Multidimensional assessment of outcome in psychiatry: the use of graphical displays. The South-Verona Project 2

MIRELLA RUGGERI, Istituto di Psichiatria, University of Verona, Italy
MARCO RIANI, Istituto di Statistica, University of Parma, Italy
PAOLA RUCCI, Istituto di Psichiatria, University of Verona, Italy
ANNIBALE BIGGERI, Dipartimento di Statistica, University of Florence, Italy
MICHELE TANSELLA, Istituto di Psichiatria, University of Verona, Italy

ABSTRACT *In psychiatry, the assessment of outcome, to be relevant for clinical practice, should be multidimensional. This demands suitable statistical tools both to represent and to analyse the complex relationships between variables. This paper aims to provide guidelines for selecting graphical displays of multidimensional data that enable better capturing of the relationships between variables and summarize information available for individual cases as well as for groups of patients. Multivariate graphical techniques such as Chernoff faces, stars, parallel co-ordinates and Andrews plots are applied to a set of data drawn from the South Verona Outcome Project, a naturalistic study based on a multidimensional model for the assessment of outcomes, routinely conducted at the Institute of Psychiatry of the University of Verona, Italy. The assessment includes global functioning, psychopathology, social disability, subjective quality of life, and satisfaction with services, number of service contacts and days of hospitalization.*

The selected sequence of graphical displays allows a quick understanding of the multivariate data set not otherwise obtainable with numerical indexes and specifically enabled us to: (a) picture the characteristics of the data set on each single variable; (b) identify relationships between two or more variables; (c) identify peculiarities of individual patients and of group of patients. In psychiatry and in other areas of medicine a graphical approach to multidimensional data is a useful analytical tool for increasing the impact of outcome studies, in everyday clinical practice and in monitoring and evaluating of services.

Key words: psychiatry, outcome, graphical displays, multivariate analysis, exploratory methods, Andrews curves

Introduction

In line with a widespread trend in many areas of medicine (Ellwood, 1988; Epstein, 1991; Hadorn and Uebersax, 1995; Spitzer, 1996), the need for multidimensional data collection is increasingly recognized in psychiatric epidemiology. A multidimensional perspective is, for example, needed when assessing treatment outcomes. In fact, many authors have stated that, in order to be valid and useful for clinical practice, outcome studies of psychiatric care should be multidimensional and combine optimal indicators of both the 'service level' and the 'patient level' (Wing, 1986; George, 1989; Jenkins, 1990; Ruggeri and Tansella, 1995; 1996; Cairn, 1996; Knudsen and Thornicroft, 1996; Thornicroft and Tansella, 1996). At the 'service level', process variables such as number of service contacts and days of admission to hospital must be considered. At the 'patient level' the effectiveness of interventions has to be investigated on various dimensions, including clinical variables (the severity and course of symptoms), social variables (social functioning, social support, quality of life), and the users' interaction with the services (needs for care, family burden, satisfaction with services).

Outcome studies that fulfil the above requirements are rare. The need to learn about the effectiveness of treatments thus requires more research being dedicated to 'real world' services evaluation. On the other hand, this pressure towards performing outcome studies that fully account for the complexity of the routine practice is counterbalanced by the difficulty of understanding and interpreting the data collected, and by the fact that statistical tools that allow representation and analysis of the complex relationships between variables are not easily available to clinicians and researchers (Gibbons, 1993; Biggeri, Rucci, Ruggeri and Tansella, 1996).

The tendency to treat different primary responses as univariate responses, even when multivariate data are available, is still common (for example in clinical trials it is customary to report separate analyses of multiple end-points), but it has been recently stigmatized (Cox and Wermuth, 1996: 8 and 122). Disregarding the relationships among responses can in fact lead to biased conclusions on the role of specific determinants. When some predictors affect a response variable through another variable and, in general, when complex aspects of reality are investigated, univariate methods can indeed be misleading and use of multivariate descriptive and exploratory techniques has to be considered mandatory.

Graphical displays provide a useful support for the construction of a model that accounts for empirical relationships found in the data. In spite of a certain amount of literature on graphical displays in various medical areas (Tukey, 1977; Cleveland and McGill, 1984; Chambers, Cleveland, Kleiner and Tukey, 1983; Wilkinson, 1992; Everitt, 1994; Powsner and Tufte, 1994; Sasieni and Royston, 1996), the use of graphical techniques in epidemiological psychiatry is scanty (Dunn, 1983, 1986).

The aim of this paper is to show how to explore multidimensional data sets using some selected graphical techniques[1] and how to represent data complexity while preserving a clear presentation. Specifically, multivariate graphical techniques are applied to data drawn from a study based on a multidimensional model of outcome assessment, the South-Verona Outcome Project (SVOP), conducted in a community-based psychiatric service (CPS), and described in detail elsewhere (Tansella and Ruggeri, 1996). This paper belongs to a series that describes the data collected in the SVOP (see Ruggeri et al., 1998).

Methods

Variables

In the SVOP all patients examined at least once by a doctor in the South-Verona community-based psychiatric service (CPS) in two given three-month periods each year (1 April to 30 June or 1 October to 31 December) are assessed with a set of standardized instruments. For each patient, the key-professional completes the Global Assessment of Functioning Scale (GAF, Endicott and Spitzer, 1976; 0 = worst functioning; 90 = best functioning), the Brief Psychiatric Rating Scale (BPRS, 'expanded version', Lukoff, Nuechterlein and Ventura, 1986; 1 = no symptom, 7 = very severe symptom), 8 items drawn from the section on Social Roles of the Disability Assessment Scale (DAS-II, WHO, 1988; 0 = no dysfunction, 5 = maximum dysfunction); the patient fills in the Lancashire Quality of Life Profile (LQL, Oliver, 1991; 1 = couldn't be worse, 7 = couldn't be better) and the Verona Service Satisfaction Scale (VSSS, Ruggeri and Dall'Agnola, 1993; Ruggeri, Dall'Agnola, Agostini and Bisoffi, 1994; 1 = terrible, 5 = excellent). Data on socio-demographic characteristics, psychiatric history and service utilization are routinely recorded in the South-Verona Psychiatric Case Register (PCR) (Tansella, 1991).

