndrome (Hwang, Scherer, & Ainina, 2003), using their cut-off scores to assess a prevalence that is not specific to a professional body and/or to a national culture may lead to erroneous conclusions. This can have important implications for researchers who base their conclusions on those a priori categories, but also for practitioners and professionals whose aim is not to study the process of burnout but to get clear-cut indicators so as to identify risk groups and/or plan specific interventions.

1.2. Cluster analysis

Though aware that this issue might remain insoluble unless norms are established for every profession and culture, we propose testing an alternative technique – Cluster Analysis – that enables the categorization of participants on the basis of their profiles of responses on a selected set of variables (here, symptoms on the MBI), while at the same time providing an idea of their level vis-à-vis those variables (Henry, Tolan, & Gorman-Smith, 2005). As the categorization is based on naturally occurring resemblances between patterns of responses from diverse participants, it provides criteria specific to the population under study. Moreover, it supplies the optimal number of groups that best describe the population under study, i.e., that “maximizes within-group similarity and minimizes between-group similarity” (Henry et al., 2005).

Finally, Cluster Analysis makes it possible to identify groups that could not have been spotted by way of classical categorizations (i.e., low, medium, high) but that nevertheless naturally occur because they do have an existence and a meaning for participants (Leiter & Maslach, 2016). The identification of such groups is important both empirically and theoretically. Empirically, it allows the identification of specific groups or at-risk groups, enabling the selection and the deployment of specific prevention and intervention programs (Clatworthy, Buick, Hankins, Weinman, & Horne, 2005). It may, in turn, substantially reduce individual (e.g., suffering, occupational outcome) and healthcare costs. Theoretically, this identification of specific groups allows us to move beyond classical categorizations and to challenge and refine theory. In the specific case of burnout, it allows us to rise above “all or nothing” conceptualizations (i.e., people suffer from burnout or they do not) and to identify subgroups of burnout according to the individual experience of work and/or specific working conditions. This idea is fairly consistent with past research in health psychology, which highlighted the existence of specific patterns or subtypes of burnout that may appear according to how employees experience and react to different working conditions (Farber & Heifetz, 1982). It is also consistent with more recent person-centered approaches, which considered “inconstant patterns” – or profiles – of burnout (i.e., high scores on one or two dimensions only) as early indicators of burnout (Boersma & Lindblom, 2009; Leiter & Maslach, 2016; Maslach & Leiter, 2008).

1.3. The identification of subgroups

The first studies that explored the existence of subgroups or profiles within the burnout literature used qualitative methods. For example,

[1] The others are described as presenting an “average degree of burnout” (second tertile) or a “low degree of burnout” (first tertile).

Farber's qualitative studies on psychotherapists and teachers (Farber, 1990, 2000) yielded the identification of three subtypes of burnout: a "worn-out" type (low dedication or passive coping style, with low stress and too little gratification), a "classic/frenetic" type (high dedication and active coping style in pursuit of accomplishment), and a "under-challenged" type (intermediate dedication, individuals faced with monotonous and unstimulating work conditions with few rewards).[2]

Following those qualitative approaches, others explored the impact of those "inconsistent" patterns by artificially creating groups by way of median splits (Maslach & Leiter, 2008) or by exploring temporal inconsistency among the levels of burnout (Leiter et al., 2013). Subsequent studies used more precise methods such as Cluster Analysis (Boersma & Lindblom, 2009; Lee, Cho, Kissinger, & Ogle, 2010). These studies confirmed the existence and pertinence of subgroups. For example, Önder and Basim (2008) asked 248 Turkish nurses to complete the MBI-HSS. Their results highlighted three distinct clusters: a "high burnout" profile, with a high score on exhaustion and depersonalization, and a low score on personal accomplishment (14.52% of the sample); a "low burnout" profile, with all three scores in the opposite direction (34.68%); and a low "personal accomplishment" profile with medium scores on exhaustion and depersonalization and low scores on personal accomplishment (50.80%). This last result suggests that these nurses are at risk of burnout through a lack of personal accomplishment.

More recently, Latent Profile Analysis – LPA – was proposed as an alternative of Cluster Analysis (Hätinen, Mäkikangas, Kinnunen, & Pekkonen, 2013; Leiter & Maslach, 2016; Mäkikangas, Hyvönen, & Feldt, 2017; Tuominen-Soini & Salmela-Aro, 2014), with the same aim of highlighting subgroups of participants or profiles. For example, using LPA, Leiter and Maslach (2016) highlighted five distinct profiles in two studies on healthcare employees: the two anticipated profiles (the burnout and the engaged profiles, respectively 8% and 44% of the study) and three "inconsistent" profiles: a disengaged profile (high cynicism, moderate scores on the other measures, 7%), an overextended profile (high exhaustion, moderate scores on the other measures, 11%), and an ineffective profile (high inefficacy, moderate scores on the other measures, 31%).

