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Network Analysis of Social Representations for Community Detection

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This article proposes a new approach to the study of social representations which aims at studying them from the perspective of network analysis and graph theory. To do so, we consider networks integrating both the constituent elements of the representations (opinions, beliefs) and the individuals who adhere to these elements or are bearers of them. In this perspective, a representation network is presented as a set of nodes (opinions, beliefs, individuals) and links (the adherence of an individual to an opinion is considered as a link between this individual and the opinion to which he adheres). This procedure allows us to apply the algorithms developed in the field of network analysis for the detection of communities to the studied representation network. Three studies illustrate the proposed approach by showing that it makes it possible to identify the heterogeneity or homogeneity of a group interviewed during a social representation study.

Key words : social representation, group, network analysis, community, betweeness centrality.

When he proposes his theory of social representations, Moscovici (1976) both draws inspiration from and departs from Durkheim (1898) who had suggested the notion of collective representation. Indeed, for Durkheim, collective representations correspond to forms of shared

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knowledge or beliefs that are different from individual representations because they are "external to individual consciousnesses[1]" (p. 295). They are not the fruits of individual acts of thought but that of the aggregations of these acts of thought. By being inscribed in the globality of a society, in its practices, in its traditions and its institutions, they impose themselves to all. It is in this way that the representations of which Durkheim speaks are 'collective'. The notion thus inspires Moscovici because it refers to a phenomenon of collective thought, distinct from individual thought. But he distances himself from it because he finds it too static and ill-adapted to modern societies. He prefers the notion of social representation more adapted according to him to the "perspective of a society which changes" (Moscovici, 1989, p. 82) and to the taking into account of the communication relationships between the social groups which form this society. In Moscovici's proposal, as in Durkheim's, the representations are indeed the fruits of an amalgam of individual acts of thought that form a whole exceeding the parts. But for Moscovici the determinants of the phenomenon are situated at the level of social groups and their interactions, not at the level of the globality of a society. This is what leads him to write that a representation: "translates the relationship of a group to a socially valued object [...] insofar as it differentiates one group from another" (Moscovici, 1976, p. 73). Based on these propositions, much exploratory research has been conducted on social representations (SR). In these works, researchers usually try to identify the contents of a SR in a given social group, or to compare the contents of the same SR shared by different groups (e.g., Papastamou & Moliner, 2021; Lo Monaco et al., 2016; Sammut et al., 2015). But these researches rarely question the homogeneity of the social groups they solicit. When they do, it is most often to try to explain a posteriori unconvincing results by the observed heterogeneity of these groups. But when we observe great heterogeneity in a SR, how should we interpret it? Should it be attributed to the heterogeneity of the group surveyed? Or should we conclude that there are no shared beliefs and therefore no SR in the group surveyed? This article proposes a new approach to the study of SRs which we believe could help answer this question.

SOCIAL REPRESENTATIONS

SR theory (Moscovici, 1976) has been widely disseminated and now appears as one of the major theories of social psychology (see Van Lange et al., 2012). This is why we will only give a brief presentation of it here, referring the reader to references that present it in detail (Moliner,

[1] Our translation (also for the following extracts from French authors).

2020; Rateau et al., 2011; Wagner et al., 1999). It should be remembered, however, that SRs take the form of sets of information, opinions and beliefs relating to a given object in the social environment of individuals. These sets are collectively produced and shared within social groups (Jodelet, 1989), so that different groups may have different representations of the same object. Although they reflect a form of naive or profane thinking (Ernst-Vintila et al., 2011; Joffe, 2003; Staerklé, 2013), SRs allow individuals to cognitively and practically apprehend their social environment (Jodelet, 1984). But they also have an identity function insofar as they allow individuals to identify or differentiate themselves within social groups and between social groups (Breakwell, 1993; Deschamps & Moliner, 2012; Moloney & Walker, 2007; Zouhri & Rateau, 2015). Finally, let us point out that for Moscovici (1976), SRs are not simple collections of opinions because they are organized sets. This last proposition has given rise to two theories of SR structuring.

According to the core theory (Abric, 1976, 1987, 1993), SRs are sets structured according to a 'core / periphery' partition. The elements belonging to the core are few in number, very consensual and very stable. It is these 'core' elements that determine the meanings that individuals associate with the object of representation (Moliner & Abric, 2015; Moliner, 2016). According to this structural approach, the 'peripheral' elements are much less consensual than the central elements and correspond to the different contexts in which individuals apprehend the object of representation. From this perspective, even in a very homogeneous group, a stabilized SR appears as a set of beliefs or opinions, only some of which are highly consensual.

According to the theory of organizing principles (Doise et al., 1992), SRs are considered in the social dynamic which, through communication relationships, places social groups in a situation of interaction. This social dynamic, when it develops around important issues, gives rise to specific positions, linked to the social insertions of individuals. That is to say that the positions expressed about a given question depend fundamentally on the social affiliations of each individual. This source of variation can generate an apparent multiplicity of positions that are nevertheless produced from common organizing principles. In this conception, there is not necessarily a consensus at the level of the opinions expressed by individuals, but there is a consensus at the level of the organizing principles of these opinions. That is, a SR appears as a set of dimensions or themes related to a given object and about which different groups express different opinions. But it is also true that within each group there will be consensus about certain opinions.

THE SOCIAL GROUP ISSUE

Considering SR as sets of opinions and beliefs shared within social groups requires clarifying two points. The first refers to the notion of sharing, while the second refers to the criteria for delimiting social groups.

The notion of sharing

If we examine most of the methods used to study SRs (Abric, 2003; Flament & Rouquette, 2003; Moliner et al., 2002; Lo Monaco et al., 2016; Rouquette & Rateau, 1998; Sammut et al., 2015) we find that for a majority of researchers, the sharing of elements of an SR corresponds to a convergence of individual opinions about a given object. But for some researchers, this convergence is accompanied by individuals' perception of it (Echterhoff et al., 2009). In this perspective, rare studies conducted within the framework of SR theory have attempted to compare the ‘actual’ and ‘perceived’ sharing of beliefs (Bonetto et al., 2019; Moliner, 2001). Overall, however, these few works suggest that perceived sharing is higher the more it concerns actually shared opinions.

Groups delimitation criteria

Moscovici (1976) wrote

> The definition of a group proceeds from a bundle of presuppositions which gives preferential weight to a certain number of criteria... Isolating these criteria is very difficult and their overlap with the cultural content particular to certain groups and common to others makes their ordering difficult (p. 72).