Variables analysed in this paper are taken from the October–December 1994 assessments (no. of patients = 257) and are:

- diagnosis (DIA). This variable consists of six diagnostic groups based on ICD-10 diagnoses (WHO, 1992) collapsed according to the classification system used by the South-Verona PCR (Sytema, Giel, ten Horn and Balestrieri, 1989) as follows: schizophrenia (F20, F21, F22, F23, F24, F25, F28, F29, F84); affective psychosis (F30, F31, F32.2, F33.3); depression without psychotic symptoms (F32, F33, F34.1, F41.2, F43), neurotic syndrome and somatization disorder (F40, F41, F42, F44, F45, F48, F54), personality disorder (F34, F52, F60, F61, F62, F63, F64, F65, F66, F68, F69), other diagnoses (including also substance abuse);
- number of psychiatric contacts (CONT) in the three months preceding the index assessment;
- days of hospitalization in the preceding year (DAYADM);
- global functioning (GAF score);

[1] This paper presents only graphical methods that explore first-order moments (means). Graphical methods such as principal component analysis, correspondence analysis and partial least-squares regression, which explore second-order moments (correlations), are not presented here for reasons of space. Moreover, the description of repeated measures analysis and survival analysis, in which extensive use of graphical displays is made, is beyond the scope of the present paper, in which cross-sectional data are analysed.

- psychopathology (BPRS mean score of 24 items);
- social disability (DAS mean score of 8 items);
- subjective quality of life (LQL mean score of 29 items);
- satisfaction with services (VSSS mean score of 54 items).

BPRS, DAS, LQL, VSSS are treated as quantitative variables measured on an interval scale because they are mean scores of items. GAF takes integer values comprised between the wide range 0–90 and therefore it can also be assumed to be quantitative and measured on an interval scale.

Summary statistics are available from the authors. All displays were obtained using S-PLUS (Statistical Sciences Inc., 1993), except for Andrews curves, obtained using a GAUSS (Edlefsen and Jones, 1993) subroutine written by one of the authors (Marco Riani). The univariate distribution of variables is shown using boxplots[2] (Figure 1). Single segments out of the whiskers indicate outliers, i.e. values far removed from the others, which are labelled in our data set by the South-Verona PCR number.

Multivariate techniques

Display of two or three variables

When two variables are considered, a scatterplot matrix can represent the pairwise relationships between them. To display more than two dimensions, one of the axes must be projected on the plane. Three-dimensional scatterplots are usually very confusing. The dynamical graphics facility of S-PLUS allows one to obtain a three-dimensional data representation in which axes can be rotated to explore portions of interest in the point cloud (Figure 2, upper right side). This technique also enables the 'highlighting' of individual cases using a function named 'brushing' and the observation of their position in all the bivariate plots (Figure 2, left side).

Display of more than three variables

Displaying more than three dimensions requires specific conventions for denoting variables. Iconal representations are used to display the location of each patient or group of patients.

Chernoff faces (Chernoff, 1973) are one iconal representation with high visual impact. Each variable is associated with an element of the face; the more pronounced is the element, the more extreme the value of the corresponding variable. It is possible to define the range of allowed values; if omitted (as in the present paper), the observed range is used (maximum–minimum). Chernoff faces allow easy identification of anomalous subjects with respect to the majority of faces in the sample (Figure 3). One problem connected with this technique is that a different correspondence between variables and features of the face may lead to a very different visual impression. Another drawback is that the number of variables that can be represented is limited by the number of somatic traits. In this study we chose the emotional impact of the somatic trait as a leading criterion for establishing a correspondence between variables and the elements of the face. An additional application of Chernoff faces is to summarize the characteristics of different groups of patients (Figure 4). In this case, an effective representation of the relationships among the mean values of many variables can be obtained.

Stars are an alternative iconal representation (Fienberg, 1979) where variables are denoted as sunrays connected by a broken line. The length of each ray ranges from 0 to 1, where 0 represents the observed minimum value of the sample and 1 the observed maximum. This method enables the display of a higher number of variables than the previous one. Differences among cases are apparent from the shape of the respective star (Figure 5), and anomalous subjects can immediately be identified. The shape of the star also gives information on the relationship among variables in each subject: high values and low values in all dimensions will result, respectively, in a diamond-like shape and in a dot; great differences between variables will result in irregular triangles. Thus, occurrence of several different star shapes suggests independence between variables, whereas if irregular triangles prevail this could indicate negative relationships. As with Chernoff faces, stars can be used to display groups of patients (Figure 6).