All these emerging studies show that the person-oriented approach to burnout grows in scale (Mäkikangas & Kinnunen, 2016). They have made it possible to shed light on how burnout develops over time (most studies using LPA or Cluster Analysis were longitudinal studies) but also to highlight the heterogeneity of the burnout experience (for a review, see Mäkikangas & Kinnunen, 2016). Those two techniques – LPA and Cluster Analysis – are thus very useful in determining profiles of participants and identifying the number of groups within a population that might or might not suffer from burnout, and those who might be at risk of burnout. In that sense, Latent Profile Analysis and Cluster Analysis are quite similar. Both are person-oriented techniques that aim to group together participants and to reduce complex multivariate data into smaller groups. They principally differ in their general logic. While LPA follows a confirmatory logic – a model-based approach that assumes that a k-number of probability distribution exists within the data (see for a discussion Beets & Foley, 2010) – Cluster Analysis follows an exploratory logic which does not imply a model of reference that has to be tested, nor an a priori number of groups. Because of this exploratory logic, the number of clusters can either be decided because of theoretically driven hypotheses or with the help of some statistical indicators such as the H Index, or the Bayesian Index Criterion (see for a review, Clatworthy et al., 2005, and also Leonard & Droege, 2008). Note that the large panel of indices available in LPA does not make the choice easier. Indeed, those indices regularly contradict each other, which entails that the researcher often has to make a decision based on the sense a solution has with regard to their hypotheses/model. Moreover, the examination of the agglomeration schedule and the dendogram in Cluster Analysis can also be very helpful in deciding the optimal number of clusters and in seeing how the clusters agglomerate and are linked together (Yim & Ramdeen, 2015). Finally, once the criterion has been chosen, the number and type of clusters are quite stable over time (Boersma & Lindblom, 2009).

1.4. *Burnout among psychologists*

If burnout is now recognized in most professions, it has initially and specifically been described among helping professions (Lloyd & King, 2004; Nelson, Johnson, & Bebbington, 2009; Prosser et al., 1999) because of frequent and emotionally costly contacts with recipients who require attention in the context of a care relationship (Maslach, 1982; Maslach & Leiter, 2008). Despite the great interest in the study of burnout in professions such as physicians and nurses (Leiter, Frank, & Matheson, 2009; Schaufeli, 2007; Schaufeli et al., 2009), psychologists have received much less attention and, to our knowledge, have never been studied in the French context. However, based on available studies (Ackerley, Burnell, Holder, & Kurdek, 1988; Farber & Heifetz, 1982; Raquepaw & Miller, 1989; Ross, Altmaier, & Russell, 1989; Rupert & Kent, 2007; Rupert & Morgan, 2005; Vredenburgh, Carlozzi, & Stein, 1999), and on a recent survey showing that French psychologists are stressed and experience difficult working conditions (Berjot, Altintas, Lesage, & Grebot, 2013), we can formulate the hypothesis that French psychologists might suffer from burnout or be at risk of suffering burnout. At least two clusters should appear: a burnout cluster and a no burnout cluster. Given the specificities of this population and past studies, we also might expect a cluster with only high emotional exhaustion, psychologists being generally high on this symptom (Raquepaw & Miller, 1989; Rupert & Kent, 2007; Rupert & Morgan, 2005; Rzeszutek & Schier, 2014; Senter, Morgan, Serna-McDonald, & Bewley, 2010) − even though the prevalence of burnout largely differs according to sociodemographic variables such as age, seniority, gender and type of practice (Rupert & Kent, 2007; Vredenburgh et al., 1999). Finally, given the actual professional context of French psychologists and their professional constraints and lack of recognition (Berjot et al., 2013), we might expect a cluster with only low scores on the personal accomplishment subscale.

As already mentioned, the aim of this study was to highlight that the use of cut-off scores can be misleading, and to propose an alternative to those scores to assess the prevalence of burnout and to identify groups at risk of burnout. To this end, we will first classify our population using different cut-off scores available in the literature. We will then run a Cluster Analysis to identify the number and types of clusters that describe our population. Finally, we will briefly study the impact of clusters on some organizational variables (i.e., type of practice and type of contract) so as to see if clusters can discriminate between those working conditions.

2. The present study

2.1. *Materials and method*

2.1.1. *Participants and procedure*

The sample for this study comprised 664 psychologists (M_{age} = 35.44, SD = 9.83), 66 of whom were men and 598 women.[3] The selection took place over eight months via a call for voluntary participation posted on the respective websites of the French Society of Psychology (FSP) and the French Federation of Psychologists and Psychotherapists (FFPP), or directly via our professional acquaintances. Only one inclusion criterion guided the recruitment of participants: occupying a position as a professional psychologist (i.e., actually

[2] Based on Farber's work, Montero-Marin et al. (2012) proposed a tool that assesses those subtypes of burnout (the BCSQ, for Burnout Clinical Subtype Questionnaire), with the aim of better adjusting therapeutic actions.

[3] As no official statistics exist about the number of psychologists working in France, it is impossible to compare this distribution to a baseline. Nevertheless, it is true that more than 80% of psychology graduates are women. Our sample might then have an over-occurrence of women.

practicing psychology in any area of the field of psychology).[4] Participants responded online on a secure server (https) hosted by an external association.

2.2. Measures

2.2.1. Sociodemographical and organizational variables

Data were collected on age, gender, seniority of position, workplace (i.e., public or private hospital, non-profit organization, governmental administration, private and independent practice, company), type of contract (i.e., permanent contract, fixed-term contract, self-employment, mixed contracts, voluntary work), and working pattern (i.e., full-time, part-time, full-time with different employers, specific cases).

