

Dimensions of the Rorschach Comprehensive System

Parallel Analysis and Principal Component Analysis of a European Adult Nonpatient Sample

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Abstract: The objective of this study is to propose a preliminary comprehensive dimensional model of the Rorschach Comprehensive System (RCS). Three European adult nonpatient samples of the RCS were combined (Belgium, France, and Finland, N=695). Principal component analysis was performed on primary scoring categories. Distribution issues were addressed by rank order transformation and the problem of R by partial correlations. The number of Components was determined through Parallel Analysis and resampling techniques (bootstrap and permutation). Twelve Components eigenvalues differed significantly from chance level (p < 0.0001). The obtained model provides a simplified representation of RCS data which accounts for 43% of the variance. This model brings new insights: Some variables traditionally considered as related belong to independent dimensions, and some others considered as independent appear related. These preliminary results set the stage for a new psychometrical approach of the RCS.

Keywords: Rorschach, principal component analysis, factor analysis, parallel analysis, bootstrap

Six relatively consistent dimensions of the Rorschach scored according to Beck (Beck, 1937) or Exner (Exner, 2003) systems have been identified by means of multivariate analyses (i.e. factor analysis FA or principal component analysis PCA): *Productivity*, a factor essentially defined by the total number of responses and which explains most of the variance of Rorschach data (Meyer, 1992b; Murstein, 1960; Schori & Thomas, 1972; Wittenborn, 1950; Wood, Krishnamurthy, & Archer, 2003); *Form Dominance*, a factor composed of form-dominant color and shading responses (Costello, 1998; Schori & Thomas, 1972; Shaffer et al., 1981; Zillmer & Vuz, 1995); *Color Dominance* regroups color and some shading responses with vague or no form (Costello, 1998; Geertsma,

Rorschachiana (2016), 37(2), 114-146 DOI: 10.1027/1192-5604/a000079

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1962; Mason, Cohen & Exner, 1985; Shaffer, Duszynski, & Thomas, 1981; Wittenborn, 1950; Zillmer & Vuz, 1995); Perceptual Accuracy, a bidirectional dimension with ordinary form qualities on the positive pole and poor form qualities on the negative one (Geertsma, 1962; Wood, Krishnamurthy, & Archer, 2003; Zillmer & Vuz, 1995); Kinesthesis, a factor composed of Human Movement and related variables (Geertsma, 1962; Schori & Thomas, 1972; Shaffer et al., 1981; Wittenborn, 1950); and Synthesis, a factor mainly composed of whole responses (W), perceptually organized responses (Zf), and synthesis responses (DQ+) on the positive pole, and pure form responses (F, F% or Lambda) on the negative one (Anderson & Dixon, 1993; Geertsma, 1962; Mason et al., 1985; Schori & Thomas, 1972; Shaffer et al., 1981; Wood, Krishnamurthy, & Archer, 2003; Zillmer & Vuz, 1995). However, these six dimensions were not identified in each of these studies, which raises the question: "what are the dimensions of the Rorschach?". In addition, the value of the Rorschach test in general and the Comprehensive System (RCS) in particular is often debated on psychometric grounds, specifically in terms of reliability, validity and norms accuracy (e.g. Wood, Nezworski, Lilienfeld, & Garb, 2003). A psychometric and dimensional approach to the RCS might shed a new light on this controversies.

While published multivariate analyses of the Rorschach differ in sample size (ranging from N = 102 to N = 586), population (normative, nonpatients, students, inpatients, schizophrenic, depressive, suicidal), extraction method (principal components analysis, principal axis), and rotation method (orthogonal, varimax, oblimin, promax), a close review of the literature brings forth the notion that factors, components, or dimensions identified in these studies substantially depend on two parameters, (a) the number and type of variables included in the analysis (variable selection) and (b) the number of dimensions extracted from the analysis (dimensionality assessment).

- (a) Concerning variable selection for example, James Wood's factor analysis (Wood, Krishnamurthy, & Archer, 2003) did not include the following variables: FC, CF + C, FC' and C'F + C'. It follows directly that under no circumstances could this study identify the *Form Dominance* or *Color Dominance* dimensions of the Rorschach, regardless of sample characteristics and methodological options. Scoring categories such as contents or special scores are almost never included in multivariate analyses of the Rorschach, and no study can be found in the literature that attempted to analyze all the RCS primary scoring categories. This point suggests that our knowledge of the dimensions of the Rorschach remains incomplete.
- (b) Dimensionality assessment is not independent of variable selection, as more variables included in the analysis imply more variance to explain and generally more dimensions to retain. Furthermore, and whatever the number of variables selected,

dimensionality assessment is challenging in multivariate analyses, as stated by Velicer & Jackson, "Decisions about how many factors or components should be retained are likely to have a much stronger impact on our conclusions from a data set than will the choice of the method" (Velicer & Jackson, 1990, p. 102).

Historically, two main criteria have been used for dimensionality assessment: Cattell scree test (Cattell, 1966) and Kaiser criterion (Kaiser, 1960). Cattell scree test aims at identifying the minimal number of dimensions to retain that could explain most of the variance (economical approach). Kaiser criterion states that any dimension retained in FA or PCA solutions should be more informative than any variable included in the analysis (extensive approach). Monte Carlo studies (data analysis simulation) showed that Cattell criterion frequently underestimates the number of dimensions to retain, leading to "underextraction", while Kaiser criterion generally overestimates this number and results in "overextraction" (Fabrigar, Wegener, MacCallum, & Strahan, 1999; Fava & Velicer, 1992; Fava & Velicer, 1996; Stellefson & Hanik, 2008; Velicer, Eaton, & Fava, 2000; Zwick & Velicer, 1986). When the number of dimensions to retain is uncertain, it has been shown that overextraction is preferable to underextraction (Fava & Velicer, 1992; Fava & Velicer, 1996; Wood, Tataryn, & Gorsuch, 1996). While a certain number of alternatives to Kaiser and Cattel criteria have been developed and studied (for examples see Jackson, 1993) a method called parallel analysis (Horn, 1965) was found to be the most accurate in recent studies (Courtney, 2013; Raîche, Walls, Magis, Riopel, & Blais, 2013; Ruscio & Roche, 2012; Zwick & Velicer, 1986). However, this technique has never been used in multivariate analysis of the Rorschach. The objective of this study is to describe a preliminary comprehensive dimensional model for the Rorschach Comprehensive System (RCS) (Exner, 2003) by means of parallel analysis and principal component analysis.

Method

Participants

In order to perform FA or PCA, a minimum of five times as many participants as the number of variables is theoretically required, a ratio of 10:1 being considered as comfortable and 20:1 as ideal (Gorsuch, 1983). With 92 primary scoring categories in the RCS, a sample size of at least N = 460 is thus required. In order to obtain a reasonable sample size, three European adult nonpatient samples of the RCS for which we were able to gather complete data sets¹ were included in

Multivariate analysis cannot be performed on descriptive statistics.

this study, with a total number of 695 participants (Finland N = 343, Belgium N = 100 and France N = 252). Most of these data are published (Mattlar et al., 2007; Mormont, Thommessen, & Kever, 2007; Sultan et al., 2004) and 106 participants from the ongoing French normative project have been added to the 146 published sample.

Table 1 provides socio-demographic information for these samples. Detailed information concerning recruitment procedures, examiners, administration and scoring procedures are available in the original articles (Mattlar et al., 2007; Mormont et al., 2007; Sultan et al., 2004). The number of subjects in the present study were 369 men and 326 women in the whole sample, and the mean age was 48 (SD = 15.5, ranging between 18 and 82).

Recruitment

In the Finnish sample, most participants were randomly selected from the Finnish Population Register (a government census of the Finnish population). Participants in the Belgian sample were recruited by graduate psychology students who administered the RCS under the supervision of senior staff members of the Clinical Psychology Service of the University of Liège. French participants were recruited by clinical psychologists in private, public and non-profit organizations in the cities of Paris, Tours, and Dijon. The additional French sample (N = 106) was collected according to the same procedure.