The author had thus already identified a thorny issue for SR studies; the delimitation of the group or groups to be questioned. Curiously, this issue has rarely been addressed subsequently (i.e., Bauer & Gaskell, 2008; Breakwell, 1993; Hogg & Abrams, 1998; Potter & Litton, 1985). But when it has been addressed, researchers have agreed that it is a serious problem. In an advocacy study, the group of participants may be defined by objective criteria, but the researcher is rarely assured that these criteria are actually recognized by the participants themselves. In other words, the researcher is rarely assured that the participants he or she interviews feel they belong to the group to which he or she has assigned them. Moreover, this problem is compounded when, as Breakwell (1993) notes, many representation studies use 'opportunistic' sampling approaches that respond to field constraints.

As a result, when studying a given representation in a given group of participants, it would be appropriate to ensure that the group is homogeneous. But it is not certain that this can be done solely by examining the consensus that is formed around certain opinions in this group. Let us imagine, for example, a group of participants actually made up of two sub-groups of equivalent size. In such a situation, we may well observe two opinions, A and B, expressed by 70% of the population surveyed. But it is also possible that opinion A is held by 40% of the participants in the first subgroup and 100% of the participants in the second, while the opposite could be true for opinion B. How then can we identify subgroups in a supposedly homogeneous population? Community detection methods can help us solve this problem. But for this, we need to consider SRs as networks.

NETWORK ANALYSIS OF SOCIAL REPRESENTATIONS

The idea that SRs can be considered as networks is not new. It first appeared with the development of similarity analysis (Degenne & Vergès, 1972; Flament, 1962, 1981). With this method, we consider that each opinion (expressed through a verbal association task or chosen in a questionnaire) can be linked to another by a link whose strength depends on the number of individuals who have expressed or chosen both opinions simultaneously. The method then consists of constructing a matrix of all the possible links between the different opinions expressed or chosen. This similarity matrix constitutes a graph where each vertex corresponds to an opinion and where each edge between two vertices has a weight relative to the number of individuals having expressed simultaneously the two opinions corresponding to these vertices. The algorithm applied to such a matrix allows to find the maximum tree. That is to say, a connected tree (there is at least one path between all the vertices), without cycle (it is possible to go from one vertex to another without passing twice by the same vertex) and whose edges have the maximum weight. This maximum tree, which can be visualized, thus constitutes a summary of the strongest links between the different opinions expressed or chosen by the population surveyed.

More recently, the study of SRs has been enriched by methods that draw on work done on social networks (e.g., Ju & O'Connor, 2013; Jung & Pawlowski, 2014; Keczer et al., 2016; Pawlowski et al., 2007; Pawlowski & Jung, 2015, Wang et al., 2018). These methods, too, are applicable to opinion similarity matrices. For example, in research on the representation of cybersecurity (Pawlowski & Jung, 2015), the network studied corresponds to a symmetrical matrix of 23 themes (the nodes), each box of which (the links) contains the number of co-occurrences observed among the interviewees. This type of matrix is then analyzed using the metric derived from graph theory (Bavelas, 1950; Beauchamp, 1965; Borgatti & Everett, 2000; Freeman, 1978). For example, Borgatti and Everett (2000) suggested that some networks may have a 'core-periphery' structure with a single group of nodes that are strongly connected to each other (network core). These authors have developed an algorithm that allows them to identify the core opinions in a given network. This algorithm is integrated into the Ucinet software (Borgatti et al., 2002).

We can thus see that SRs have been considered as networks for several decades. However, the methods that have been developed for this purpose have never really drawn all the consequences of the premises on which they were based. Indeed, if we consider a SR as a network of opinions or beliefs, this network must include the individuals who have expressed these opinions or beliefs. Neither similarity analysis nor methods inspired by the study of social networks do this. This prevents these methods from identifying subgroups of individuals. This is why we suggest a different approach.

Building a social representation network

In a SR study, especially if a verbal association task is used, one eventually obtains a data set comparable to that in table 1 where one has five participants who each produced three verbal associations.

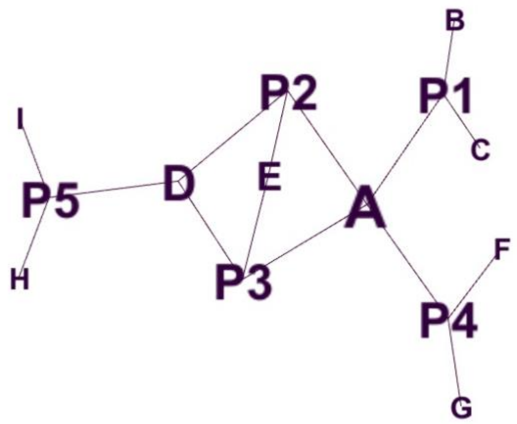
Table 1.

Verbal associations (VA...) produced by five participants (P...).

	VA1	VA2	VA3
P1	A	B	C
P2	A	D	E
P3	A	D	E
P4	A	G	F
P5	D	H	I

These data can be visualized in the form of a graph. For this purpose, we will consider that when an individual has produced a verbal association, there is a link between this individual and this verbal association. We can thus construct a graph comparable to the one presented in figure 1.

Figure 1.
Plot of data from Table 1.



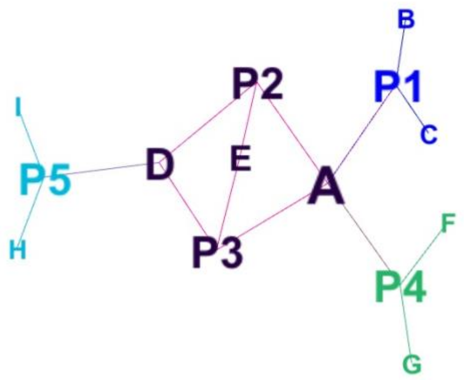
In this type of graph, each verbal association can only be linked to another one through a participant. In the same way, two participants can only be linked through a verbal association. Finally, the edges of the graph are bi-directional. This format for coding a graph is similar to what is practiced in network analysis of discourse (e.g., Hilton et al., 2020; Leifeld, 2017). But it also joins the notion of 'implicit link' proposed in several researches (e.g. Losup et al., 2014; Smith et al., 2009). Except that in the modeling we propose here, no direct link is established between two individuals having expressed the same opinion or having produced the same verbal association, nor between two opinions or two verbal associations produced by the same individual. By considering such graphs, it becomes possible to identify communities of individuals.