2.2.2. Burnout

Burnout was assessed using the French-Canadian version of the Maslach Burnout Inventory Human Service Survey (Maslach et al., 1996), translated and validated into French by Dion and Tessier (1994).[5] This questionnaire consists of 22 items and assesses burnout using its three components: (1) Emotional Exhaustion – EE – 9 items, $\alpha = 0.88$; (2) Personal Accomplishment – PA – 8 items, $\alpha = 0.77$; and (3) Depersonalization – DP – 5 items, $\alpha = 0.70$. For each statement, the respondent indicates the frequency of symptoms on a Likert-type scale going from 0 (never) to 6 (every day). The French version validated by Dion & Tessier has shown satisfactory psychometric properties (alpha = 0.90, 0.71 and 0.79, respectively for EE, PA, and DP). However, given the relative inconsistent results found for the different versions of this scale across cultures (Loera, Converso, & Viotti, 2014; Pisanti, Lombardo, Lucidi, Violani, & Lazzari, 2013), we ran an exploratory factorial analysis (with Statistica 10®, varimax rotation). The results showed that a three-factor solution adequately captured the data, explaining 47.85% of the total variance (38.7% in Dion & Tessier's study). All items loaded on their respective dimensions, with loadings going from 0.48 to 0.87 for EE, from −0.49 to −0.70 for PA and from 0.47 to 0.72 for DP. Only one cross-loading was found for item 12 (loading = −0.52 on its own dimension – AP – but −0.43 on EE). Given the general structure and the adequate alphas,[6] we decided to compute scores as suggested by Dion & Tessier and to keep all 22 items (based on Maslach et al., 1996).

3. Results

3.1. Descriptive analysis

The scores on the three dimensions of the MBI dimensions followed a normal although slightly asymmetrical distribution, as is usually the case with the dimensions of the MBI scale (respectively for EE, DP, and PA, K-S = 0.07, $p < 0.01$, 0.13, $p < 0.01$ and 0.07, $p < 0.01$). The results showed that our population of psychologists have a mean age of 35.4 years (SD = 9.83) and a mean seniority of 8.01 years (SD = 8, 43). The results also indicated that 90.1% of participants in the sample were female, 43.7% worked in a public hospital, 20.9% in non-profit organizations (20.9%), and 10.7% in governmental organizations. Most of our population have a full-time job (48.2%) or a part-time one (44.3%). Most of them have a permanent contract (69.4%), while 22.1% have a fixed-term contract (Table 1).

Table 1
Means, standard deviations, and correlations among continuous variables.

	Scale	Means Total scores	Std.Dev.	EE	PA	DP
Emotional Exhaustion	2–52	24.50	8.49			
Personal Accomplishment	15–47	33.76	5.13	−0.32		
Depersonalization	0–25	9.41	3.80	0.47	−0.30	

EE for Emotional Exhaustion, PA for Perceived Personal Accomplishment, DP for Depersonalization.

3.2. Classification of participants according to existing cut-off scores

We classified our sample according to five types of cut-off scores: the tertile method listed by Maslach et al. (1996) in their manual, two of the cut-off scores proposed in the Maslach et al. (1996) manual (those based on the overall sample and those based on a sample of mental health professionals), and two cut-off scores based on a version validated in French: those proposed by Dion & Tessier (1994: sample of nurses) and those proposed by Canoui and Mauranges (2001: sample of general practitioners). For each type of cut-off, we assessed the percentage of our sample classified as high on each symptom and classified as high concomitantly on the three dimensions. The results are very different depending on the cut-off scores used (see Table 2).

Unsurprisingly, using the standard Maslach criteria (classifying the upper third as being at high risk), our results showed that about a third of our population was at risk on each of the three dimensions of the MBI. However, only 10.8% of our population could be categorized as high concomitantly on all three manifestations. The use of the Maslach et al. (1996) cut-offs (mental health professionals) showed very high percentages on EE and on DP, low percentages on PA, for an overall prevalence of 10.5%. Finally, the use of Dion and Tessier's cut-off scores (1994) showed that about a third of our psychologists were classified as high on EE. However, many were classified as high on DP as well as on PA, for an overall prevalence of 19.6%. This prevalence with those cut-off scores was then twice as high as the one obtained with Maslach's cut-off scores (mental health).

3.3. Hierarchical cluster analysis

For our purposes, we followed the procedure proposed by Clatworthy et al. (2005) for research in health psychology. More specifically, we first of all ran a hierarchical Cluster Analysis using Ward's method and the squared Euclidean distance to determine profiles of participants according to their z scores on each subscale of the MBI (with Statistica 7®) (Hair, Black, Babin, & Anderson, 2009).[8] The hierarchical Cluster Analysis run on the participants suggested a four-cluster solution as shown by an examination of the dendogram (the distance between a four- and a five-groups solution – bottom of the figure – was small). The Bayesian Index Criterion (Schwarz, 1978) confirmed the four-cluster solution as the lowest value was observed for this solution (calculated with SPSS17®). This procedure was replicated on two subsamples chosen arbitrarily on the base of age: those with an even age ($N = 359$) and those with an odd age ($N = 305$), as advised by Clatworthy et al. (2005). Because the Bayesian Index Criterion confirmed the four-cluster solution for both subsamples and because the distribution of participants into those four clusters was about the same

[4] The title "psychologist" is protected by French law. Professionals have to complete five years of studies in psychology and be registered in a national database in order to practice psychology (they receive a registered personal number). They can practice their profession in any area of psychology (e.g. clinician, psychotherapeutic, neuropsychologist, human relation). Researchers in psychology (who do have the title of psychologist, but most of whom do not practice psychology) were excluded from the database.

[5] As no version validated into French is currently available.

[6] The alpha decreases after deletion of item 12.

[7] Given that the higher correlation between emotional exhaustion, depersonalization, and perceived personal accomplishment was 0.47, multicollinearity was not an issue.

[8] Note that this text from Yim & Ramdeen also comprises a very user-friendly explanation of what Cluster Analysis is and of the different outputs and options that are available as well as the rationale behind their use.

Table 2
Assessment of the risk of burnout using different cut-off scores and the Cluster Analysis technique.