Interrater Reliability

The interrater reliability of the samples included in this study were published in the original articles. At least 25% of the protocols from the published samples were randomly selected and independently rescored (Mattlar et al., 2007; Mormont et al., 2007; Sultan et al., 2004). Kappa coefficients were computed for the Belgian sample but were not available for French and Finnish samples (intraclass coefficients were used instead). In the Belgian sample all kappa coefficients were above 0.75 (Table 2), which is considered excellent (Fleiss, Levin, & Paik, 2013). In the French sample, percentage agreement meet Exner's criteria for good interrater agreement (Exner, Kinder, & Curtiss, 1995), though the agreement for content (80%) was relatively lower than expected (Table 2). In the Finnish sample, Mattlar et al. (2007) report interrater agreement ranging from 91% for form quality to 97% for Location, with agreement for Special Scores somewhat lower (74%) (Mattlar et al., 2007). All protocols were administered and scored according to the RCS (Exner, 2001) and none has less than 14 responses.

Table 1. Demographic Data for the Finnish, Belgian and French adult nonpatient samples

								itional ench		
		Finland N = 343		Belgium N = 100		France N = 146		mple = 106	Total sample N = 695	
Age										
18-25	0	0%	24	24%	29	20%	5	5%	58	8%
26-35	8	2%	26	26%	40	27%	8	8%	82	12%
36-45	99	29%	25	25%	35	24%	35	33%	194	28%
46-55	101	29%	16	16%	29	20%	41	39%	187	27%
56-65	59	17%	6	6%	13	9%	16	15%	94	14%
>65	76	22%	3	3%	0	0%	1	1%	80	12%
Sex										
Male	181	53%	45	45%	54	37%	89	84%	369	53%
Female	162	47%	55	55%	92	63%	17	16%	326	47%

Table 2. Belgian and French adult nonpatient samples interrater reliability statistics

	Belgium	(N = 25)	France (N = 40)		
Variable	% Agreement	lota (Kappa)	% Agreement	lota (Kappa)	
Location	.99	.98	.91	-	
Developmental Quality	.96	.92	.92	-	
Determinants	.98	.88	.80	-	
Form Quality	.88	.80	.84	-	
Pairs	.99	.97	.96	-	
Contents	.99	.89	.80	-	
Populars	.97	.91	.95	-	
Z Score	.88	.80	.86	-	
Cognitive Special Scores	-	-	.86	-	
Other Special Scores	-	-	.90	-	
All Special Scores	.99	.81	-	-	

Note. 25 cases of the Belgian sample (25%) and 40 cases of the French sample (27%) were scored independently by two judges.

Analysis

Variable Selection and Multicolinearity Issues

There are 4 types of RCS structural summary variables: (1) the total number of responses R, (2) counts of the different scoring codes in a protocol which

will be called "primary variables" in this paper (e.g. *Ma*, *CF*, *FC*, *W* etc), (3) combinations of primary variables, which will be called "secondary variables" (e.g. *WSumC*, *EB*, *Afr*, *EGO* etc.) and (4) indices (e.g. PTI, S-CON) which combine discrete signs such as EGO < 0.33 or Afr < 0.46.

Because primary variables are combined in different ways into secondary variables, there are many redundancies among RCS variables (e.g. Ma and Mp are part of Ma:Mp, SumM, EB, EA, D scores and W/M). This situation is called multicolinearity. There are two main methods of multivariate analysis: principal component analysis and factor analysis. Factor analysis (FA) is explanatory and assumes that unobservable "latent" variables (factors) causes the pattern of intercorrelations between variables. Principal component analysis (PCA) is descriptive and summarizes correlations between variables into independent dimensions (components). Andy Field stated that multicolinearity is problematic for FA but not for PCA (Field, 2000, p. 686). However, PCA is looking for linear combination (i.e. weighted sums) of variables in order to extract dimensions of the data. If such combinations are already defined in the data prior to the analysis (e.g. WSumC = 1.5*C + 1*CF + 0.5*C), PCA might tend to define dimensions according to such formulas rather than according to the genuine correlations between primary variables of the analysis (i.e. C, CF and FC).

In order to illustrate this issue, we conducted two PCA with a varimax rotation on the variables of the control cluster of the RCS. The first analysis was performed on the sample described in this paper and the second on randomly scored protocols. A parallel analysis indicates 4 components to retain (Appendix A). As it is clearly apparent in the results, the components extracted from real data simply reproduce RCS formulas (e.g. SumSh = SumC' + SumY + SumT + SumV), which is a tautological result (the result of the analysis does not really depend on the data). Indeed, the same analysis conducted on randomly scored protocols produces very similar results (Table 3), and it appears clearly that multicolinearity can substantially bias PCA of the RCS.

This illustration is trivial, but at times this issue might cloud the interpretation of PCA results, especially when dependencies between variables are less obvious. For example Gregory Meyer found a form-dominant shading component which was defined by FV, Shading Blends, FY, Color-Shading Blends, VF + V, FT, FC' and EGO on the positive pole and by Lambda on the negative one (Meyer, 1992b). This component might represent a Rorschach measure of negative affects. However, Shading Blends contain at least two shading determinants by definition. Consequently, in every protocol there is necessarily at least twice as many shading determinants as the number of Shading Blends. The opposite is not true, as it is possible to give many single shading responses. Consequently, it is hard to know if this component artificially regroups shadings into a unique dimension (because

Table 3. Principal Component Analysis of the control cluster of the RCS of real data and randomly scored protocols

		Real	data		F	andomly	scored pr	rotocols	
		Comp	onent			Со	mponent		
	1	2	3	4	-	1	2	3	4
SumSh	.97	.21	.13	.01	SumSh	.99	01	.06	.04
es	.71	.31	.63	.01	es	.67	03	.74	.03
SumY	.67	.18	.10	02	SumY	.53	.08	.05	.03
SumV	.65	01	.14	.20	SumV	.45	13	05	.02
SumT	.59	.09	.12	11	SumT	.51	.03	03	09
SumC'	.63	.25	.01	02	SumC'	.51	02	.10	.09
D	−.57	.41	63	.24	D	49	.66	55	.02
EA	.29	.89	.11	.29	EA	.04	.99	01	.05
SumM	.19	.59	.08	.77	SumM	.06	.70	01	.71
WSumC	.29	.87	.10	32	WSumC	01	.73	01	68
FM + m	.15	.29	.94	0	FM + m	.02	03	.99	0
FM	.09	01	.90	.12	FM	.05	02	.80	0
m	.16	.55	.52	15	m	04	03	.58	0
EB	08	20	01	.96	EB	.05	.02	.00	.99

Note. RCS = Rorschach Comprehensive System. SumSh = SumY + SumV + SumT + SumC', es = SumSh + FM + m, EA = SumM + WSumC, EB = SumM-WSumC, D = trunc[(EA-es)/2.51]. Concerning randomly scored protocols, primary scores (SumM, FC, CF, C, FM, m, SumC', SumY, SumY, SumV) were pemuted (random sampling without replacement) and summary scores (SumSh, es, WSumC, EA, EB, D) were computed on the permuted values. The parallel analysis was performed using the BAPPA technique, 4 components eingenvalues significantly differ from random-based eigenvalues, $\alpha < 0.0001$. Component loadings of an absolute value > 0.3 are in bold types.

more shading blends necessarily implies more shadings) or if it represents a genuine pattern of intercorrelations between shading determinants variables.

Because of the potential bias that multicolinearity might imply in PCA, only the number of responses *R* and RCS primary variables were retained for the analysis (i.e. the primary source of Rorschach information) (e.g. *Ma*, *CF*, *H*, *W*), excluding all secondary variables (e.g. *EGO*, *WSum6*, *Intellectualization*, *EB* etc.) and indices. This focus on primary variables reduces multicolinearity issues in RCS data.

The Problem of R

Most Rorschach variables are correlated to some degree with the total number of responses *R* which confounds their interpretation (Cronbach, 1949; Fiske & Baughman, 1953; Meyer, 1992a, 1992b; Murstein, 1960; Perry & Kinder, 1990). For example, a higher number of Human Movement responses might simply be

the result of an increased "productivity" rather than a reliable measure of kinesthetic tendencies. In fact, the *Productivity* dimension has been found to be the largest source of variance of Rorschach scores in most factor analytic studies (Rorschach first factor) (Meyer, 1992b). However, these results might be misleading.