Detecting communities in social representation networks

Empirically, a community within a network appears as a subset of nodes (a cluster) that have more links to each other than to other nodes in the network. There are many algorithms available today to detect these communities (Yang et al., 2016). Many of these algorithms use a modularity measure (Newman & Girvan, 2004) to guide their progress. This measure compares the density of links within communities in a network to the density of links between communities. It varies between -1 and 1, with a value of 1 indicating an optimal network partition (no links between communities). Thus, starting from a first random partition, the algorithms evaluate its modularity and make the initial partition evolve in order to progressively maximize its modularity, until the latter does not evolve anymore. With some algorithms, in particular with the Louvain algorithm (Blondel et al., 2008), the process is constrained by a 'resolution' parameter determined by the user and which conditions the size of the communities. The value of this parameter is inversely proportional to the size of the communities and to the modularity. Thus, a resolution set to 0 leads the Louvain algorithm to identify a single community that gathers 100% of the nodes of the network with a modularity of 1. To identify the communities of a network with this algorithm, we will gradually increase the resolution parameter. Each new increase of this parameter produces a new partition whose relevance is evaluated by the user of the algorithm. If this relevance is judged insufficient the user increases the value of the resolution parameter and continues the process. This is what was done to obtain the partition presented in figure 2 from the Louvain algorithm finally parameterized with a resolution of 0.7 to obtain four communities with a modularity of 0.56[2]. In this partition, each community of the network is identified by a color. We can easily recognize that the density of links in the four communities is more important than the density of links between communities.

Figure 2.

Communities in the verbal association network of Figure 1



(Gephi software, Louvain algorithm, resolution=0.7, modularity=0.56).

RESEARCH OVERVIEW

In order to illustrate our proposed approach, we conducted three studies using the same data set. These data are verbal associations, produced by elementary school teachers, with the term 'gifted child'. In France, the issue of gifted children is particularly crucial in the school

[2] The network models and community detections in this article were performed with the open source software Gephi (version 0.9.7 , www.gephi.org).

environment. These children require special care (Lautrey, 2004). However, there is no consensual definition of giftedness (Sanchez et al., 2022) and teachers lack scientific knowledge about it. However, teachers are regularly confronted with these children and are required to make decisions about them. Thus, it can be assumed that this is an issue that is conducive to the existence of SR in the elementary school teacher population (Sanchez et al., 2022; Tavani et al., 2009).

The first study presents a network analysis of the gifted child's SR and provides an illustration of the community detection approach in the survey population.

The second study compares the results obtained in the first study to the results obtained through a ‘classic’ partition performed based on the participants' age.

The third study compares the results obtained in the first study to those obtained through a hierarchical classification analysis.

STUDY 1: NETWORK ANALYSIS OF SOCIAL REPRESENTATION OF GIFTED CHILD

Method

For this study, 160 French primary school teachers (M age = 40.81, SD = 8.91, 93.8% females) were asked to produce 4 verbal associations (word or short expression) from the term “gifted child”. Prior to analysis, the participants' productions were stripped of their stop words (articles, pronouns, conjunctions, auxiliary verbs, etc.). The short expressions were reduced to their words. Conjugated verbs have been put in the infinitive. Adjectives and past participles have been put in the masculine singular. Short expressions were split into several words. According to this treatment, the verbal association ‘high potential children’ becomes a sequence of three words: ‘high’, ‘potential’ and ‘child’. No grouping of words was performed. For example, the words ‘intelligence’ and ‘intelligent’ were considered as two different words[3]. Finally, the data were inserted into a table comparable to Table 1.

Results

The analyzed corpus is composed of 975 words, of which 394 are different words and 248 are hapaxes. Table 2 shows the terms produced by at least 10% of the surveyed population.

[3] Data : https://drive.google.com/file/d/1mpw-1MXFt7dnf7U2fqIHq7T54Ldqa6L2/view?usp=share_link

Table 2.

Numbers (n) and frequencies (%) of terms produced by at least 10% of the population.

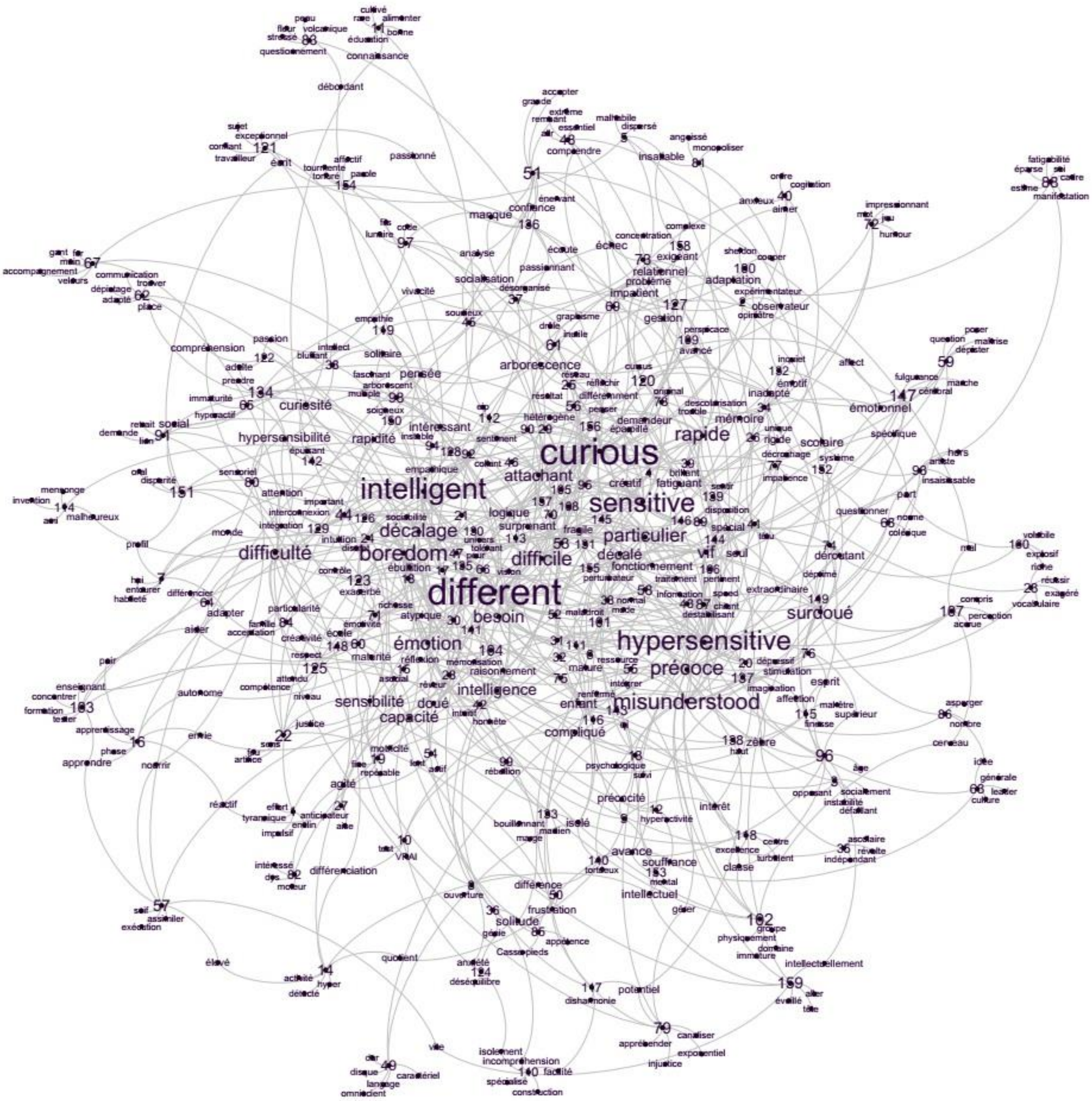
	n	%
curious	35	21.88%
different	35	21.88%
intelligent	26	16.25%
hypersensitive	23	14.38%
sensitive	23	14.38%
boredom	17	10.63%
misunderstood	17	10.63%