	Upper third	Dion & Tessier (1994) Nurses (n = 123)	Maslach et al. (1996) Overall sample (n = 11 067)	Maslach et al. (1996) Mental health (n = 730)	Canoui & Mauranges (2001) (N = 480)[7]	Cluster analysis
Cut-off scores						–
EE	> = 28	> = 28	> = 27	> = 21	> = 30	
DP	> = 11	> = 8	> = 13	> = 8	> = 12	
PA	< = 32	< = 34	< = 31	< = 28	< = 33	
		Overall = 9.8%	Overall = not given	Overall = not given	Overall = 5%	
% of our population						
EE	33.60%	33.60%	37.40%	63.10%	26.70%	
DP	31.50%	65.50%	19%	65.50%	25.80%	
PA	38.10%	54.70%	29.50%	14.60%	47.60%	
	Overall = 10.8%	Overall = 19.6%	Overall = 7.8%	Overall = 10.5%	Overall = 9.2%	Overall = 22.9%
z Scores						
EE	0.41	0.39	0.56	0.46	Means and SD not available	1.03
DP	0.42	0.33	0.73	0.49		1.31
PA	−0.34	−0.45	−0.5	−0.45		−0.85

Note: EE = Emotional Exhaustion, DP = Depersonalization, PA = Personal Accomplishment.
z scores calculated with mean and standard deviations of the original respective samples.

as for the whole population, we chose to pursue the analysis on the whole sample.

To confirm the four-cluster solution (Blashfield & Aldenderfer, 1988; Ransom & Fisher, 1995), we then ran a k-mean Cluster Analysis on the numbers of clusters emerging in the hierarchical Cluster Analysis.

As shown in Fig. 2, cluster 1 (labeled “High risk of burnout” profile, $N = 152$; 22.9%) included psychologists who had concomitantly relatively high levels of emotional exhaustion and depersonalization and a low level of perceived personal accomplishment (i.e., z scores above 1 standard deviation for EE and DP, and very near 1 standard deviation for PA). Cluster 2 (“Risk of burnout through low personal accomplishment” profile, $N = 180$; 27.1%) included psychologists who had concomitantly low levels of emotional exhaustion and depersonalization but also a low level of personal accomplishment. Cluster 3 (“Risk of burnout through emotional exhaustion” profile, $N = 186$; 28%) was characterized by a moderate to high level of emotional exhaustion, and moderate levels of depersonalization and personal accomplishment. Finally, Cluster 4 (“No risk of burnout” profile, $N = 146$; 22%) was characterized by low levels of emotional exhaustion and depersonalization and a high level of personal accomplishment. Moreover, as indicated by the dendogram (see Fig. 1), we can see how those four clusters are linked together. On the one hand, clusters 1 (high risk) and 2 (low personal accomplishment) agglomerate themselves into a higher-order group and on the other hand clusters 3 (high emotional exhaustion) and 4 (No risk of burnout) agglomerate themselves into another higher-order group.

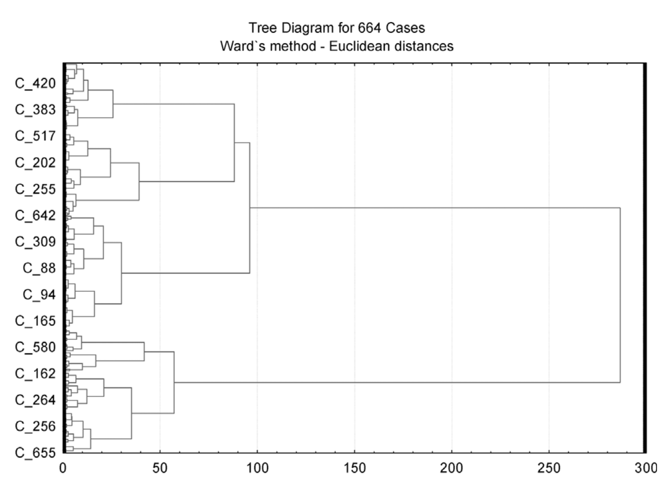

Fig. 1. Dendogram for the 664 participants.

Finally, we ran a two-way ANOVA with repeated measures with clusters as an independent variable and each dimension of the MBI as

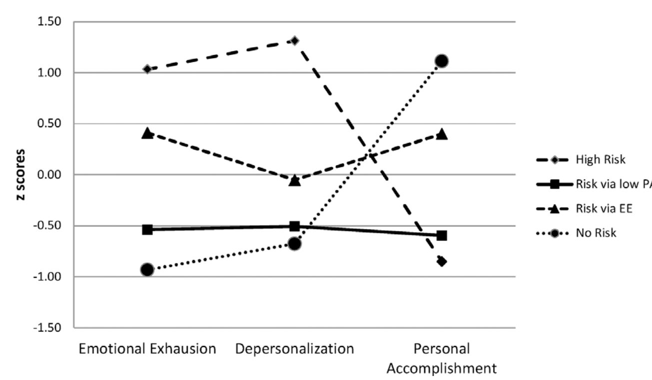

Fig. 2. Plot of means for each variable according to clusters (N = 664).

Table 3
Global scores, mean scores and z scores (and standard deviations) for each dimension of the MBI scale according to clusters.

	Cluster 1 High risk of burnout *n = 152*	Cluster 2 Low personal accomplishment *n = 180*	Cluster 3 Risk of emotional exhaustion *n = 186*	Cluster 4 No risk of burnout *n = 146*
Emotional exhaustion				
Total score (SD)	33.28_a (7.89)	19.92_b (5.07)	27.98_c (4.72)	16.58_d (4.42)
Mean (SD)	3.70	2.21	3.11	1.84
z score	1.03	−0.54	0.41	−0.93
Depersonalization				
Total score (SD)	14.39_a (3.24)	7.48_b (2.20)	9.22_c (2.29)	6.84_b (2.24)
Mean (SD)	2.88	1.50	1.84	1.37
z score	1.31	−0.51	−0.05	−0.68
Personal accomplishment				
Total score (SD)	29.41_a (4.33)	30.70_a (3.18)	35.81_b (2.81)	39.47_c (2.89)
Mean (SD)	3.68	3.84	4.48	4.93
z score	−0.85	−0.60	0.40	1.11

Note: For each dependent variable, means with different subscripts indicate a significant difference at $p < 0.05$ using the Tukey HSD test.