Two powerful tools to further explore multivariate data are parallel co-ordinates (Wegman, 1990) (Figure 7)

[2]The boxplot is a well-known display where the line in the middle indicates the location of the median, the lower boundary of the box marks the first quartile, the upper boundary the third quartile. Half of the cases have values within the box, while the whiskers include the cases that are ±1.5 (length of the box) apart from the median. Dot plots are another recommended display to summarize univariate distributions of variables and they are to be preferred to boxplots when subgroups of different size are compared (Sasieni and Royston, 1996). They are not shown here as our focus was to compare the distribution of variables on the 257 subjects selected for this study. In this case boxplots are equally effective and more readable.

and Andrews plots (Andrews, 1972) (Figure 8). In *parallel co-ordinates* variables are shown as parallel vertical lines and lines connect the values attained by each patient on the variables. This method is able to display a potentially unlimited number of variables. As for the number of cases, when the sample size is small individual lines are easily identified whereas a large sample results in too many lines; however, outliers may emerge even in this case. The degree of intersection between individual lines gives hints about the pattern of correlation among variables (high positive correlation resulting in no intersection); still, this kind of information is less impressively displayed by this method than by Chernoff faces and stars.

In *Andrews plots* each case is represented by a linear combination of sine and cosine functions, whose coefficients are determined by the values of the variables. These plots are useful in detecting clusters of cases because the curves for related cases tend to be close together and in phase. As with the parallel co-ordinates technique, only a limited number of observations can be plotted on the same diagram as too many curves can lead to confusion. As with Chernoff faces, the ordering of variables is important: in fact a quite different picture is obtained if variables are permuted. The first variables selected play a more important part in the construction of the plot, so it is good practice to insert the most relevant variables in the first positions. Following this criterion, we ranked the variables collected in the SVOP as follows: GAF, BPRS, DAS, LQL, VSSS, CONT, DAYADM. A major strength of Andrews plots is that combining variables enables one to precisely identify cases who are located 'at the boundary of normality' in many dimensions, i.e. multivariate outliers.

Results

Univariate analyses

Socio-demographic and diagnostic characteristics of the patients assessed (n = 257) are reported in Table 1. Inspection of the boxplots of Figure 1 shows that variables have a different spread, some of them being roughly symmetrical (LQL, GAF), others (CONT, DAYADM) highly skewed with a long series of outliers. Specifically, there is a long tail of patients with more than 15 contacts and more than eight days of hospitalization; only one patient has a very poor functioning (GAF), none is an outlier on LQL, whereas more outliers can be found in DAS, BPRS and VSSS. This heterogeneity is a frequent finding when many variables are taken into account and suggests that caution is to be exercised when considering the relationships between these variables, as skewed variables need to be transformed and outliers require specific treatment. In this figure it is also apparent that some subjects are univariate outliers and others display extreme values on more than one variable, but an accurate identification of multivariate outliers is not possible by this method.

Table 1: Sociodemographic and diagnostic characteristics of the patients assessed (n = 257)

Characteristic	Number of subjects
Age (years) (mean)	47.87 (SD 15.54)
Gender:	
male	90 (35%)
female	167 (65%)
Marital Status	
married	126 (49%)
not married*	131 (51%)
Living Situation	
lives alone	25 (10.3%)
with family	231 (89.3%)
sheltered accommodation	0
other	1 (0.4%)
Qualification	
basic	201 (78.2%)
higher**	56 (21.8%)
Employment	
employed	101(39.3%)
not employed***	156(60.7%)
Diagnosis****	
schizophrenic psychosis	56 (21.8%)
affective psychosis	26 (10.1%)
neurotic depression	88 (34.2%)
other neuroses	37 (14.4%)
personality disorder	32 (12.5%)
substance abuse and other	15 (7.5%)

* Single/divorced/widowed.

** A level or equivalent, higher diploma or degree.

***Also includes housewife, retired, student.

****ICD-10 diagnoses grouped according to the classification system used by the South Verona PCR (see text for more details).