We note that the most frequent terms were produced by only 21.88% of the participants. This finding suggests a relative heterogeneity of the responses collected. It is corroborated by the ratio between hapax and different words (248/394=.629). This ratio is an indicator of the rarity of items in a corpus (Moliner & Lo Monaco, 2017). In this case it tells us that nearly 63% of the words in our corpus were produced by only one participant. If we compare this ratio to a theoretical distribution where 50% of the words in the corpus would have been hapaxes, we find a significant difference $\chi 2$ (1, N=788) = 13.42, $p<.001$. At first analysis, it seems that our corpus is relatively heterogeneous, which may lead us to think that there are no shared opinions within the population interviewed.

Figure 3 shows the network of the representation studied. This network was constructed using the approach described above. The size of the words is proportional to their frequency of occurrence.

Figure 3.

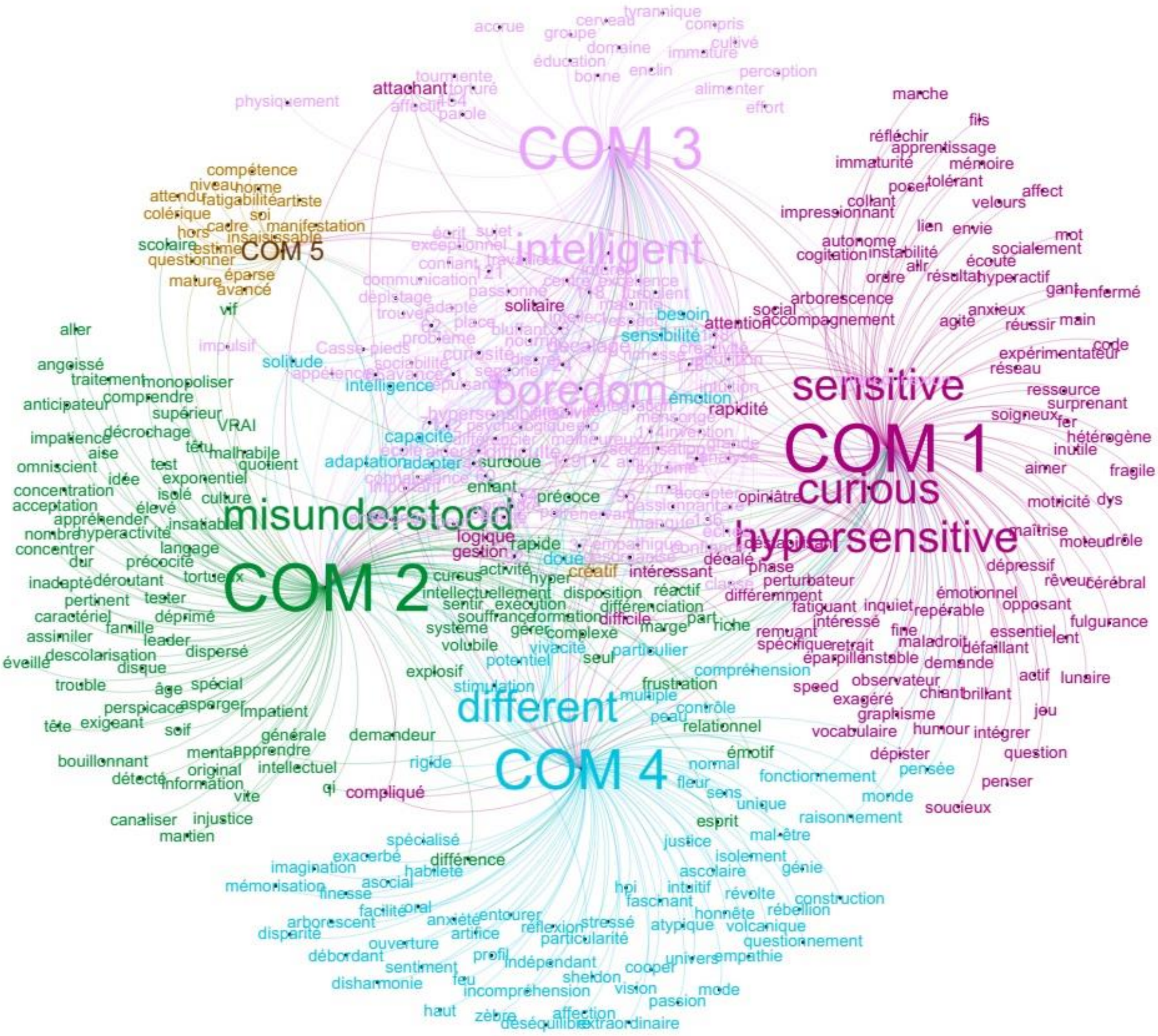
Network of the representation of the gifted child. 554 nodes, 975 links



We have applied to this network the Louvain algorithm with a resolution of .45. This treatment reveals 5 communities. The first one gathers 45 participants (28.12% of the total), the second 44 (27.5%), the third 32 (20.00%), the fourth 34 (21.25%) and the fifth 5 (3.12%). The modularity of this partition has a value of .65. Considering that this index can vary from -1 to 1, we can consider that this value indicates a good quality of this partition. Figure 4 shows the result of this partition. In this figure, participants from the same community have been grouped into a single node. The size of the labels of each community is proportional to the number of participants that it groups. The size of the words is proportional to their frequency of occurrence, but the label sizes of the verbal associations in Table 2 have been enlarged so that they can be seen on the graph.