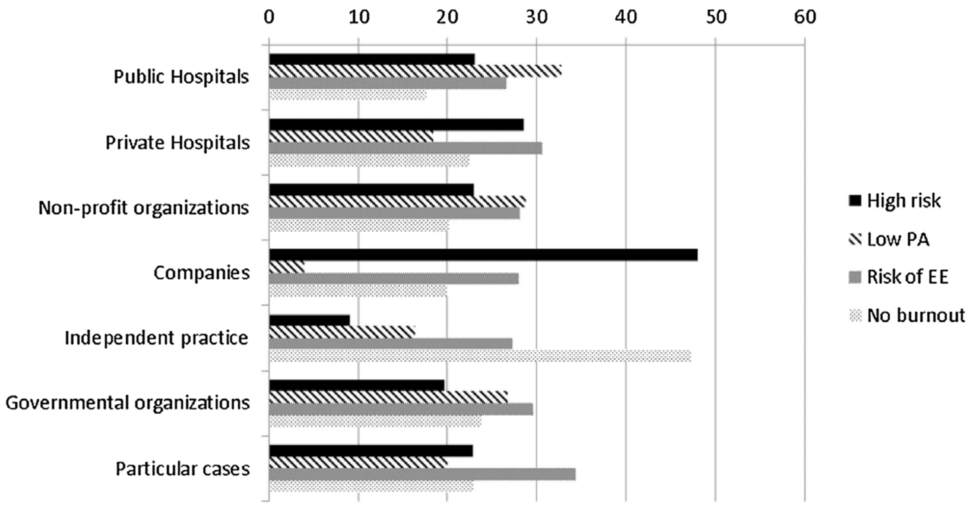

Fig. 3. Percentage of psychologists in each cluster according to workplace.

dependent variables (z scores). The main effect of clusters ($F[3,660] = 258.1$; $p < 0.001$, $\eta^2 = 0.54$) as well as the interaction between clusters and dimensions were both significant ($F[6,1320] = 2306.6$; $p < 0.001$, $\eta^2 = 0.58$). As shown in Table 3, clusters differed on emotional exhaustion, with the "High risk of burnout" cluster presenting the highest score on this dimension and the "No risk of burnout" cluster the lowest. They also differed on depersonalization except between the "Low personal accomplishment" and the "No risk of burnout" clusters, which did not differ from each other. Finally, clusters also differed on personal accomplishment, the "No risk of burnout" cluster presenting the highest score, followed by "High emotional exhaustion", and the other two clusters.

3.4. Demographical and organizational factors associated with burnout profiles

The distribution of the workplace according to clusters was significant (*Chi2 corrected* = 45.2, $dl = 18$, $p < 0.001$). As shown in Fig. 3, psychologists working in private hospitals (28.6%), and in companies (48%) were particularly numerous in the "High risk of burnout" cluster. On the contrary, only 9.1% of psychologists with an independent practice appear in that cluster, while 47.3% appear in the "No risk of burnout" cluster. We notice also that the "Low personal accomplishment" cluster was principally composed of psychologists working in public hospitals (32.8%) and to a lesser extent of psychologists working in non-profit organizations (28.8%) and governmental organizations (26.8%). The "Risk of emotional exhaustion" cluster was composed of psychologists working in private hospitals (30.6%) and in governmental organizations (29.6%).

The distribution of clusters according to the type of contracts was also significant (*Chi2 corrected* = 529.7, $dl = 18$, $p < 0.001$). While those with an independent status were particularly numerous in the no burnout cluster (51.40%), 37.41% of the psychologists working with a fixed-term contract were in the "Low personal accomplishment" cluster and 52.6% of those having several contracts were in the "Risk of emotional exhaustion" cluster (see Fig. 4).

The distribution between clusters and working time was equivalent (*Chi2 corrected* = 19.6, $dl = 15$, *ns*). Working time did not seem to be linked to burnout.

Finally, the impact of clusters on age and seniority was significant (respectively $F[3,660] = 8.5$; $p < 0.001$, $\eta^2 = 0.04$ and $F[3,660] = 3.4$; $p < 0.002$, $\eta^2 = 0.02$). Psychologists in the "High risk of burnout" cluster were the youngest ($M = 33.67$, $SD = 9.39$), significantly younger than those in the "No risk of burnout" cluster ($M = 38.62$, $SD = 10.24$, $p < 0.001$). Psychologists in the "Low personal accomplishment" cluster ($M = 33.94$, $SD = 9.29$) also differed significantly from those in the "No risk of burnout" cluster, who were the oldest ($p < 0.001$). Psychologists in the "Risk of emotional exhaustion" cluster were in between ($M = 35.86$, $SD = 9.77$). As for seniority, psychologists in the "low personal accomplishment" cluster had the lowest seniority ($M = 7.01$, $SD = 9.91$), significantly different from that of psychologists in the "No risk of burnout" cluster ($M = 9.64$, $SD = 8.81$, $p = 0.03$), who had the highest seniority. Psychologists in the "High risk" cluster ($M = 7.11$, $SD = 8.26$) also differed significantly from those in cluster 4 ("No risk"). Again, psychologists in the "Risk of emotional exhaustion" cluster were in between ($M = 8.42$, $SD = 5.59$).