Misleading because the problem of R is not only a correlational one, it is also a problem of multicolinearity. R is mathematically related to many other Rorschach variables: R is equal to the sum of locations (W, D, Dd), to the sum of developmental qualities (DQo, DQ+, DQv, DQv/+), to the sum of form qualities (PQx+, PQxo, PQxu, PQx-, PQxnone), to the sum of primary determinants and to the sum of primary contents. As mentioned by Gregory Meyer in his factor analysis of the RCS:

R and all of the other determinants loaded positively on Factor 1, whereas *Lambda* had a strong negative loading. This appears to be a response articulation factor, or a factor that reflects the somewhat tautological position that frequent responding leads to increased scoring across all determinant categories. (Meyer, 1992a, p. 124)

This citation means that within the Rorschach, the number of responses is problematic because of the problem of *R*. This point shows how pervasive the problem of *R* is, and suggests that this issue should better be addressed prior to the analysis.

Actually, R does not only confuse the interpretation of other Rorschach variables, but also the correlations between them. For example the correlation between detail responses D and pure form responses F is r(F,D) = 0.72. However, these variables are highly correlated with R as r(R,F) = 0.69 and r(R,D) = 0.79. Consequently, a substantial part of the correlation between F and D can be explained by their mutual association with R (R confuses the Rorschach correlation matrix). A possible solution to the problem of R is the use of partial correlations. Partial correlations remove the effect of a set of variables from the correlation matrix of another set of variables. If the correlation matrix of the Rorschach is controlled for R, then the correlations of Rorschach variables with R are exactly equal to zero. Concerning F and D, the partial correlation controlled for R is r(F,D,R) = 0.39 (vs. r(F,D) = 0.72). This technique has been employed successfully as a way to control the confounding effect of R on correlation matrix (Anderson & Dixon Jr, 1993; Exner, Viglione, & Gillespie, 1984; Mason et al., 1985; Shaffer et al., 1981). Conceptually, R is not a scoring category and it is therefore justified to treat it differently (i.e. as a control variable) in a correlational analysis. However, partial correlations are a particular type of Pearson correlation which is

not a robust measure of dependency as it can be sensitive to distribution issues. If partial correlations are a very efficient means to address the problem of *R*, distribution issues of Rorschach variables should be addressed first.

Distribution Issues

In order to address distribution issues, Rorschach primary variables were transformed into ranks (log transformation is not possible on most Rorschach variables, and square-root transformation was less satisfying). However, this procedure was not efficient for nine very low base rate variables (90% or more of the participants gave none of these responses): Level 2 Deviant Verbalizations (DV2) and Deviant Responses (DR2), Contamination (CONTAM), Color Naming (Cn), pure Vista (V), pure Texture (T), pure Achromatic Color (C), pure Diffuse Shading (Y), and Reflections not well defined on a formal level (F). To address these issues, pure shadings were added to their non-form-dominant counterpart (i.e., C + C + F; Y + YF; V + VF; T + TF). The Reflection variables were added together (Fr + Fr). DV2 and DR2 were added to their level 1 counterpart (DV1 + DV2, DR1 + DR2). Finally 76 variables were included in the analysis.

This procedure implies that partial rank order correlations were used for the PCA. Spearman correlations are simply Pearson correlations computed on the ranked values of the variables. Consequently, partial rank order correlations makes as much sense as Spearman correlations.

Dimensionality Assessment

Parallel analysis is a technique based on *eigenvalues*. The eigenvalue of a dimension represents the part of variance it explains or accounts for. In parallel analysis (PA), random datasets (generally 1000) of the same size as the original data (number of variables and number of observations) are generated under the condition of multivariate normality (Horn, 1965). Each random dataset is then submitted to PCA and consequently, 1000 eigenvalues are computed for each component of PA. The actual eigenvalues of the original dataset are then compared to the 95th percentile of the distribution of PA eigenvalues which are used as a cut-off (Cota, Longman, Holden, Fekken, & Xinaris, 1993). Consequently, PA retains components which significantly account for more variance than random-based components.

Although PA is an efficient means to estimate the number of dimensions to retain in multivariate analysis (Courtney, 2013; Raîche, Walls, Magis, Riopel, & Blais,

² Color naming (Cn) and Contamination (CONTAM) were excluded from the analysis as it would not make sense to add them to any other coding.

2013; Ruscio & Roche, 2012; Zwick & Velicer, 1986), it does present some limitations. PA is parametric as it is based on normally distributed random variables. Therefore, PA is not appropriate for non-normal data such as RCS variables.

Another important limitation of PA is that the observed eigenvalues of a particular sample might underestimate or overestimate the actual eigenvalues of the population under study. In other words, the observed eigenvalues of a sample are not necessarily a good estimation of the population's eigenvalues. In a recent simulation study (Ruscio & Roche, 2012), PA identified the correct number of dimensions in 76% of 10,000 target samples of various sample sizes, number of true dimensions, number of variables, item response scales and factor structure (correlated or orthogonal). This result suggests that better eigenvalues estimations are required to address the limitations of PA. The Bootstrap And Permutation Parallel Analysis technique (BAPPA) presented in this study was developed to address these two limitations (normality assumption and eigenvalues estimation).

BAPPA is a combination of PA and resampling techniques (bootstrap and permutation) developed to determine the number of dimensions to retain in multivariate analysis more accurately. In this technique, random data are generated by permutations (random sampling without replacement). This technique proposed by Buja and Eyuboglu (1992) is non-parametric and presents the advantage that randomized variables keep their original properties (mean, s.d., skewness, kurtosis). As for the observed values and in order to estimate them more accurately, the eigenvalues of 1000 bootstrap replicates of the original data are computed (see Figure 1). Then, the 1st percentile of the observed eigenvalues is compared to the 99th percentile of the random-based eigenvalues. Consequently, the confidence interval of the eigenvalues and the random-based eigenvalues are almost mutually exclusive and the relative risk in the determination of the number of components to retain is α < 0.0001. The mean correlations of 1000 bootstrap replicates are then computed in order to get more precise estimations of the correlations between variables that take sampling fluctuations into account. Finally, a PCA with a varimax rotation is performed on the boostrap correlation matrix according to the number of dimensions to retain defined by the parallel analysis. The varimax rotation is preferred to oblique rotations because orthogonal rotations are more parsimonious. Indeed, more parameters are estimated in oblique rotation (pattern matrix, structure matrix, correlations between dimensions matrix) which makes them less reproducible (Kieffer, 1998). The packages "nFactors", "boot", "psych" and "GPArotation" from the R statistical software allowed us to perform these analyses. The R script for the Bootstrap and Permutation Parallel Analysis (BAPPA technique) is available on demand.

In other respects, it is recommended to use several criteria in order to estimate the number of dimensions to retain in multivariate analysis (Courtney, 2013;

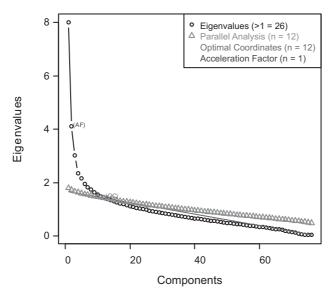


Figure 1. Bootstrap And Permutation Parallel Analysis scree plot. For each component, the 1st percentile of 1000 bootstrap eigenvalues is compared to the 99th percentile of 1000 random samples' eigenvalues generated by permutations.

Gaskin & Happell, 2014; Ruscio & Roche, 2012). Three more criteria were used in this study: the acceleration factor (Raîche et al., 2013), optimal coordinates (Raîche et al., 2013), and the Kaiser criterion (Kaiser, 1960). The acceleration factor indicates the "elbow" of the scree plot mathematically rather than on visual inspection (it is the mathematical counterpart of Cattell Scree test). Optimal coordinates predict the eigenvalue of a component (i.e. the variance it accounts for) according to the preceding eigenvalues using regression formulas. It serves to indicate an unpredictable drop in the eigenvalues. Kaiser criterion determines the number of components which account for more variance than any original variable. In Ruscio and Roche (2012) Monte Carlo study, the acceleration factor, optimal coordinates and Kaiser criterion identified the correct number of dimensions in 46%, 74% and 9% of the cases respectively. The different stages of the analysis procedure are in Appendix B.

Appropriateness of PCA

The Chi-square for Bartlett test of sphericity is 17 987 with 2 850 degrees of freedom, p < 0.001: the correlation matrix significantly differs from the identity

matrix which means that variables are not uncorrelated. The Kaiser-Meyer-Olkin index of sampling adequacy is 0.698 which corresponds to the upper end of the "middling" range (Kaiser, 1974). There are 143 correlations with an absolute value above 0.09 in the Anti-Image Covariance matrix (-5% of the correlations). The data can reasonably be submitted to PCA (Dziuban & Shirkey, 1974; Zillmer & Vuz, 1995).