Figure 4.

Partition of the network of the gifted child's representation.



We immediately notice that the most frequent words in Table 2 are distributed in different communities of the network. This finding suggests that the heterogeneity of our corpus might be caused by the heterogeneity of the surveyed population. Table 3 shows the number and frequency of words produced by at least 10% of the participants in communities 1, 2, 3 or 4. Given the small number of participants in community 5, we will not consider it in the following analyses. In Table 3, we can see that in 3 of the communities some words reach frequencies of appearance higher than 40%. This is the case for the word ‘curious’ in community 1, the word ‘intelligent’ in community 3 and the word ‘different’ in community 4.

Table 3.

Numbers and frequencies of words produced by at least 10% of participants in one of the four communities.

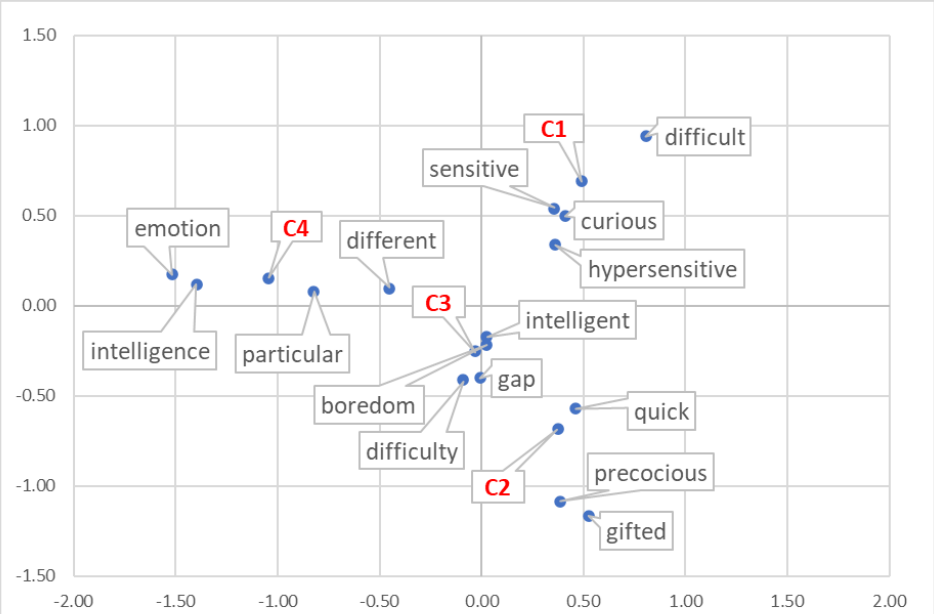
	C1 n=45		C2 n=44		C3 n=32		C4 n=34	
curious	20	44.44%	7	15.91%	3	9.38%	4	11.76%
difficult	12	26.67%	2	4.55%	0	0.00%	0	0.00%
sensitive	12	26.67%	2	4.55%	5	15.63%	2	5.88%
hypersensitive	11	24.44%	4	9.09%	5	15.63%	2	5.88%
different	8	17.78%	7	15.91%	5	15.63%	15	44.12%
intelligent	5	11.11%	4	9.09%	14	43.75%	3	8.82%
boredom	3	6.67%	3	6.82%	9	28.13%	2	5.88%
quick	3	6.67%	9	20.45%	1	3.13%	1	2.94%
particular	2	4.44%	3	6.82%	0	0.00%	8	23.53%
gap	1	2.22%	2	4.55%	8	25.00%	1	2.94%
difficulty	1	2.22%	3	6.82%	7	21.88%	2	5.88%
emotion	0	0.00%	0	0.00%	2	6.25%	11	32.35%
intelligence	0	0.00%	0	0.00%	2	6.25%	7	20.59%
precocious	0	0.00%	12	27.27%	2	6.25%	1	2.94%
gifted	0	0.00%	10	22.73%	2	6.25%	0	0.00%

In order to get an overall view of the distribution of the words in Table 3 across the four largest communities, we subjected these data to a correspondence analysis (Figure 5). This analysis first reveals a significant deviation from independence in the Table 3 data ($\chi 2(42, N = 270) = 223.00, p<.0001$).

It then identifies two dimensions that account for 74.87% of the total inertia of Table 3 (dimension 1 = 41.42%, dimension 2 = 33.45%). Finally, it reveals the opposition of community 4 to the other three communities.

Figure 5.

Correspondence analysis on the data in Table 3.



The participants of community 4 produced the terms ‘emotion, ‘intelligence’, ‘particular’ and ‘different’ more often than the participants of the other communities. But the correspondence analysis also shows an opposition between communities 1 and 2. Community 2 participants more often produced terms that refer to the exceptional character of gifted children (“rapid”, “precocious”, “gifted”), whereas Community 1 participants more often produced terms that evoke their intellectual curiosity (“curious”) and their sensitivity (“sensitive”, “hypersensitive”).

In order to test whether age differences could distinguish participants from communities 1 to 4, we compared the mean ages. Analysis of variance shows a significant effect of community ($F_{3\text{-}151}$=7.16, p<.001, η2=.12). Table 4 shows the results of pairwise comparisons between the four communities.

Table 4.

Comparison of age means between the 4 communities (Fisher LSD). Standard deviation in parentheses.