4. Discussion

The aim of this study was to emphasize that the use of cut-off scores that are not specific to a professional population and/or extracted from another linguistic version of the scale has little sense and can lead to very different results according to which scores are used. The aim was also to propose an alternative technique, namely Cluster Analysis, which can be used instead of cut-off to group together participants of a specific profession according to their responses on the MBI (see Appendix A for a detailed procedure using Statistica 7; see also Yim & Ramdeen, 2015 for a detailed and easy procedure using SPSS[9]). We did this by surveying a large sample of French psychologists whose working conditions suggest that they may suffer from burnout or be at risk on some dimensions (i.e., especially emotional exhaustion and lack of personal accomplishment because of professional constraints and a significant lack of recognition).

As expected, the categorization of our sample according to different cut-off scores yielded very different results confirming that their use can be highly misleading. Our analysis yielded also four different profiles, based on participants' levels on the three dimensions of burnout.[10] On the one hand, we found two consistent profiles, a "High risk of burnout" profile (22.90%) and a "No risk of burnout" profile (22%). Note that the prevalence of burnout found with this method is close to that found when using Dion & Tessier's scores. This prevalence is also relatively consistent with those that can be found in the literature. Moreover, the organizational variables that were linked with the clusters in our population were coherent with past studies (Rupert & Kent, 2007), showing that psychologists are more at risk of burnout when working in

[9] Using z scores and 1 standard deviation as standpoints which, as will be discussed, can be criteria but are not restrictive enough.

[10] Practitioners may find all kinds of advice on the Internet on how to run Cluster Analyses using different tools such as Statistica, SPSS, SAS, or R. The procedure using the Statistica 10 software is displayed in the Appendix A.

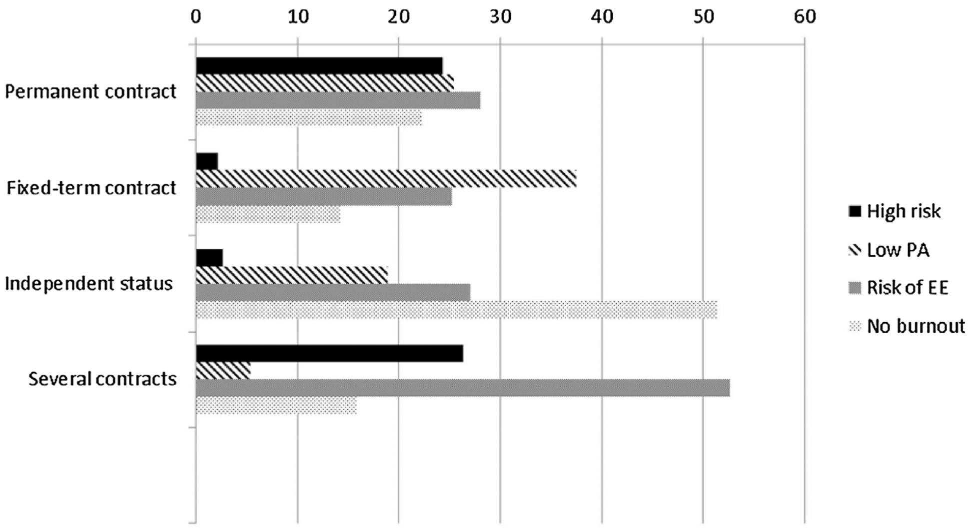

Fig. 4. Percentage of psychologists in each cluster according to type of contract.

companies or in private hospitals than when they are independent (Farber & Heifetz, 1982; Rupert & Kent, 2007). It is important to note, however, that those results are only indicators of links between some of our sociodemographic variables – in particular the type of practice – and burnout. It is also possible that the lower prevalence of burnout among those psychologists in independent practice may be explained by other individual variables that may have influenced their resistance to burnout and/or their personal choice of practice (Garden, 1987; Garden, 1989; Rzeszutek & Schier, 2014).

On the other hand, our analysis also highlighted two inconsistent profiles: a "Risk of burnout through emotional exhaustion" cluster and a profile labeled "Risk of burnout through low personal accomplishment". If those two groups cannot be classified as suffering burnout nor as *not suffering* burnout, they can nevertheless be described as groups "at risk of burnout", composed of professionals who may one day suffer burnout if environmental demands and threats remain high while resources remain low. This is in line with previous research which has described inconsistent patterns as an indicator of risk of burnout (Leiter & Maslach, 2016; Maslach & Leiter 2008). Although burnout is supposed to be quite stable over time (Schaufeli et al., 2009; Shirom, 2005), it has been shown that workers with an inconsistent pattern tend to resolve the contradiction toward consistency either toward burnout or no burnout (Maslach & Leiter, 2008). In their study, the feeling of being treated unfairly at work predicted the resolution of the inconsistency toward burnout.

Although more studies are necessary to draw definitive conclusions about the nature of these two specific patterns, the low sense of accomplishment experienced by French psychologists may be understood in the light of their current working conditions. In a recent study, Berjot et al. (2013) asked French psychologists to answer an open question about professional situations they had experienced that had particularly affected them personally or professionally. The results showed that about 30% of the occurrences concerned psychologists' psychological experience of work: of these psychological experiences, approximately 54% concerned the lack of recognition and the denigration of psychologists' skills. These results are quite consistent with the experience of therapeutic practice described by Farber & Heifetz (1982) – even if our population also included psychologists whose job is not strictly therapeutic – and suggest the existence of burnout subtypes that may appear according to how employees experience and react to different working conditions (Montero-Marin et al., 2012). They are also consistent with existing organizational models such as the Job Demands-Resources model (Demerouti, Bakker, Nachreiner, & Schaufeli, 2001), which predicts that work demands will particularly impact emotional exhaustion while the lack of resources will impact depersonalization and personal accomplishment (Bakker, Demerouti, & Euwema, 2005; Bakker, Demerouti, Taris, Schaufeli, & Schreurs, 2003).