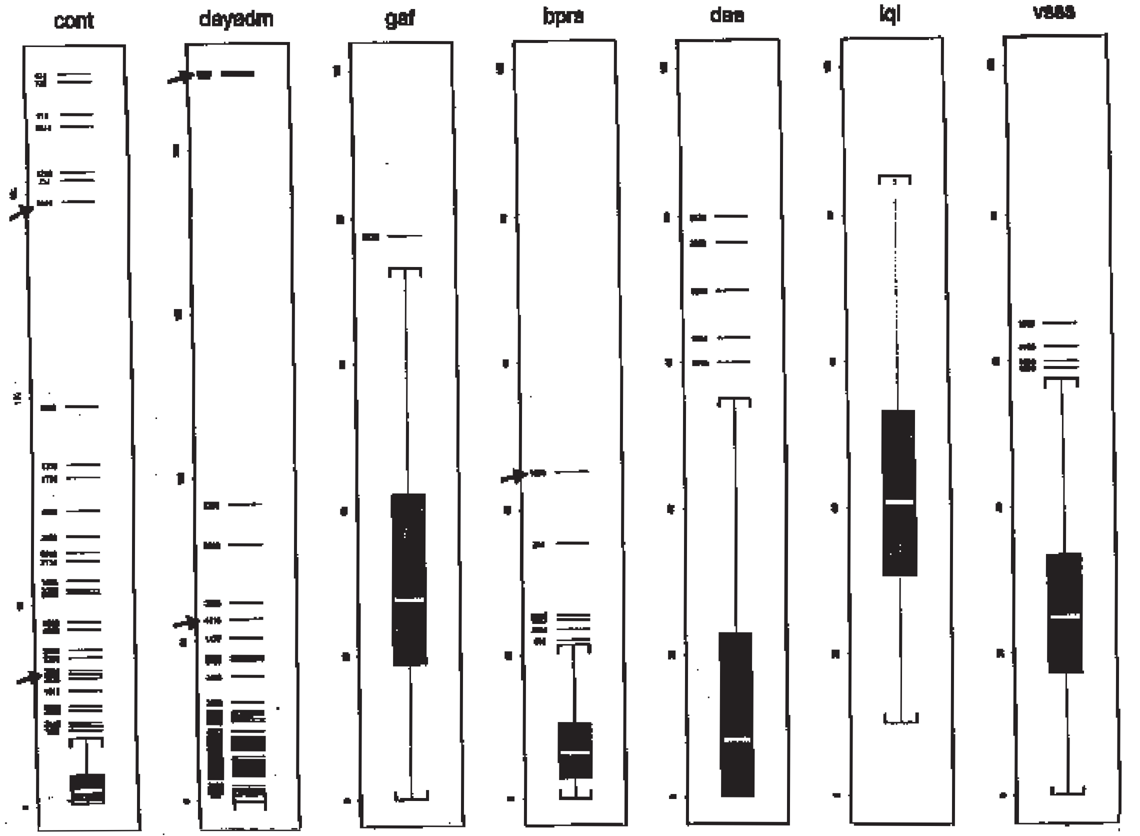

Figure 1: Boxplots of the number of contacts (CONT), days of admission (DAYADM), global functioning (GAF), psychopathology (BPRS), disability (DAS), subjective quality of life (LQL), satisfaction with services (VSSS). Outliers are displayed as segments and marked with a label, corresponding to the South-Verona Psychiatric Case Register number. All variables except number of contacts and days of admission were rescaled so as to range from 0 (best condition) to 100 (worst condition). An arrow points at two outliers (n. 1604 and n. 4116) whose characteristics are discussed in detail in the text

Display of two or three variables
Figure 2 shows the S-PLUS screen in which pairs of variables are plotted against each other and are represented as histograms in the bottom row of the triangular scatterplot matrix. The linear association between DAS and GAF, LQL and VSSS, BPRS and GAF, BPRS and DAS is apparent from the respective scatterplots (the corresponding Spearman correlation coefficients are available from the authors) as well as the substantial lack of linearity in the pairwise relationships between the other variables. This method still fails to capture the multidimensional relationships between variables because the association between two variables could be strengthened or weakened by a third variable.

By using the function brushing of S-PLUS, two cases, one previously identified in the boxplot (see arrows in Figure 1) as an outlier in three dimensions (n. 1604) and the other one identified as an outlier in two dimensions (n. 4116), are marked by heavier dots. A three-dimensional representation of BPRS, DAS and CONT is visible on the upper right corner of Figure 2: case n. 1604 emerges from the bulk of the sample whereas case n. 4116 is located at the boundary of the points cloud.

Display of more than three variables
The relationships between more than three variables are first explored at the individual level, plotting the Chernoff faces of patients (Figure 3), sorted by increas-

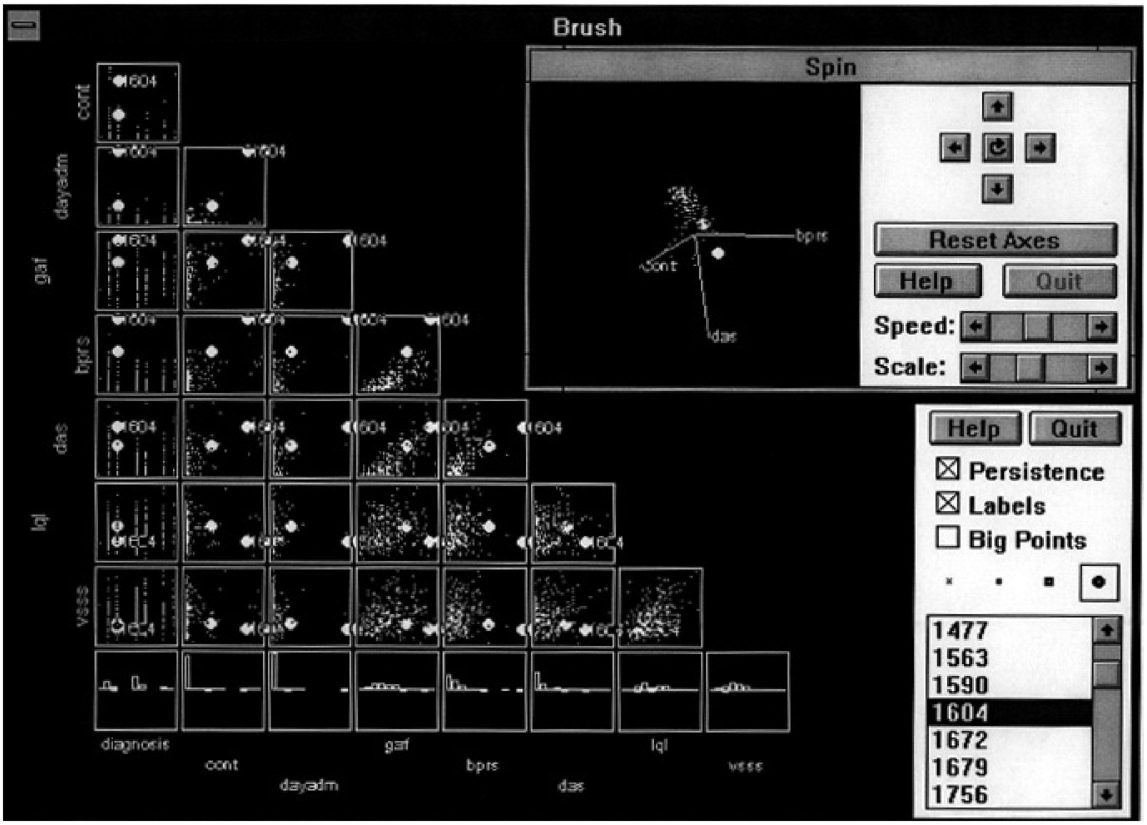

Figure 2: S-PLUS screen showing the scatterplot matrix of the number of contacts (CONT), days of admission (DAYADM), global functioning (GAF), psychopathology (BPRS), disability (DAS), subjective quality of life (LQL), satisfaction with services (VSSS). In the insert on the upper right corner the point cloud is shown in three dimensions with reference to the axes BPRS, DAS and CONT. On the right of the figure, the panel with the interactive functions of dynamic graphics is shown. By means of the function 'brushing' of S-PLUS, two units (n. 1604 and n. 4116) are highlighted and their location is displayed in each bidimensional plot. The three-dimensional plot on the upper right side shows that case n. 4116 is located in the boundary of the points cloud and n. 1604 is completely external to it