Results

Concerning dimensionality assessment, the acceleration factor (which is similar to Cattel criterion) indicated 1 dimension to retain, whereas Kaiser criterion indicated 26. The BAPPA technique (bootstrap and permutation parallel analysis) showed that optimal coordinates and parallel analysis converged and that the eigenvalues of 12 components significantly differ from random based eigenvalues (p < 0.0001). Table 4 presents the component model obtained and the variance it explains. Table 5 presents the component structure. These components are independent (uncorrelated). The cut-off for component loadings was set to .30 since this value has been supported as a reasonable criterion for detecting variables that adequately represent the component in samples of at least N = 350 (Hair, Black, & Babin, 2010).

The Kinesthetic component (RC1) essentially measures the tendency to give active and cooperative human interactions responses (Ma, H, (H), DQ+, COP, Pair, Zf) as opposed to pure form responses (F, DQo). The Apperceptive component (RC2) represents a global vs. analytical dimension with whole responses W, perceptually organized responses Zf and Blends on the positive pole vs. detail responses D and ordinary developmental qualities DQo on the negative one. The Pure Color component (RC3) groups Pure Color responses and related variables (C, FQxnone, DQv, Blood) as well as abstraction responses (AB, Hx). This component represents instances when the pattern recognition process implied by the Rorschach has been ignored or by-passed. The Reflection component (RC4) is principally defined by reflection responses Fr + rF, diffuse shading Y + YF and natural contents Na, Cl and Ls. It describes the tendency of the participant to interpret the symmetry of the inkblots as a mirror image, possibly occurring with card rotation. The Instinctual component (RC5) describes the tendency of the participant to perceive animal interactions in the inkblot (FM, A, DQ+, Pair) together with aggressive (AG) and fabulized responses (FAB1). The Explosive component (RC6) is strongly defined by inanimate movement m, fire Fi, explosion Ex, and related variables (science Sc, color dominance CF).

Table 4. Eigenvalues and percentages of explained variance by each component

Rorschach Components	Eigenvalues	Proportion of Variance	Cumulative proportion of Variance
RC1: Kinesthetic	4.64	0.06	0.06
RC2: Apperceptive	3.45	0.05	0.11
RC3: Pure Color	3.30	0.04	0.15
RC4: Reflection	2.97	0.04	0.19
RC5: Instinctual	2.78	0.04	0.23
RC6: Explosive	2.77	0.04	0.26
RC7: Misperception	2.34	0.03	0.29
RC8: Vista-Texture	2.09	0.03	0.32
RC9: Face	2.09	0.03	0.35
RC10: Form Dominance	2.09	0.03	0.38
RC11: Conventionality	2.04	0.03	0.40
RC12: Digressive	1.81	0.02	0.43

Note. RC = Rotated Component.

It represents the tendency to perceive burning or exploding objects in the inkblots. The Misperception component (RC7) is essentially defined by Poor Form responses FQ- but also by Anatomy, Human Detail and Sex responses (An, Hd and Sex). It describes the tendency to give responses which do not fit with the location used in the response. The association with anatomical responses will be discussed later. The Vista-Texture component (RC8) is composed almost exclusively of Vista (FV, V + VF) and Texture responses (FT, T + TF). It measures the tendency to interpret the shadings of the inkblots in a relatively sophisticated manner (implying impressions of depth or tactile impression). The Face component (RC9) loads in substantial to moderate proportions Human detail Hd and (Hd), animal detail Ad, uncommon details Dd and space location S, which are all are related to the perception of faces or mask in the inkblots. The Form Dominance component (RC10) substantially loads well defined color (FC), achromatic (FC') and diffuse (FY) responses. An elevation of this component score implies that participants were able to incorporate colors and shadings in their responses without impairment to the pattern recognition process implied by the Rorschach. The Conventionality component (RC11) includes ordinary form qualities FQxo and Popular responses P on the positive pole vs. unusual form qualities FQxu and uncommon details Dd on the negative one. It might be conceived as a conventionality vs. originality dimension. The Digressive component (RC12) is moderately correlated with personal justifications PER, deviant responses DR1 + DR2 and achromatic responses C' + C'F. Personal responses PER and deviant responses DR both represent digression from the task and that might explain their association

Table 5. Components Loadings for Principal Component Analysis with varimax rotation of the Rorschach Comprehensive System primary scoring categories

Rorschact	RC1	RC2	RC3	RC4	RC5	RC6	RC7	RC8	RC9	RC10	RC11	RC12
Ma	.75	.09	.11	.02	.17	.09	.04	07	10	.07	.00	.08
Н	.75	.08	07	06	07	.04	04	.00	.04	.02	.09	.08
COP	.65	.09	.07	09	.12	.07	.00	03	10	.05	.04	06
DQ+	.62	.26	06	.17	.48	.22	04	.09	.08	.07	.01	.01
Cg	.54	.03	08	01	10	02	.00	.12	.18	.19	.01	.04
(H)	.53	03	.01	.13	.00	01	05	03	12	.19	.08	.08
DQo	45	35	28	34	27	18	.09	16	.07	.09	.12	.01
Мр	.45	.05	.06	.07	.05	.03	.10	.20	.33	.02	.13	15
Pair	.43	40	09	20	.38	13	13	.06	11	.01	.15	.10
D	13	80	20	09	.05	17	06	01	01	03	.14	01
W	.18	.78	.23	.15	01	.20	.09	.05	17	.13	.12	.06
Zf	.39	.69	05	.17	.25	.24	.09	.03	.02	.15	.14	.01
F	− .37	38	24	20	28	13	.12	35	.02	26	.07	.02
R8910	03	35	09	15	.08	.16	.17	.01	18	.28	.02	25
FQxnone	13	.05	.75	.08	19	.04	13	.15	12	.01	01	.08
С	09	.17	.74	.07	04	.14	11	.11	09	.01	.06	01
DQv	20	.01	.60	.18	20	.11	08	.23	27	.02	07	.17
AB	.23	.06	.57	03	.18	.03	.14	.05	.13	12	.00	02
Hx	.24	.04	.48	.01	.16	03	.13	03	.14	01	03	11
Bl	11	.19	.37	08	.24	.17	.16	19	.06	.04	.02	.17
ALOG	.11	16	.22	.01	.21	.09	.14	17	.07	.20	07	.04
Fr + rF	.05	.19	08	.66	.08	01	06	04	.09	.08	.07	15
DQv/+	.02	.03	.09	.63	06	.15	.01	.01	02	08	.07	.17
Cl	.01	05	.03	.52	02	.08	12	.02	08	14	08	.08
Y + YF	02	.04	.23	.49	01	.17	06	.22	02	.06	09	.21
Na	.01	.12	.20	.48	.08	.27	08	.19	.05	02	07	.18
Ls	03	.13	05	.45	.06	.10	.11	.05	15	.17	.05	13
FM	.00	.11	04	.08	.71	01	19	.16	.03	.05	.03	.01
Α	30	17	22	04	.56	18	15	.00	25	08	.25	.02
AG	.18	05	.14	07	.49	.16	.10	18	.01	01	06	.18
FAB1	.23	.06	.08	.06	.43	.02	.20	07	.02	.06	.03	05
FAB2	.18	.03	05	.04	.24	.08	.19	.22	01	14	02	.01
INC1	.00	07	04	.00	.22	01	.20	.17	.06	.07	.05	05
m	.07	.16	.14	.19	.04	.66	09	.22	.05	11	.00	.16
Fi	.08	.01	.08	.11	.17	.64	06	01	08	.05	.00	.05
Sc	.13	.03	10	.11	01	.59	.07	01	.02	.00	03	.10

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Table 5. (Continued)