Working environments with high demands (e.g., high workload, focus on profitability) *and* low resources (e.g., lack of recognition) will foster burnout. This might explain the high number of psychologists working in public hospitals or in governmental organizations in the "Risk through low PA" cluster, as these are environments in which recognition and material/financial resources are generally low. This might also explain the high number of psychologists working in companies in the "high risk of burnout" cluster (to a lesser extent in private and public hospitals), as they experience both highly constraining environments (e.g., profitability, time pressure, lack of personal space to practice) and low resources (e.g., low recognition: Berjot et al., 2013). In any case, the links that we observed between our cluster and organizational variables are consistent with the literature and show that the categorization identified by Cluster Analysis is discriminative and makes sense with regard to the working conditions of our psychologists.

These results add, then, to the existing literature showing that distinct and specific profiles exist within professions (Lee et al., 2010; Önder & Basim, 2008). While Lee and colleagues (2010) highlighted four clusters among their sample of students, Önder and Basim (2008) highlighted only three clusters among their nurses (including one with low PA). Studies that used non-specific samples (i.e., employees), such as the Leiter and Maslach (2016) or the Boersma and Lindblom (2009) studies, generally found more clusters (five in the first one and six in the second), surely revealing the heterogeneity of the sample and their specific experience of their working environments. In any case, all studies highlighted at least two consistent clusters (i.e., the high risk and the low risk of burnout clusters) but differed in the number of inconsistent clusters they found. While most studies found a "low personal accomplishment" profile, all did not observe the other two theoretically possible clusters (exhaustion alone, and cynicism/depersonalization alone). This is the case of our study, which did not find a "depersonalization only" cluster. It is indeed quite difficult to imagine an energetic psychologist who thinks he is efficient while being cynical and distant toward his patients.

Finally, some studies found very distinctive profiles. This was the case of the Boersma and Lindblom study (2009) and of Lee et al.'s study, but also of Leiter and Maslach's study (2016, Study 2 only), which observed a profile with workers presenting high levels of personal accomplishment combined with high levels of exhaustion *and* depersonalization (respectively called the "persevering group", "burnout with intact professional efficacy", and "disengaged"). This suggests that inconsistent patterns can also comprise two (instead of only one) dimension of the syndrome. As stated by Leiter and Maslach (2016), more research is needed to explore the conditions in which such profiles appear.

Most previous studies using CA or LPA aimed at analyzing the development of burnout over time and/or identifying the organizational factors that could explain the switch from one profile to another. Our study confirmed the usefulness of taking this person-centered approach as it reproduced the existence of inconsistent profiles. But it also confirmed that all theoretically possible profiles are not always identifiable within a particular population and encourages future research to pursue such an approach. It also adds that this approach − in particular using CA − can also be used to assess the prevalence of burnout, which can be useful to researchers but also to practitioners who need to categorize a professional population so as to prevent and/or design intervention programs. Even if this approach necessitates running the analysis on each sample, it is nevertheless more valid and less risky than using existing cut-off scores that make no sense for the population under study. Finally, Cluster Analysis allows us to visualize the relations between clusters. In our case, the "High risk of burnout" cluster more closely resembled the "Low personal accomplishment" cluster than it did the two others, suggesting that those psychologists in this last cluster may be more at risk of suffering from burnout one day than the other two. This piece of information might be useful for practitioners or companies who wish to identify the organizational factors where action may need to be taken rapidly.

4.1. Implication for practice

Because of its exploratory nature, Cluster Analysis allows the researcher or practitioner to describe their population and obtain specific criteria to classify it. It also highlights specific groups that may benefit from different and more focused interventions (i.e., the groups at risk through one or other of the symptoms). But Cluster Analysis can also be used in a more restrictive way if one needs more restricted criteria. Indeed, depending on the focus, a more fine-grained solution may be preferable to a standard solution that is recommended by statistical indices. This may be the case if practitioners are seeking or required to diagnose burnout, i.e., to pinpoint those who are likely to develop a stress-related illness, requiring sick leave or justifying health insurance benefits. Cluster Analysis, though less powerful than LPA, does nevertheless possess its own criterion and indices but for non-statisticians is above all far less complicated and difficult to master as a technique than LPA.[11] Finally, Cluster Analysis does not necessitate a large sample, as is the case for confirmatory analysis such as LPA.

4.2. Limitations

Lastly, it is important to point out that this study suffers from certain limitations. First of all, the sample, as just mentioned, may not be representative of the population of French psychologists as a whole. Indeed, most of the survey participants were women, and although they indeed represent a disproportionate portion of psychologists in France (and a disproportionate portion of psychology students), the actual distribution in the sample might over-represent women. However, no official statistics exist about the characteristics of this population. It is therefore impossible to estimate to what extent the distribution does or does not reflect reality. Moreover, the way participants were recruited may have partially biased the results, as two thirds of the participants responded to the study through the website of one of the two national associations.

Conflict of interest

None.

Thumbnail sketch

This study shows how the use of cut-off scores to assess burnout prevalence can lead to ambiguous or erroneous conclusions. An alternative statistic, based on participant resemblance to the dimensions of the Maslach Burnout Inventory, is suggested. This statistic enables the identification of four distinct risk profiles, and so suggests a more appropriate set of measures and analyses.