ing level of psychopathology. Only the subset of the 26 patients with an ICD-10 diagnosis of affective psychosis (see below) is shown for clarity (the raw data for these patients are available from the authors). Variables are displayed as elements of the face (global functioning = width of eyes; psychopathology = angle of eyebrow; disability = nose length; subjective quality of life = shape of the face; satisfaction with services = curvature of smile). Faces in the first row are characterized by a combination of low psychopathology, low disability, good functioning, high subjective quality of life and good satisfaction with services. As soon as psychopathology increases, the heterogeneity of faces indicates that no simple pattern of associations between variables is present at the individual patient level.

Secondly, Chernoff faces are used to display the mean values of more than three variables in different groups of patients. Figure 4, shows the icons of the six diagnostic groups based on ICD-10 diagnoses. Qualitative differences and similarities between groups are emphasized in this display. For example, patients with schizophrenia display a severe psychopathology markedly associated with poor functioning and severe disability; patients with personality disorders show the poorest subjective quality of life coupled with severe disability; and patients with affective psychosis only differ from those with depressive neurosis for lower satisfaction with service and more severe disability. Recurring patterns of association can also be identified: the association between psychopathology and functioning is apparent in all diagnostic groups, similar to the

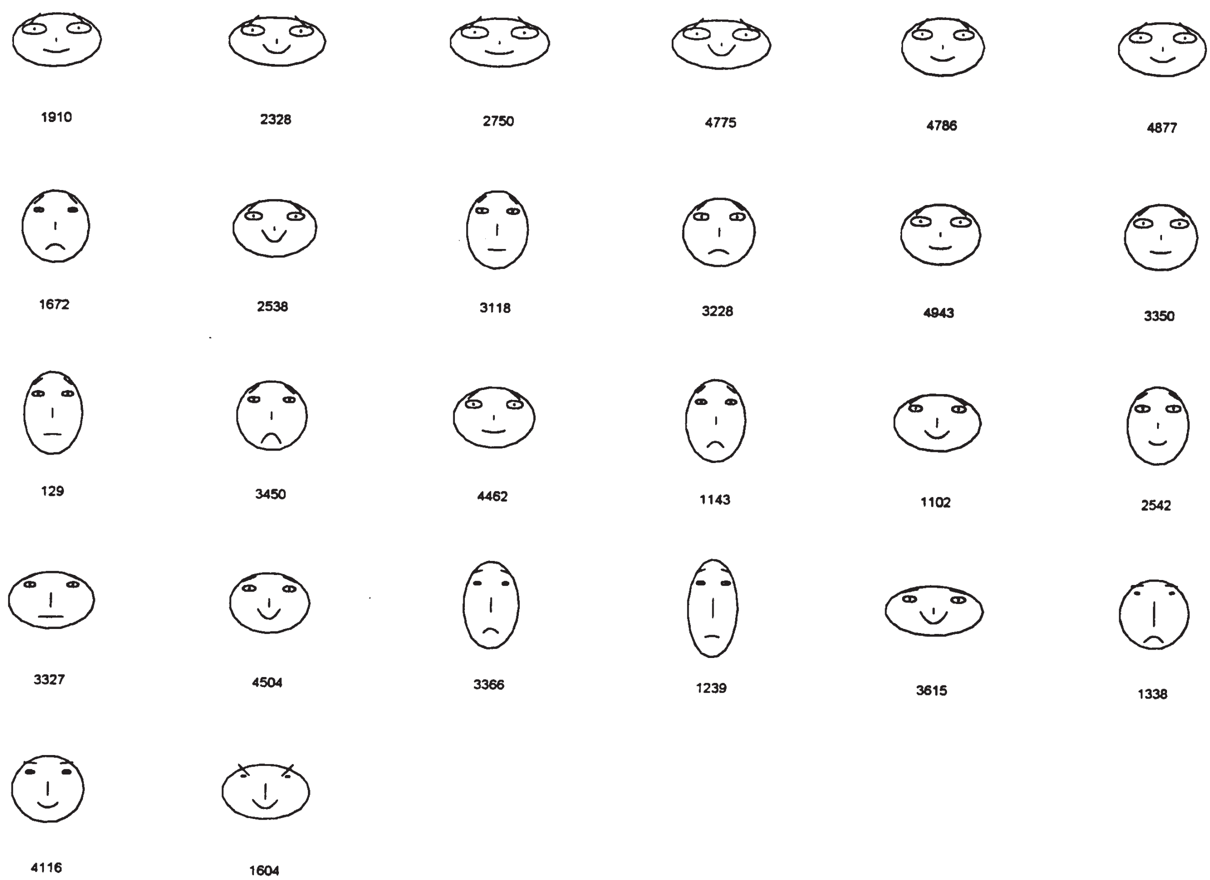

Figure 3: Chernoff faces. Variables are associated to the elements of the face: *satisfaction with services* = curvature of smile: up = satisfied with services, down = dissatisfied with services; *subjective quality of life* = shape of the face: large = good, narrow = poor; *disability* = nose length, short = low, long = severe; *psychopathology* = angle of eyebrow, external = low, internal = severe; *global functioning* = width of eyes: large = good, narrow = poor. Chernoff faces representing patients with an ICD-10 diagnosis of affective psychosis (n = 26), identified by the South-Verona Psychiatric Case Register number and sorted by increasing levels of psychopathology, are shown. Worst and best conditions represent the true minimum and the true maximum of the sample