	(
	RC1	RC2	RC3	RC4	RC5	RC6	RC7	RC8	RC9	RC10	RC11	RC12
Ex	05	.11	.13	.07	13	.58	08	01	.02	08	02	20
CF	.00	.27	.26	.13	.04	.48	.11	.19	13	.14	.00	.09
Blend	.31	.32	.22	.34	.27	.34	.00	.31	.07	.31	.02	.11
Ау	.22	.01	02	11	08	.26	.18	20	.18	.24	.02	04
FQx-	11	.09	09	10	.10	.01	.62	02	0.2	.06	18	14
An	08	.03	02	09	02	03	.52	.04	03	.03	.02	.09
Sx	.15	.08	.04	07	01	.02	.44	.09	.15	02	.03	.15
Ge	16	11	01	.26	14	05	.39	.04	19	.10	05	03
Bt	01	.28	07	24	.08	.10	− .31	.28	27	.08	14	.02
MOR	.01	.24	.09	.01	.20	08	.26	.21	01	.06	.05	.23
Ху	.07	.08	.08	.01	14	.06	.17	05	11	.07	06	14
INC2	.01	02	.12	03	.11	07	.17	07	.07	.07	03	.07
FV	.05	.08	05	.05	.06	.05	.22	.48	.07	.06	03	12
FT	.02	01	.06	.08	.05	07	06	.46	.12	.19	.15	.14
T + TF	.02	.02	.13	.07	06	.06	03	.43	10	.00	05	.09
V + VF	.07	.07	.17	.19	.01	.14	.24	.34	.00	08	05	06
(A)	.09	.10	05	.05	.15	05	.12	28	.04	.22	.01	01
Food	.07	.02	03	19	.16	.09	.14	.25	07	.06	.00	.19
ld	.17	04	.12	.21	.18	03	.00	.21	07	09	17	.20
Hd	.04	19	02	11	.03	.03	.31	.02	.54	10	01	16
Ad	25	12	.01	20	04	18	07	13	.45	.07	03	.07
Dd	11	27	15	.04	02	01	.00	06	.44	02	41	.08
(Hd)	04	.18	.01	11	01	.07	.02	23	.38	.31	.07	15
S	.03	.26	07	.05	17	.29	.20	.01	.38	.27	10	.09
FQx+	.22	.15	.03	.21	.07	01	.02	.15	.35	.09	01	01
FC	.20	.06	08	10	.09	.07	14	.05	05	.60	04	.03
FC'	.17	.22	.00	02	05	.03	.05	.03	08	.46	.03	.17
FY	.03	06	.05	.05	.04	11	.10	.13	.06	.45	10	13
Art	.15	.18	.33	.18	16	04	.10	06	.02	.37	.09	.11
(Ad)	.05	10	.04	02	.00	03	.09	07	.19	.31	02	24
FD	.18	.19	14	.22	.13	.07	.03	.13	.19	.26	12	.14
FQxo	.13	18	14	.02	.03	.08	23	.02	08	.00	.78	.03
FQxu	.00	05	07	.07	01	.02	25	02	12	.11	63	.25
Р	.28	03	01	.01	.13	05	15	05	02	.05	.62	.13
PSV	08	.15	.02	.03	04	14	.08	05	01	10	.23	.11
PER	.04	.03	03	.09	.01	.03	.07	.00	02	06	02	.49

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Table 5. (Continued)

	RC1	RC2	RC3	RC4	RC5	RC6	RC7	RC8	RC9	RC10	RC11	RC12
DR1&2	.12	03	.21	.05	.15	.09	.20	.01	09	.01	.04	.46
C' + C'F	01	.11	.27	.24	07	.05	11	.04	.04	.11	08	.36
Hh	.29	.00	07	08	15	.13	22	.09	.02	.15	.08	.34
DV1&2	19	.07	01	08	.14	01	03	.16	.25	01	.05	.26

Note. Loadings absolute value > .30 are in boldface. RC = Rotated Component. Variables were ranked and partial out for response frequency R prior to the analysis. PCA was performed on the bootstrap correlation matrix.

in this component. The association with achromatic responses C' + C'F will be discussed later.

Ten RCS variables present significant cross loadings in this model (*DQ*+, *DQo*, *Mp*, *Pairs*, *Zf*, *F*, *Blend*, *Hd*, *Dd* and (*Hd*)), and 13 variables are not significantly loaded by any component (*ALOG*, *FAB2*, *INC1*, *INC2*, *DV1*&2, *MOR*, *PSV*, *Ay*, *Xy*, (*A*), *Food*, *Id* and *FD*).

Discussion

The components presented in the results section describe the participant's behavior within the boundaries of the Rorschach test. However, it is essential for clinical practice to understand how these test behaviors relate to real life situations (i.e. to validity criterion). We propose some hypotheses concerning the psychological constructs measured by Rorschach components based on the available empirical evidence (Exner, 2000; Mihura et al. 2013). Mihura et al. (2013) meta-analysis considered articles written in English that were published from 1974 to November 2011 (including previous meta-analysis), and included 1,156 validity coefficients for 55 variables of the RCS structural summary obtained from 215 independent samples with a combined independent sample size of 25,795 participants. Considering externally assessed criteria, 13 variables presented excellent support, 17 good support, 10 modest support and 13 little or no support. These results represent the most comprehensive evidence for RCS variables in the peer-reviewed literature, though authors mention that a substantial amount of validation criteria used in this meta-analysis are relatively blunt and overlapping (Mihura et al. 2013, p. 578).

The Rorschach Component Model

Kinesthetic Component

This dimension is the most important in terms of variance accounted for and it has previously been described as a kinesthetic or human content factor (Geertsma, 1962; Schori & Thomas, 1972; Shaffer et al., 1981). There is strong evidence that the sum of human movements M assesses mental abilities such as planning, imagination, and empathy and for DQ+ as an indicator of synthesis abilities. Mihura et al. (2013) found good support for Cooperative movements COP as related to the tendency to perceive socially positive interpersonal interactions and for pure human contents H as indicating that self and others are conceived as a whole (Mihura et al., 2013). A significant part of the synthesizing process, as well as some interpersonal features, seems to be embedded in a single dimension defined by human movement M, which might represent a form of social cognition. In other respects, it is interesting to note that the Kinesthetic component has pure Form and not Color on the negative pole. This result tends to indicate that Hermann Rorschach's original conception of the Erlebnistypus (M: WSumC) should not be considered as a single dimension but rather as psychological profiles of distinct psychological traits that are present in various proportions in every person (Rorschach, 1921).

Apperceptive Component

This component describes the tendency of a person to see things as a whole or in detail. Its positive pole has been previously described as a synthesis factor (Anderson & Dixon, 1993; Geertsma, 1962; Mason et al., 1985; Schori & Thomas, 1972; Shaffer et al., 1981; Wood, Krishnamurthy, & Archer, 2003; Zillmer & Vuz, 1995). In the RCS, the ratio between whole responses (W) and detail responses (D) is interpreted as the amount of cognitive effort invested in information processing. Mihura et al. (2013) did not find any study for their meta-analysis of this index. However, they report good evidence for perceptually organized responses (Zf) as related to the ability to sustain cognitive effort and for Blend responses as assessing psychological complexity. Though Exner and Mihura interpret synthesis variables (W, Zf, Blend) as a mental ability, our results suggest that the Apperceptive component might rather be conceived as a cognitive style opposing synthetic to analytical tendencies. Mihura et al. (2013) also found good support for the Affective Ratio (Afr) (which is related to the number of responses to the chromatic cards R8910) as indicating engagement in activating affective situations (Mihura et al., 2013). The present result suggests that this interpretation might need to take into account the apperceptive style of a person. Indeed, people who tend to process information analytically could give more responses to the chromatic cards because they are more scattered than the 7 first cards of the test - especially card

X – (Weinberger-Katzav & Andronikof, 2012). In this case an elevated Afr could be related more directly to cognitive features rather than affective ones.

Pure Color Component

This component seems to capture a psychological process distinct from both Form color FC and Color-form CF. The overall pattern of the Pure Color component (vague, no form, blood, Hx) suggests that these responses occur when a disruptive emotional process is experienced. In addition, Abstractions AB and Art are part of the intellectualization index of the RCS (2AB + Art + Ay) which is interpreted as a defense mechanism against such experiences (Andronikof-Sanglade, 1993; Exner, 2003). However, Mihura et al. (2013) found little support for the interpretation of Pure C responses and no relevant studies for the Intellectualization index. This lack of support could be explained by the difficulty to distinguish CF and Pure C responses (Viglione & Taylor, 2003) and psychometric issues. Scoring criteria for Pure C might be reconsidered in order to carry out further interscorer reliability researches and the Pure C score might be replaced by the Pure Color component score in validation studies as it presents better psychometric properties.