	Community 1	Community 2	Community 3	Community 4
	m=42.37 (1.26)	m=44.31 (1.27)	m=39.96 (1.49)	m=35.75 (1.45)
Community 1		ns	ns	p<.001
Community 2			p<.05	p<.001
Community 3				p<.05

We see that the average age of participants in community 4 is significantly lower than that of participants in the other three communities. Similarly, the average age of participants in community 3 is lower than that of participants in community 2.

Discussion

On the basis of the results just presented, it seems to us that it is now possible to explain the heterogeneity of the responses of the 160 participants in this study (see Table 2). As we mentioned in the introduction to this article, such a case may correspond either to an absence of SR in the surveyed population or to heterogeneity in this population and therefore to the presence of different SRs. Our results lead us to believe that we are in the presence of this second case, at least for communities 1, 3 and 4 where we note that certain terms are produced by more than 40% of the participants (Table 3). These are obviously not massive consensuses, but if we compare them to those observed in Table 2, they suggest a greater homogeneity of responses within the communities than in the total population of 160 participants. Furthermore, the consensus observed within communities 1, 3, and 4 did not involve the same terms, which is consistent with our interpretation. The age differences observed between the four communities could perhaps explain these differences in SR, particularly because they could correspond to differences in terms of professional experience. Indeed, we have seen that community 4 was opposed to the other three in terms of the verbal associations produced (cf. Fig. 5). However, it is in this community that the participants are the youngest (see Table 4) and therefore probably the least experienced.

STUDY 2: THE AGE HYOTHESIS

In this second study, the question arises as to whether the results obtained in the previous study could have been obtained using a simpler approach than the one implemented. Indeed, we have just seen that the participants of the different communities detected in Study 1 were distinguished according to their age. According to a much simpler approach to the problem posed by Table 2, one could have put forward the hypothesis that the weak consensus found in the group of 160 participants was caused by a hetorogeneity of this population with respect to the age of the participants. It is this hypothesis that was tested in the present study.

Method

The 160 participants were divided into two subgroups based on whether their age was younger (youngest: N = 80, M age = 33.44, SD = 5.14) or older (oldest: N = 80, M age = 48.18, SD = 4.82) than the group median age (MD = 40.5). The most frequent verbal associations produced in the two subgroups of participants were then tallied and compared.

Results

Table 5 shows the number and frequency of words produced by at least 10% of either subgroup.

Table 5.

*Numbers and frequencies of words produced by at least 10% of the youngest or oldest participants (*frequency comparison, $\chi 2$ significant, $p<.05$).*

	youngest		oldest		
different	22	27.50%	13	16.25%	
intelligent	17	21.25%	9	11.25%	
curious	13	16.25%	22	27.50%	
sensitive	11	13.75%	12	15.00%	
need	9	11.25%	2	2.50%	
difficulty	9	11.25%	5	6.25%	
particular	9	11.25%	4	5.00%	
emotion	9	11.25%	4	5.00%	
boredom	8	10.00%	9	11.25%	
hypersensitive	8	10.00%	15	18.75%	
misunderstood	8	10.00%	9	11.25%	
difficulty	6	7.50%	8	10.00%	
quick	5	6.25%	9	11.25%	
precocious	3	3.75%	12	15.00%	*

There was only one significant difference between the two subgroups. Older participants were more likely to cite the term ‘precocious’ than younger participants (3.75% vs. 15.00%, $\chi 2(1, N = 270) = 4.71$, $p<.05$).

To the extent that the two subgroups of participants have larger numbers than the communities identified in Study 1, we wanted to further explore this by dividing these two subgroups around their median age. We then formed four subgroups with 40 participants each. Table 6 shows the number and frequency of words produced by at least 10% of one of the four subgroups.

Table 6.

Numbers and frequencies of words produced by at least 10% of participants in one of the four age groups.

	Age class1 m=29.12 (.45)		Age class2 m=37.75 (.45)		Age class 3 m=44.42 (.45)		Age class 4 m=51.92 (.45)	
different	11	27.50%	11	27.50%	6	15.00%	7	17.50%
intelligent	9	22.50%	8	20.00%	2	5.00%	7	17.50%
sensitive	7	17.50%	4	10.00%	8	20.00%	4	10.00%
curious	5	12.50%	8	20.00%	12	30.00%	10	25.00%
hypersensitive	4	10.00%	4	10.00%	7	17.50%	8	20.00%
precocious	2	5.00%	1	2.50%	3	7.50%	9	22.50%

Correspondence analysis applied to the data in Table 6 shows that the departure from independence in this table is not significant.

DISCUSSION

The results just presented do not support the age hypothesis. At least, they suggest a very limited influence of participants' age on the verbal associations they produced. In other words, based on the age hypothesis, we would not have been able to identify the disparities encountered in Study 1.

STUDY 3: HIERARCHICAL CLUSTER ANALYSIS OR NETWORK ANALYSIS?

Among the statistical tools used to identify clusters in a group of individuals based on their correspondence to a given criterion, hierarchical clustering analysis occupies a prominent place. Does this technique give the same results as the network analysis we performed in Study 1? This is the question we tried to answer in this third study. The aim of this study was to compare the results obtained in Study 1, using the network analysis and the Louvain algorithm, with those that could be obtained using a classical classification method, in this case the ascending hierarchical classification.

Method

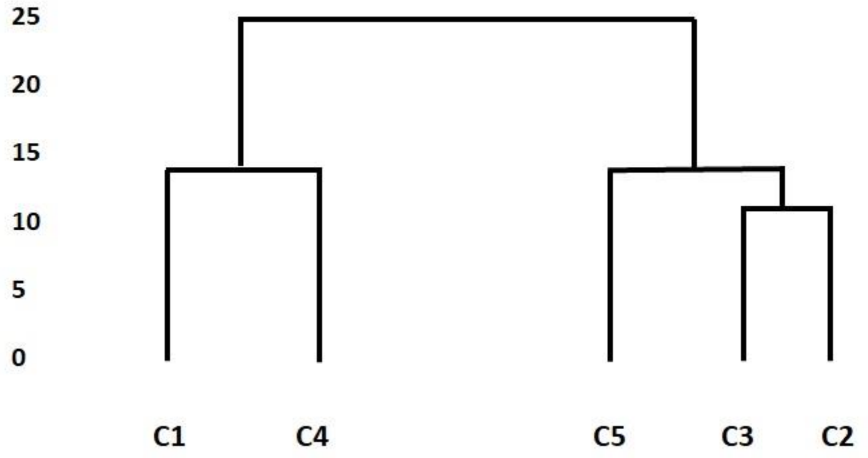
To perform this analysis, we constructed a table with 394 columns (verbal associations) and 160 rows (participants). In each box of the table there could be the value 1 or 0, depending on whether the participant on the row of that box had produced the verbal association on the column of that box. This table was subjected to an ascending hierarchical classification analysis (Euclidean distance, Ward's method). For this analysis, we set the maximum number of clusters to 5 in order to obtain a number of classes comparable to the number of communities observed in Study 1. We then compared the rankings obtained from the Louvain algorithm (Study 1) to those obtained from the hierarchical classification. To do this, we examined each pair of participants. When two participants were classified in two different classes or in the same class by both the Louvain algorithm and the hierarchical clustering, we considered that the two methods converged. When, on the contrary, two participants were classified in the same class by one method and in two different classes by the other, we considered that the two methods diverged.