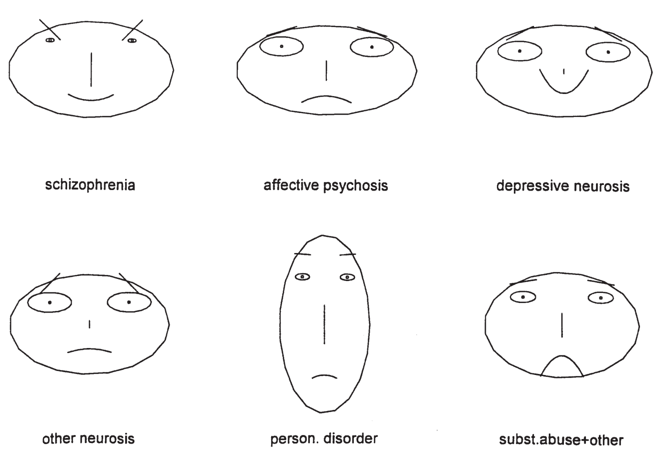

Figure 4: Chernoff faces representing six ICD-10 diagnostic groups are shown (see text for more details). The mean values of the variables are displayed

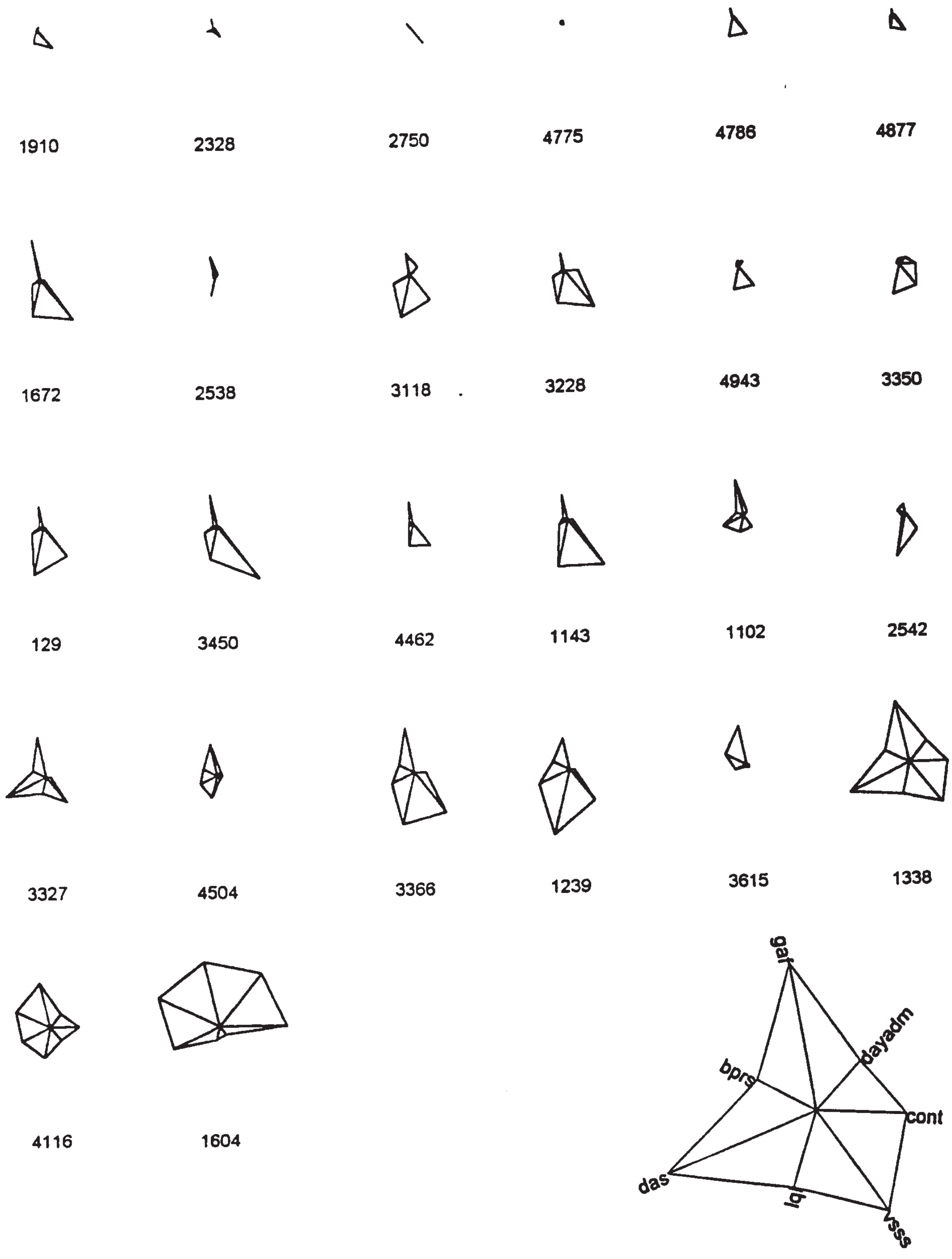

Figure 5: Stars. Number of contacts (CONT), days of admission (DAYADM), global functioning (GAF), psychopathology (BPRS), disability (DAS), subjective quality of life (LQL), satisfaction with services (VSSS) are displayed as sun rays connected by lines and oriented counterclockwise starting from the number of contacts (the ray pointing at the east direction, see legend). The length of each ray can range from 0 to 1, where 0 represents the best condition in the sample and 1 the worst condition. Stars represent patients with an ICD-10 diagnosis of affective psychosis (n = 26), sorted by increasing levels of psychopathology