In other respects, the Weighed Sum of the Colors WSumC (0.5*FC +1* CF + 1.5*C) is an important score of the RCS and is thought to represent the total affectivity of a person (Rorschach, 1921), affective resources (Exner, 2003) or the degree to which emotions influence thoughts and experiences (Mihura et al., 2013). However, the present results suggest that the different color responses are related to distinct dimensions and that there is no psychometric support for the computation of WSumC as a single score. This point could explain the controversial findings on the validity of WSumC as indicating the degree to which emotions influence thoughts and experiences (WsumC of patients with borderline PD does not differ from CS International Norms; Wood, Garb, Nezworski, Lilienfeld, & Duke, 2015). According to our results, the interpretation of the color ratio of the RCS (FC:CF + C & Pure C) are probably more reliable than WSumC.

Reflection Component

This component presents three interesting features: (a) the association of variables composing the *Isolate* index ([2Na + 2Cl + Ls + Ge + Bt]/R) with reflections, (b) the presence of diffuse shadings Y + YF and (c) the absence of *Pairs*. (a) An elevation of the *Isolate* index is interpreted in the RCS as a lack of engagement in social interaction as evaluated through sociometric measures: people with a high *Isolate* index are rarely cited in peer designation studies (Exner, 2003). Although Mihura et al. (2013) did not find strong evidence for this interpretation, it is to be noted

that none of the four studies considered in the analysis (George & Kumar, 2008; Holaday & Blakeney, 1994; Holaday, Moak, & Shipley, 2001; Perfect, Tharinger, Keith, & Lyle-Lahroud, 2011) used sociometric methodologies (i.e. did not replicate Exner (2003) original method) nor specifically assessed the isolation construct. Mihura et al. (2013) found good support for reflection responses (Fr + rF) as indicating narcissistic tendencies. Though the *Isolate* index and Fr + rFare interpreted separately, their association could be coherent: the more people would focus on the self, the less they would pay attention to others.(b) Mihura et al. (2013) found good support for the sum of all diffuse shadings (FY + YF + Y)as related to experiences of distress or helplessness. The overall pattern of this component (narcissistic trends linked with social isolation and feelings of helplessness) might represent a measure of feeling of estrangement. (c) Reflections are part of the egocentricity index of the RCS (EGO = [3(Fr + rF) + Pair]/R) which is supposed to measure self-focus and/or self-esteem. The lack of support for the EGO index reported in Mihura et al. (2013) meta-analysis might be explained by the confusing effect of Pair responses on the EGO index (Pair and reflection responses Fr + rF do not belong to the same dimension).

Instinctual Component

In the RCS, animal movement responses FM are typically interpreted as an unintentional form of thinking produced by unmet needs or desires. From a psychological perspective, the presence of aggressive movements AG (0.49) and fabulized responses FAB1 (0.43) is coherent with this interpretation. Mihura et al. (2013) found small but significant support for the interpretation of FM as a measure of pressing primary needs and for aggressive movements AG as assessing aggression or anger. Fabulized responses FAB1 were found to reflect childish or immature forms of ideation (Exner, 2003). This component seems to tap the instinctual demands of a person and probably constitute a better measure of this construct than the FM score alone.

Explosive Component

Inanimate movements (*m*) are interpreted in the RCS as a measure of situational stress or of the thought disturbance implied by situational stress. Mihura et al. (2013) found excellent support for inanimate movements as a measure of mental distraction or agitation. The association of inanimate movements and Color-Form responses was observed in three previous studies (Costello, 1998; Meyer, 1992b; Zillmer & Vuz, 1995). This association might be explained by the presence of exploding or burning contents (*Ex*, *Fi*) on this component. The presence of Color-Form *CF* suggests that this component captures interfering modes of

ideation related to stressful representations as well as deficits in the regulation of expressed emotions. It should be noted that this Component is not correlated with diffuse shading (FY, YF + Y).

Misperception Component

This dimension is defined by poor form responses FQ- but also by Anatomy, Human Detail and Sex responses (An, Hd and Sx). Previous studies found a bidirectional dimension of Perceptual Accuracy composed of ordinary form qualities FQo on the positive pole and poor form quality FQ- on the negative one (Geertsma, 1962; Wood, Krishnamurthy, & Archer, 2003; Zillmer & Vuz, 1995). Poor form responses FQ- seem to be distinct from adequate form qualities (FQo and FQu) which constitute another dimension of the RCS.

Mihura et al. (2013) found excellent support for the interpretation of FQ- as a measure of distorted perception or failures in reality testing. The intriguing presence of anatomy, sex and human detail contents (An, Sx & Hd) in this component led us to review the probability for these contents categories to be scored as FQ-according to the RCS form quality tables. We calculated the frequency of poor form qualities FQ- for every content categories of the RCS form quality tables (Table 6) and found that these three contents (An, Sx, Hd) presented the highest probability to be scored as poor form quality FQ-, which might explain the association between FQ- and these contents.

Vista-Texture Component

This component groups all Vista responses (FV, V + VF) and all Texture responses (FT, T + TF). Geertsma (1962) found a distinct Vista dimension of the Rorschach but his study did not include Texture responses. From an empirical point of view, textures are interpreted as a need for emotional closeness and/or tactile contacts whereas vistas are interpreted as self-depreciation and/or feelings of guilt (Exner, 2003). There is good evidence for the interpretation of texture and modest evidence for the meaning of vista in the literature (Mihura et al., 2013). However, according to the results presented in this study, these two concepts seem embedded in a single dimension which might represent a typical state of mourning.

Face Component

Human and animals details (Hd, (Hd), Ad) associated with space locations S and/or uncommon locations Dd could be substantially related to face responses possibly implying passive human movement Mp (e.g. looking angry, looking sad). These responses seems to constitute an independent component of the RCS. It suggests

Table 6. Frequency of form qualities and proportion of poor form qualities for Form Quality table Content categories of the Rorschach Comprehensive System

_			,		
Content	FQ-	FQo	FQu	Total	p.FQ-
Hd	297	34	77	408	.73
An	214	57	42	313	.68
Sx	48	7	19	74	.65
Xy	36	12	14	62	.58
Α	522	178	323	1024	.51
Ge	36	3	43	82	.44
Н	68	60	27	155	.44
Ad	142	81	184	407	.35
Bt	125	74	172	371	.34
Fd	20	13	27	60	.33
Cg	39	18	64	121	.32
Hh	44	34	77	155	.28
Sc	175	119	411	705	.25
Ex	3	4	7	14	.21
Cl	9	8	29	46	.20
Na	19	33	66	118	.16
ld	7	9	40	56	.13
Art	27	58	133	218	.12
(A)	6	12	33	51	.12
(Hd)	9	25	65	99	.09
Fi	3	14	18	35	.09
(H)	13	77	98	188	.07
Bl	1	8	6	15	.07
Ls	20	91	194	305	.07
Ау	2	12	24	38	.05
(Ad)	0	1	6	7	0

Note. FQ- = poor form quality; FQo = ordinary form quality, FQu = unusual form quality.

the necessity to distinguish face responses from other human or animal detail contents (Weinberger & Andronikof, 2012). Human and animal details are generally not interpreted individually (they do not have direct empirical support), and there is no support for the interpretation of *S* responses as a measure of oppositionality (Mihura et al. 2013). We hypothesize that this Component is related to mistrust attitudes. Indeed, Human Detail *Hd*, fictional human detail (*Hd*), animal detail *Ad* and space location S are all included in the computation of the Hypervigilance Index of the RCS which is interpreted as chronic mistrust attitudes (Exner, 2003).

In addition, one study focused on face or eyes responses as related to paranoid ideation and found very significant results (Du Brin, 1962). This study was not included in the RCS (Exner, 2003) nor in Mihura et al. (2013) meta-analysis. Additional research is clearly needed for the interpretation of this Component.

Form Dominance Component

This dimension is composed of form controlled color and shading responses (*FC*, *FC*', *FY*). It has been previously described as a Form Dominance factor (Costello, 1998; Schori & Thomas, 1972; Shaffer et al., 1981; Zillmer & Vuz, 1995). This result is interesting because color responses (*FC*, *CF*, *C*) are generally thought to be quite independent from achromatic responses (*FC*', *C'F*, *C'*) and diffuse responses (*FY*, *YF*, *Y*). It appears that this distinction is not psychometrically justified when form dominance is implied. *FC*, *FC*' and *FY* are generally not interpreted as single variables and they do not have direct empirical support in the RCS (Exner, 2003) nor in Mihura et al. (2013) meta-analysis. As form dominant determinants imply no impairment in the pattern recognition process, this component seems to indicate that the person controls or intellectualizes the use of colors and shadings, suggesting emotional control.