Acknowledgement

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Appendix A. Dataset

Several statistical tools are available to run Cluster Analyses (e.g., SPSS, SAS, R, Statistica).

Readers will find a easy-to-follow procedure using SPSS in Yim and Ramdeen (2015). This paper also includes a very simple description of what CA is and of some of its principal measures (including a very straightforward description of how to decide on the number of clusters from the dendogram).

We will describe here a short step-by-step tutorial to run Cluster Analysis on the MBI's scores using Statistica 7©.

Dataset

In Statistica, your participants must be entered in row and your scores entered in three distinct columns.

12. Standardize your scores

The first step (as Statistica, unlike SPSS, does not do this automatically) is to standardize the three scores.[12] Click on "Data", then on "Standardize". Then select your variables (here, the three scores corresponding to the three dimensions of the MBI), and click on OK. Your variables are then standardized.

[11] (Scores − Mean Score)/Standard deviation. This way, zero will represent the mean of your sample, and −1 and +1 the standard deviations.

[12] As explained by Yim and Ramdeen (2015), the single linkage technique will cluster together cases that share the minimum distance. This is not what we are aiming for as this means that some clusters can be formed simply because of one case that is very close to the one in the next cluster.

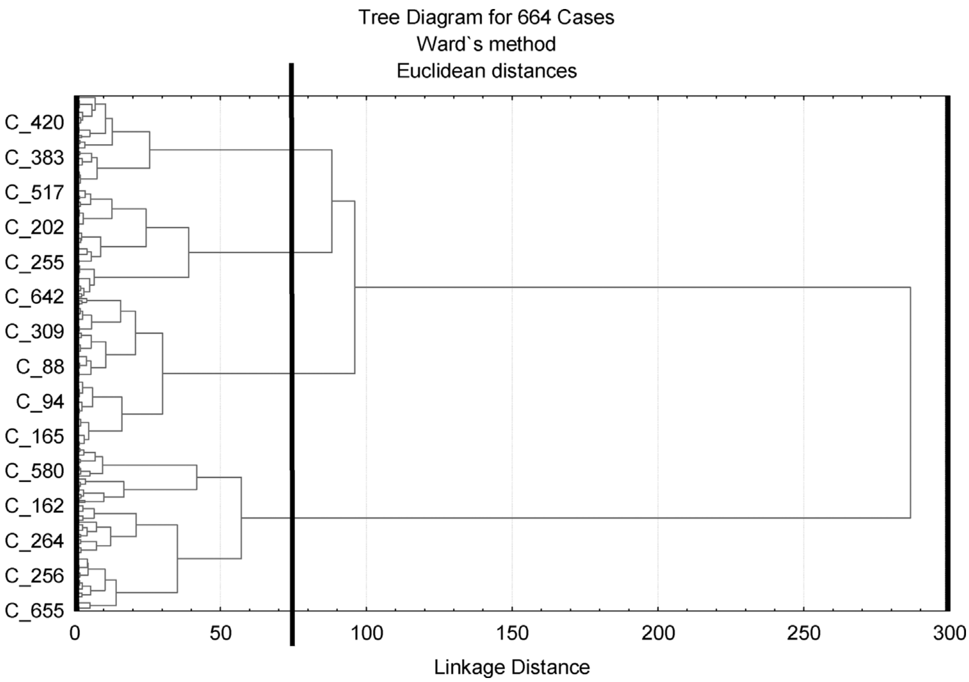

Fig. A1. Dendogram (horizontal).

13. Cluster Analysis – Step one: Hierarchical

Once your scores are standardized, click on Statistics, then on "Multivariate Exploratory Techniques", then on "Joining Tree Clustering" (which corresponds to the hierarchical analysis). Once in this menu, enter your three variables (the standardized ones).

In the Advanced tab, choose clustering on "Cases" (rows) instead of "Variables" (columns), and choose as an amalgamation rule (Linkage Method) the "Ward Method" as advised by Clatworthy et al., 2005 (by default the "Single Linkage" is available, but we do not want to select this one[13]). The default distance measure in Statistica is Euclidian Distances, which is the one that is wanted here, so, do not modify the distance measure.

Once this is done, click OK. On the next page, you can choose either the Vertical or the Horizontal dendogram (See Fig. A1 for an example on our data).

The vertical lines correspond to the distance between clusters. The horizontal lines represent the differences between these distances. They also connect the "cases" (individuals, then further on, small clusters). As we wish to obtain a number of clusters that make sense and are different from each other, we will draw a vertical line in a spot that contains long horizontal lines (once they become small, this means that the two clusters that have previously been agglomerated are more similar to each other), but not the longest ones. Then, count the number of lines that are crossed to get the number of clusters. Here, we choose four clusters.

Cluster analysis – Step two: K-means clustering

Once you have determined the number of clusters, go back to the Statistics menu, and again select "Multivariate Exploratory Techniques", then "K-Means Clustering" (which corresponds to the clustering). Once in this menu, enter your three variables (again, the standardized ones) and choose to cluster on "Cases" (not variables). Then select the number of clusters on which you want to perform the analysis (here four), and click OK.

The next menu gives you access to all the statistics you need. Of interest is the Graph of Means (see Fig. 2), which gives you the standardized scores of each of your clusters on each variable. Scores that are around zero are average, those near or above 1 are high and those near 1 or under are low. You can also obtain descriptive statistics including the number of participants in each cluster and save the classification in you dataset so as to have a variable with the cluster's number for each of your participants.

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[13] Cut-off scores reported by Cathébras, Bego, Laporte, Bois, and Truchot, 2004.

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