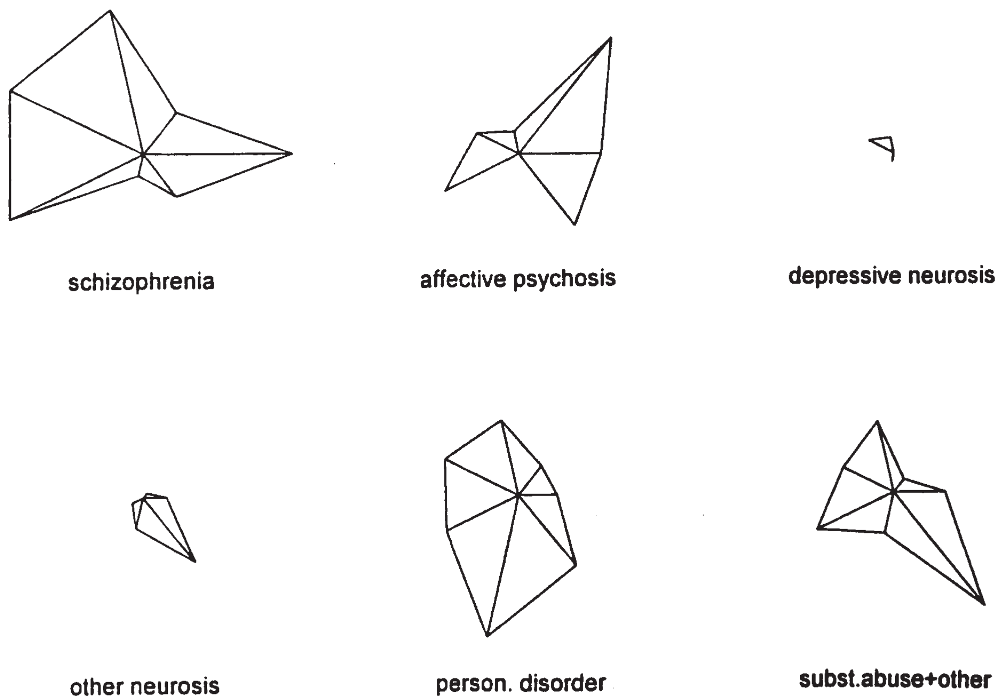

Figure 6: Stars representing six ICD-10 diagnostic groups are shown (see text for more details). The mean values of the variables are displayed

association between disability and psychopathology, with exception of affective psychosis. Subjective quality of life and satisfaction with services do not show a simple pattern of association with each other and with the other variables.

One limit of Chernoff faces is that, due to the assignment of variables to somatic traits, some variables may be less impressively displayed than others: in this case psychopathology and disability have a lower visual impact than quality of life or satisfaction with services. This is not the case when the stars method is used: Figure 5 shows stars representing individual patients with an ICD-10 diagnosis of affective psychosis sorted by increasing levels of psychopathology. The variables are shown as lines of varying length and are recoded so as to range from 0 to 1, where 0 denotes the best and 1 the worst possible condition. The area of the star thus proportionally increases with the severity of the condition of a patient: some patients display high values in most dimensions and have roughly a diamond-like shape (for example, patients n. 1338 and n. 4116); one patient has low values in all variables (n. 4775) and thus appears as a dot; many other patients appear as irregular triangles because some dimensions have low values and others have high values.

Comparison between diagnostic groups (Figure 6) highlights the severity of schizophrenic patients, who have a highest number of contacts, a significant number of days of admission, poor functioning, severe psychopathology and disability. By contrast, patients with depressive neurosis display the best condition in the sample.

Inspection of multivariate outliers

The parallel co-ordinates of Figure 7 display the same subgroup of 26 patients with affective psychosis considered above. Two outliers for number of contacts and days of admission (patient n. 1604 and n. 1338) can be immediately identified. By following their lines it can be observed that both of them have largest values for functioning (variable 3), psychopathology (variable 4) and disability (variable 5) but their scores differ on the remaining two variables. As individual lines are highly intersecting in the Figure, it is clear that, in this group of patients, the pattern of correlation among variables is complex, but it should be noted that no effective display of the association among variables is provided by this Figure.

Andrews curves (Figure 8) show one patient who markedly differs from the others (n. 1604) and two others whose waves present different shapes (n. 1338 and n. 4116) from the bulk of the sample. Going back to Figures 1 to 7, it can be observed that patient n.1604 was very easy to pick up by the naked eye in the various figures, due to the extreme values reached in many dimensions, while n. 4116 and 1338 were not clean-cut multivariate outliers.

Discussion

To date, scientific evaluation of outcome of psychiatric care is in an hypothesis-generating rather than hypothesis-testing phase. Researchers need to better understand the phenomena investigated, using exploratory statistical methods that highlight the relevant characteristics of the data, and are still not able to superimpose a model or use techniques with strong assumptions (for example about probability distributions or linearity of effects). In this phase it is not possible to rank all indicators of outcome in order of importance and it is often difficult to establish causal relationships. Thus, a model based on a reduced set of indicators can only be devised and tested in new data sets during a subsequent phase.