Conventional Component

Ordinary form qualities FQxo are generally opposed to poor form qualities FQx- thus defining a Perceptual Accuracy dimension (Geertsma, 1962; Wood, Krishnamurthy, & Archer, 2003; Zillmer & Vuz, 1995). Mihura et al. (2013) found good evidence for the interpretation of adequate form qualities (FQxo & FQxu), conventional form qualities FQxo and popular responses P as indicating adaptation to reality. Our findings suggest that ordinary form qualities FQxo should rather be opposed to unusual form qualities FQxu, and the component conceived as a conventionality/originality dimension. The negative correlation of uncommon locations Dd with this component (-.41) tends to corroborate this interpretation. This finding is interesting because it implies that reality distortions could happen in the context of conventionality.

Digressive Component

Personal responses *PER* are scored when examinees justify a response by referring to a personal experience. This reference cannot be shared with the examiner and constitutes an argument from authority. It might be a subtle means to avoid a particular difficulty during the inquiry and there is some evidence for this interpretation in the literature (Mihura et al., 2013). Deviant Responses *DR1* + *DR2* are a less

subtle way to avoid the difficulty in responding to a particular card or in justifying a response. Deviant Responses indicate instances when the person does not focus on the task anymore but digresses quite freely. Deviant Responses DR1 + DR2 are generally not studied alone; they do not have direct empirical evidence. Achromatic colors (FC', C'F and C') are interpreted in the RCS as an experience of irritating emotions. Mihura et al. (2013) found good support for this interpretation. Overall, this component seems to capture digressive strategies in face of irritating emotions, though this interpretation requires further validation studies.

General Remarks

Protocol Level vs. Response Level

Some associations of variables seem to reflect relatively common responses (e.g. Ma, H, DQ+, COP and Pairs; or Pure C, DQv, FQxnone). Had such associations not been found in the results, the validity of the dimensional model would be questionable. From this point of view however, other associations such as aggressive interactions (Ma, H, DQ+, AG, Pairs), or human reflection (Fr, H, DQ+) might have been expected and were not found. In addition, some associations of primary variables cannot relate to a typical set of codes for common responses. For example Ma and Mp belong the Kinesthetic component but these codes cannot be attributed to the same response and the same is true for Na and Ls. In the same line of thought, the association between FM, A and FAB1 is surprising from a response level perspective since a response implying animals perceived in a fabulized relation would probably be scored with human movement determinant (Ma or Mp). Furthermore, some components include opposite scores such as W vs. D for the Apperceptive component or FQxo and P vs. FQxu and Dd for the Conventionality component. Finally, If there was a strong association between common sets of response codes (i.e. typical responses) and protocol variables, we should have found a "bat component" (W, DQo, A, FQo, P). Overall, the components described in this study seem to tap general tendencies in the responses rather than prototypical responses. From this perspective some unexpected associations are particularly interesting from a psychological point of view (e.g. Vista & Texture; Reflection & Isolate contents).

Cross Loadings

Ten variables present substantial cross loadings in the RCM. Five of them are related to the notion of complexity vs. simplicity (*DQ*+, *DQo*, *Zf*, *F*, *Blend*). This result suggest that complexity/simplicity should not be considered as a dimension of the Rorschach but rather as psychological profiles. Psychological profiles could be defined psychometrically in the RCM by means of clustering techniques

(e.g. hierarchical clustering on principal components with Ward's method). The other principal aspect of RCM cross loadings seem to be related to variables of the Face component (*Mp*, *Hd*, (*Hd*), *Dd*). This point suggest that the creation of a face content scoring category might be relevant for the scoring of Rorschach responses.

Variables Without Significant Loading

Most variables without significant loading in the RCM are Special Scores. As the RCM is based on nonpatient samples it is coherent that most variables related to psychopathological processes do not contribute to this normative model.

Dimensional Approach to the Rorschach Test

The RCM accounts for 43% of the variance of RCS primary variables. Though this percentage is substantial, this finding suggests that most Rorschach information cannot be described dimensionally and that many Rorschach variables provide relatively specific information. Consequently, a dimensional approach to the RCS is relevant *to a certain extent*, and it appears clearly this approach cannot be sufficient in clinical practice as it would result in a substantial loss of information.

Conclusion

Multivariate analysis of the Rorschach is challenging for methodological reasons. In previous researches, the variety of methods, the mixing of primary and combination scores and the different selection of variables to be included do not allow for a clear picture of the dimensional structure of the test. Rorschach data present basic psychometric issues: most variables are correlated to some degree with the total number of responses (problem of *R*); there are many redundancies between RCS scores (multicolinearity issue) and many variables significantly deviate from normality. In addition, modern techniques for dimensionality assessment such as parallel analysis (i.e. the question number of dimensions of the test) has never been used in multivariate analysis of the Rorschach.

The present study includes nothing but RCS primary scores – and all of them³ – excluding combinations or derivations of variables (e.g. *EGO*, *Wsum6*) in order to address multicolinearity issues. Distribution issues were addressed by rank order

³ Color naming Cn and CONTAM presented too low base rates and were not included.

transformations and the problem of R by partial correlations. Analyses were performed on a relatively large European adult nonpatient sample (N = 695). Parallel analysis combined with resampling techniques showed that 12 components eigenvalues significantly differ from random-based eigenvalues (p < 0.0001), resulting in a model accounting for 43% of the variance within RCS data. Since resampling techniques were used (bootstrap and permutations), results take sampling fluctuation into account and are expected to be generalizable and reproducible at least in adult nonpatient samples in Belgium, Finland and France. Consequently, the Rorschach Component Model (RCM) proposed here might constitute a reasonable basis toward the development of new scales that could enhance accuracy of RCS results. This model could greatly facilitate cross cultural studies or researches on the effect of examiners competency on Rorschach data. For researchers who might be interested in this model, the computations of the 12 components have been added to the Supplementary Scales report of CHESSSS (Fontan et al. 2013). However, the RCM presented here is only a preliminary model, and we plan to develop this approach on a much larger international sample.

The purpose of principal component analysis is to summarize information. From this point of view the RCM or another model of the same kind could provide a general dimensional and normative frame that would describe the main tendencies of personality that the Rorschach can assess (provided that components are validated against specific external criteria). However, it appears that this approach is somehow limited, that most Rorschach information cannot be described dimensionally and that sole reliance on a dimensional model of the Rorschach would result in a substantial loss of information (the RCM accounts for 43% of the variance of RCS data). From another point of view, while the psychometric properties of the RCS are often criticized, the main feature of this system is the highly individualized interpretation of a person's psychological functioning. Consequently, with a combination of the RCM and the RCS, the strength of each approach would balance the weaknesses of the other.

Acknowledgments

Authors thank Mike Solomon from the Tavistock clinic for his help in the preparation of the manuscript.

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Received July 27, 2015 Revision received December 16, 2015 Accepted May 25, 2016 Published online January 4, 2017

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Appendix A

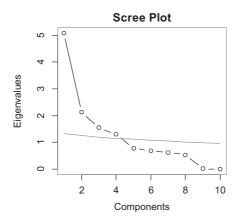


Figure A1. Parallel analysis.

Appendix B

Table B1. Stages of the analysis procedure

Stage	Objective	Operation
1	address multicolinearity	Exclude all summary scores such as <i>EB, EA, Wsum6</i> etc.
2	address distribution issues	Look for very low base rate variables and add them to the most closely related variables (e.g. C' was found to present a very low base rate and was added to C'F)
3	address distribution issues	Rank all variables
4	control the effect of R on every variables	Compute the residuals of the regression of all variables using R as the independent variable. These residuals will be used in the following analyses
5	dimensionality assessment	Compute the 1st percentile of the eigenvalues using random sampling with replacement of the observation (bootstrap)
6	dimensionality assessment	Compute the 99th percentile of random-based eigenvalues using random sampling without replacement for each variable (permutations)
7	dimensionality assessment	Determine the number of components to retain ($\alpha = 0.0001$).
8	simulate sampling fluctuations	Compute the mean correlation between each pair of variables using bootstrap resampling
9	extract independent dimensions	Perform principal component analysis on the bootstrap correlation matrix
10	interpretation	Apply varimax rotation