Results

Figure 6 shows the dendrogram of the hierarchical classification, which shows a first group of clusters on the left (C1 and C4) and a second group on the right (C2, C3 and C5). Cluster 1 has 39 participants, cluster 2 has 72 participants, cluster 3 has 19 participants, and clusters 4 and 5 each have 14 participants.

Figure 6.

Dendrogram of the bottom-up hierarchical classification.



Comparing the rankings produced by the Louvain algorithm (study 1) to the one obtained by the hierarchical classification, we count 8322 convergent rankings. Considering that in a set of 160 items, there are 12720 possible pairs, we can see that 65.42% of these pairs were classified in a convergent way between the two methods. Compared to an equiprobable distribution where 50% of the pairs would have been classified convergently by the two methods and 50% divergently, this percentage differs significantly ($\chi 2$ (1, N = 25440) = 620.00, p<.0001). This indicates a relative convergence of the two methods.

Table 7 shows the number and frequency of verbal associations produced by at least 20% of participants in one cluster[4].

Table 7.

Number and frequency of verbal associations produced by at least 20% of participants in one of the classes.

	CL1 n=39		CL2 n=72		CL3 n=19		CL4 n=14		CL5 n=14	
hypersensitive	20	51.28%	1	1.35%	0	0.00%	0	0.00%	2	14.29%
sensitive	18	46.15%	1	1.35%	0	0.00%	0	0.00%	4	28.57%
curious	12	30.77%	15	20.27%	7	36.84%	1	7.14%	0	0.00%
intelligent	8	20.51%	9	12.16%	3	15.79%	2	14.29%	4	28.57%
different	6	15.38%	17	22.97%	5	26.32%	3	21.43%	4	28.57%
boredom	2	5.13%	9	12.16%	3	15.79%	3	21.43%	0	0.00%
emotion	1	2.56%	1	1.35%	10	52.63%	0	0.00%	1	7.14%
need	1	2.56%	4	5.41%	4	21.05%	1	7.14%	1	7.14%
emotional	1	2.56%	0	0.00%	4	21.05%	0	0.00%	0	0.00%
misunderstood	1	2.56%	1	1.35%	1	5.26%	0	0.00%	14	100.00%
quick	1	2.56%	7	9.46%	1	5.26%	2	14.29%	3	21.43%
sensitivity	0	0.00%	0	0.00%	1	5.26%	8	57.14%	0	0.00%
hypersensitivity	0	0.00%	0	0.00%	0	0.00%	6	42.86%	0	0.00%
intelligence	0	0.00%	4	5.41%	1	5.26%	4	28.57%	0	0.00%

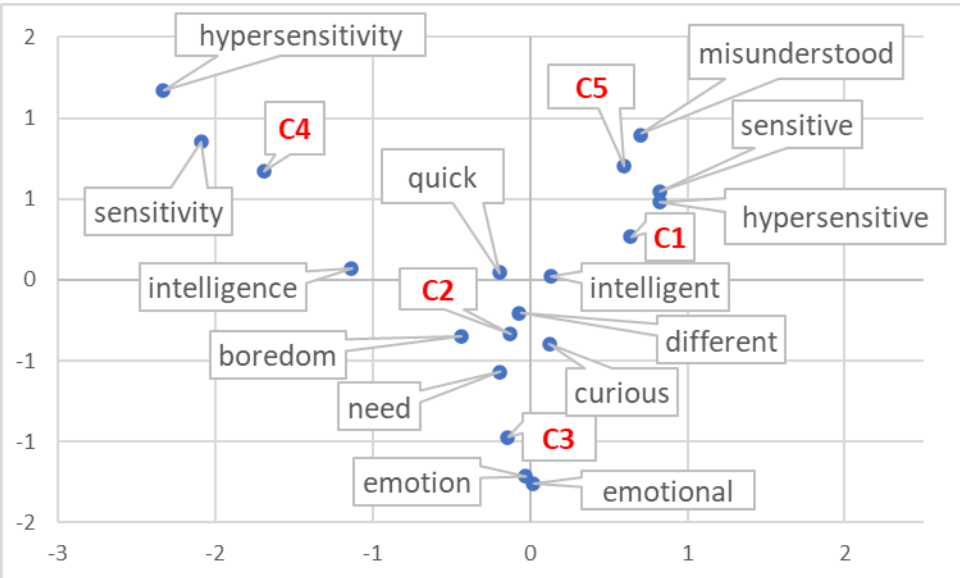
In order to get an overview of the data in Table 7, we subjected them to a correspondence analysis (Figure 7). This analysis reveals a significant deviation from independence for these

[4] Contrary to what has been done in previous studies, we have retained the 20% threshold here to avoid having to take into account too many verbal associations.

data ($\chi 2$ (52, N = 243) = 329.22, p<.0001). It then identifies two dimensions that account for 63.45% of the total inertia of Table 7 (dimension 1=39.00%, dimension 2=24.45%). As can be seen (Figure 6), the first dimension (horizontal axis) opposes cluster 4 to all the others. In this cluster, the most frequent verbal associations concern the sensitivity of gifted children. The second dimension opposes cluster 3 to cluster 5. In the first cluster, it is the question of emotion that dominates, while in the second it is the question of the lack of understanding of gifted children.

Figure 7.