Summary

While six relatively consistent dimensions of the Rorschach have been identified through factor or principal component analysis (*Productivity, Form Dominance, Color Dominance, Synthesis, Perceptual Accuracy* and *Kinesthesis*), the dimensional structure of the Rorschach remains uncertain as no study to date included all Rorschach primary scoring categories. In addition, Parallel Analysis has never been used with the Rorschach whereas it is the most recommendable technique for dimensionality assessment (number of dimensions to retain). The objective of this study is to propose a preliminary comprehensive dimensional model of the Rorschach Comprehensive System (RCS). Three European adult nonpatient samples of the RCS were combined (Belgium, France and Finland, N = 695). Principal component analysis was performed on primary scoring categories. Distribution issues were addressed by rank order transformation and the problem of R by partial correlations. The number of Components was determined through Parallel Analysis and resampling techniques (bootstrap and permutation). Twelve Components eigenvalues differed significantly from chance level (p < 0.0001). The model obtained provides a simplified

representation of RCS data which accounts for 43% of the variance. This model brings new insights: some variables traditionally considered as related belong to independent dimensions, and some others considered as independent appear related. The Rorschach Component Model (RCM) includes Kinesthetic, Apperceptive, Pure Color, Reflection, Instinctual, Explosive, Misperception, Vista-Texture, Face, Form Dominance, Conventionality and Digressive components. Hypotheses concerning the psychological constructs measured by these dimensions are formulated. These results set the stage for the development of a dimensional approach to the RCS which might provide more robust findings in empirical researches and thus more sound inferences concerning patients in clinical practice. However, results also demonstrate that most RCS information cannot be described dimensionally and that clinical interpretation of the test should not rely on a purely dimensional approach.

Résumé

Six dimensions relativement consistantes du Rorschach ont pu être identifiées par le biais d'analyse factorielle ou d'analyse en composantes principales (Productivité, Dominance Formelle, Dominance de la couleur, Synthèse, Acuité perceptive and Kinesthésie). Néanmoins la structure dimensionnelle du Rorschach demeure incertaine dans la mesure où aucune étude n'a inclus l'ensemble des variables issues directement de la cotation. De plus l'analyse parallèle n'a jamais été utilisée avec le Rorschach alors qu'elle est actuellement la technique la plus recommandée pour l'évaluation de la dimensionaalité des données (le nombre de dimensions à extraire). L'objectif de cette étude préliminaire est de décrire un modèle dimensionnel complet du Rorschach en Système Intégré. Trois échantillons normatifs européens ont été combinés (Belgique, France et Finlande, N = 695). Une analyse en composantes principales a été réalisée sur l'ensemble des variables issues de la cotation. Les variables ont fait l'objet de transformation par rang afin de traiter les problèmes de distribution, et le problème du nombre de réponse à été traité par le recours à des corrélations partielles. Le nombre de composantes a été déterminé par une combinaison d'analyse parallèle et de techniques de rééchantillonnage (bootsrap et permutations). Les valeurs propres de 12 composantes présentent des valeurs significatives (p < 0,0001). Le modèle obtenu fournit une représentation simplifiée des données du Rorschach qui rend compte de 43% de la variance. Ce modèle fournit de nouveaux éléments de compréhension du Rorschach : certaines variables traditionnellement considérés comme connexes appartiennent à des dimensions indépendantes, tandis que d'autres variables que l'on pensait indépendantes semble appartenir à une même dimension. Le Modèle des Composantes du Rorschach inclus les composantes Kinesthésie, Apperceptive, Couleur Pure, Reflet, Instinctuelle, Explosive, Erreur Perceptive, Vista-Texture, Visage, Dominance Formelle, Conventionalité et Digressive. Certaines hypothèses concernant les construits psychologiques mesurées par ces dimensions sont formulées. Ces résultats ouvrent la voie à l' élaboration d'une approche dimensionnelle du Rorschach qui pourrait fournir des résultats plus robustes dans les recherches empiriques et donc des inférences donc plus solides concernant les patients dans la pratique clinique. Cependant, les résultats montrent également que la plus grande part de l'information contenue dans les données du Rorschach ne relève pas de l'approche dimensionnelle qui est insuffisante pour l'interprétation clinique du test.

Resumen

Mientras han sido identificadas seis dimensiones relativamente consistentes del Rorschach por medio del análisis factorial o de componentes principales (*Productividad, Dominancia Formal, Dominancia del Color, Síntesis, Precisión Perceptual y Kinestesias*) la estructura dimensional del Rorschach permanece insegura, dado que hasta la fecha ningún estudio incluyó todas las categorías primarias de codificación del Rorschach. Además, el Análisis Paralelo nunca ha sido usado

con el Rorschach mientras que es la técnica más recomendable para la evaluación de la dimensionalidad (el número de dimensiones a retener). El objetivo de este estudio es proponer un preliminar modelo dimensional comprehensivo del Rorschach Sistema Comprehensivo (RSC). Tres muestras europeas de adultos no pacientes del ESC fueron combinadas (Bélgica, Francia y Finlandia, N = 695). Un análisis de componentes principales fue realizado sobre categorías de codificación primarias. Cuestiones de distribución fueron enfocadas a través de orden de rango y el problema de R por correlaciones parciales. El número de Componentes fue determinado mediante Análisis Paralelo y técnicas de re-muestreo (bootstrap4 y permutación). Doce Componentes de valores propios se diferenciaron significativamente del nivel de azar (p < 0.0001). El modelo obtenido provee una representación simplificada de los datos RSC que justifica el 45% de la varianza. Este modelo contribuye nuevos insights: algunas variables tradicionalmente consideradas como relacionadas pertenecen a dimensiones independientes y algunas otras consideradas como independientes parecen vinculadas. El Modelo Componente Rorschach (MCR) incluye Componentes Kinestésicos, Aperceptivos, Color Puro, Reflejos, Instintivos, Explosivos, Percepción Errónea, Vista-Textura, Cara, Dominancia Formal, Convencionalidad y Digresivos. Hipótesis son formuladas concernientes a los constructos psicológicos medidos por estas dimensiones. Estos resultados crean el marco para el desarrollo de un enfoque dimensional al RSC que podría proveer hallazgos más robustos en investigaciones empíricas y así inferencias más sólidas respecto de pacientes en la práctica clínica. Sin embargo, los resultados también demostraron que la mayoría de la información RSC no puede ser descrita dimensionalmente y que la interpretación clínica del test no debiera recurrir a un enfoque puramente dimensional.

要約

因子分析あるいは主成分分析により、ロールシャッハ法の比較的一貫性のある6つの次元 (生産性、形 態優位性、色彩優位性、統合性、知覚の正確さ、運動感覚)が同定されてきているが、ロールシャッ ハの主要なすべてのスコアリングカテゴリーを含んだ研究は現在まで、ないので、ロールシャッハ法の次元の 構造は依然として明確にはなっていない。加えて、次元の査定(保つべき次元の数)には最も推薦される 方法で、ある平行分析がロールシャッハ法には全くもちいられてこなかった。本研究の目的は、ロールシャッハ 包括システム (RCS) における予備的な包括的な次元のモデルを提案することである。 3 つのヨーロッパ の患者ではないRCSのサンプル (ベルギー、フランス、フィンランド、N=695) が合わせて分析された。 主要なスコアリングカテゴリーに主成分分析が遂行された。分布の問題が、順位への変換および部分 相関によるRの問題によって対処された。成分の数は平行分析と再サンプリング法(ブートストラップと組 み換え) によって決定された。12の成分の固有値が有意で、あった (p<0.0001) 。得られたモデルは RCSのデータの簡略化された表彰を提供しており、それは分散の43%を説明している。このモデルは新しい 見識をもたらしている:伝統的に関連しているとみなされているいくつかの変数は独立した次元に属しており、 独立しているとみなされていたいくつかの他の変数は関連しているようで、あった。ロールシャッハ法の成分モデ ル (RCM) には、運動感覚、統覚、純粋色彩、反射、衝動、爆発、誤った知覚、陰影-材質、 、形態の優位性と、因襲性、本質からそれる成分が含まれる。これらの次元によって測定される心理 学的な構成要素に関する仮説が定式化された。これらの結果は、ロールシャッハ包括システム法の次元 によるアプローチ法の発展のお膳立てをした。この接近法の発展は、実証的な研究におけるより確かな発見 を提供するであろうし、よって臨床実践において患者に関連するより健全な変化をもたらすであろう。しかしな がら、この結果はまた、ロールシャッハ包括システム法の多くの情報が次元的には説明できないことを示して おり、この検査の解釈も純粋に次元アプローチにもとづくことができないことを示している。

In Spanish: Tomar datos en forma aleatoria de un conjunto de datos.