Correspondence analysis of the data in Table 7



DISCUSSION

As we have just seen, the two methods we have just compared produce relatively convergent classifications. This convergence is reflected in some of the conclusions reached by these methods. With both methods, we identify a group of participants who, more than the others, consider gifted children in terms of their sensitivity. With both methods we also find a group of participants for whom the question of emotions seems important. But it seems to us that both methods have their specificities. For example, the two methods each identify a group of participants in which we do not find a consensus higher than 30% (community 2 in study 1 and cluster 2 in study 3). But the network analysis suggests that in this group, the dominant opinions refer to a very naive conception of gifted children, essentially perceived as exceptional (see

Table 3), which is not highlighted by the hierarchical classification. This type of discrepancy encourages us to think that network analysis proposes an original approach to the SRs.

GENERAL DISCUSSION

The three studies that have just been presented represent a first exploration of the possibilities of network analysis of SRs. From our point of view, they can certainly not be considered as a validation of this approach. At this stage, it would indeed be risky to consider that network analysis could become a reliable method for studying SRs. From our point of view, at least four questions would have to be answered.

The first one concerns the statistical significance of the partitions proposed by the algorithms applied to graphs. Indeed, these algorithms do not propose any statistical criteria to judge the relevance of a given partition. In other words, when we decide that the partition of a graph is relevant, there is nothing to ensure that this partition differs significantly from a random partition. In the context of the study of representation networks, we believe that it would be useful to have such a criterion. For example, one could decide that a partition is relevant when the ratio between the number of links and the number of nodes of the largest cluster of this partition is significantly different from the same ratio in the initial graph, minus the nodes and links of the largest cluster of the partition. For example, for the partition that we have presented in figure 4, we started with a resolution value of 0 that we progressively increased (.05, 10, .15, .20, etc...). With a resolution of .40 the Leuven algorithm produced a partition in 9 communities. The largest of these communities included 93 participants. The graph of this community included 279 vertices and 507 edges. By extracting these vertices and edges from the initial graph (comprising 554 vertices and 975 edges, cf. Figure 3), the latter now comprises only 275 vertices and 468 edges. The comparison of the proportions of the number of vertices divided by the number of edges in the two graphs shows no significant difference (chi square test). On the other hand, if we reproduce this procedure with a resolution value of .45, the algorithm gives the partition of figure 4. In this case the comparison of the proportions of vertices and edges between the graph of the largest community and the remaining graph shows a significant difference (149/215 vs 405/760, $\chi 2$ (1, N = 975) = 4.57, p<.05). From our point of view, this approach is satisfactory when the initial graph contains one or more communities. But if this is not the case, the approach is not applicable. It would therefore be appropriate to establish a statistically significant threshold that would allow us to decide that a graph is homogeneous in the sense that it contains only one community.

The second question that we believe should be answered is that of consensus in verbal association tasks. At what threshold can we consider that there is, in a given group, a consensus or consensuses about a given question? In the case of questionnaire surveys, the problem is relatively simple to solve. It is sufficient to compare the percentage of responses to a given question with a standard of equiprobability. But in the case of studies based on a verbal association task, this problem becomes more complex because there is no norm relative to the frequency of verbal associations, at least for French. Thus, when we find that, for a given stimulus, 20%, 30% or 40% of the participants in a study produced the same response, what can we compare these frequencies to? One could think of comparing them to an arbitrary threshold, considering that beyond this threshold there is a relative consensus in the population surveyed. But where to set this threshold? The work of Debrenne (2011; Debrenne & Ufimsteva; 2011) provides a lead. To build his *Grand Dictionnaire Associatif Français*[5], Debrenne interviewed thousands of French-speaking participants and proposed a list of 100 words. For each word, the participants had to produce a verbal association as quickly as possible. We can see that for the 1377 words of the *Grand Dictionnaire* the average frequency of the most frequent verbal associations is relatively low (M = .23, SD =.15). We can therefore see that the values we have presented in Table 2 are all below this average value. But in the following tables, we find several values that are well above. This being said, the methodology used by Debrenne is not exactly comparable to what is done for the study of SR where participants are generally asked to produce several verbal associations for the same inducer. Further research is therefore probably needed to establish a reliable standard of associative frequency in French or in other languages.

The third question is that of the social identity of individuals who, although all members of the same profession (i.e., primary school teachers in these studies), fall into different communities when they talk about gifted children. Indeed, one might wonder whether all these individuals conceive of their profession in the same way. For example, it could be that for some, the educational mission of a teacher is necessarily based on taking into account the diversity of his or her students, while for others it must be aimed at the greatest number. We would then have individuals who are differently positioned with regard to the issue of gifted children. For some, this issue would question their ability to adapt to diversity and therefore to be fully-fledged teachers. For others, the non-conformity of gifted children would only refer to rare and

[5] http://dictaverf.nsu.ru/index.php

ultimately artifactual cases. This scenario is reminiscent of the notions of ‘structural configuration’ and ‘situational configuration’ (Moliner, 1993). In the first case, the object of representation is a component of the group's identity, whereas in the second, it is not. More generally, this problematic refers to the link between social identity and SR. It suggests research avenues that are still relatively unexplored, such as the one suggested by Hogg and Abrams (1998), who propose to combine studies of representation with studies of social identity, focusing on the process of self-categorization and on common group membership.

Finally, the fourth question concerns the centrality of opinions and individuals in a representation network. Indeed, the construction of a network as we advocate it here allows us to calculate for each node several indices reflecting the more or less central position of these nodes in the network (see for example Valente et al., 2008). Among these indices, the betweenness centrality (Freeman, 1977) is undoubtedly the one that should attract our attention. The betweenness centrality of a node within a network is calculated from the number of times this node is on the shortest path between two other nodes. For example, in Figure 1, nodes P1, P4 and P5 correspond to the individuals with the highest betweenness scores (.29). They are in effect obligatory passages between nodes B, C, F, G, I, H and all the other nodes of the network. But the betweenness centrality of the verbal associations A and D is even stronger (.65 for A and .38 for D). While it is easy to see from Figure 1 that these two verbal associations ultimately link all the participants in the network (P1, P2, P..., etc.), it is perhaps less easy to understand what this means, from a psychosocial perspective. Do individuals occupying a position of high betweenness in a representation network play a particular role? Do they have specific qualities? Do the opinions occupying the same central positions also play a particular role? One guesses that there are many questions that are still open.

CONCLUSION

The questions that have just been raised constitute the limits of this research. We know that the approach we have just outlined still presents many uncertainties that call for future research. But we want to believe that this research will be fruitful. With network analysis, we would then have a new and relatively easy-to-implement method for studying SRs.

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