Graphical exploratory methods are very flexible and deserve more attention than they currently receive in applied research. The techniques shown in this paper are important for understanding and summarizing multidimensional data and thus for generating hypotheses. They differ from one another in their limitations and are complementary. The examples shown are one of the very first applications of these methods in psychiatry.

Application of graphical techniques allowed us to hypothesize relationships among variables to be further

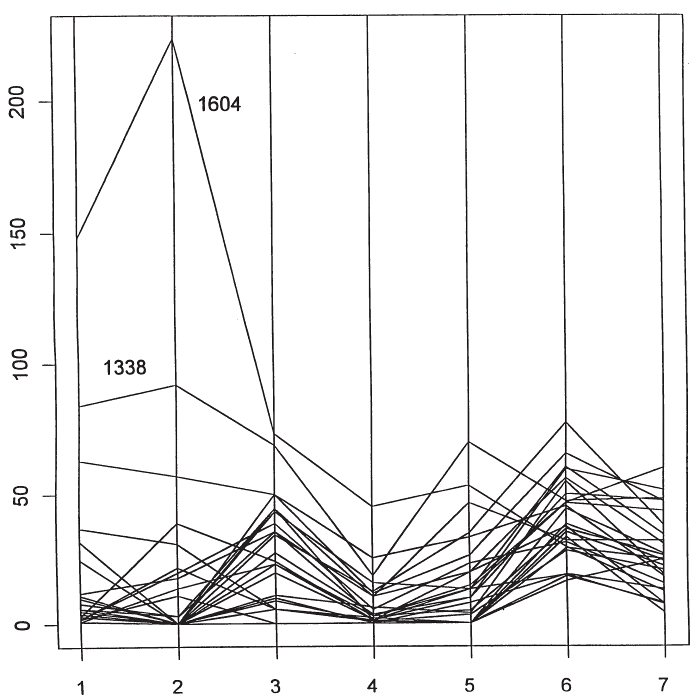

Figure 7: Parallel coordinates. Each line represents a patient with affective psychosis (n = 26 patients) and numerical labels on x-axis denote respectively number of contacts (1), days of admission (2), global functioning (3), psychopathology (4), disability (5), subjective quality of life (6) and satisfaction with services (7). All variables except number of contacts and days of admission (for which raw values are reported) were recoded so as to range from 0 (best condition) to 100 (worst condition)

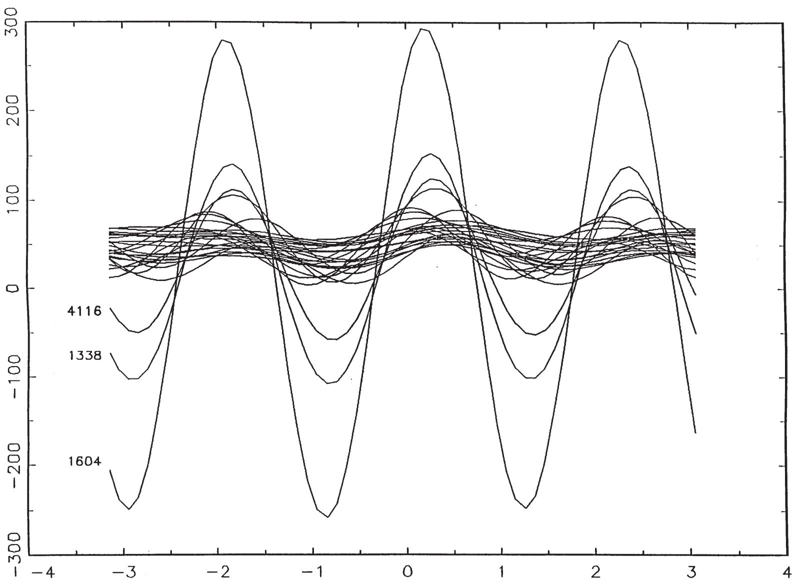

Figure 8: Andrews plots. Each curve represents a single patient with affective psychosis (n = 26 patients) and it is obtained as a trigonometric function of the variables considered

explored and to investigate peculiarities of groups and of individual patients. Subjects displaying extremely high or extremely low values on one or more variables represent a phenomenon to be controlled statistically and to be analysed and discussed in detail from the clinical point of view. We found that when patients have extreme characteristics in most dimensions, all graphical displays of individual cases are able to identify them. A major advantage of Chernoff faces and stars is that they give a unitary picture of individual patients: Chernoff faces have a high visual impact; stars take advantage of the homology they establish between the overall severity of the patient's condition and the area covered on the display. Andrews curves appear to be the most effective method in highlighting multivariate outliers: they depict each patient as a trigonometric function of several variables, thus striking differences in phase and period among curves emphasize individual 'typicalities'. On the other hand, Andrews curves are unable to capture relationships among variables, which are more effectively displayed by scatterplot matrix, dynamical graphics and Chernoff faces, and only to some extent by stars and parallel co-ordinates.

Overall, application of graphical displays allowed a quick understanding of the main characteristics of the data – an understanding that could not otherwise possibly be obtained so effectively – and throws some light on the relationship among variables found in the South-Verona Outcome Project. A series of hypotheses on the indicators of outcome to be tested in further studies have been generated. Specifically, our exploratory analysis ended with two points to be addressed in subsequent model-based (confirmatory) analyses:

- the relationship between GAF–DAS–BPRS on the one hand, and LQL–VSSS on the other hand, should be considered for formal statistical testing;
- a series of multivariate outliers emerges and subsequent analyses should be performed including and excluding those patients and comparing the results.

Moreover, identification of patients with a peculiar combination of outcome indicators (such as low subjective quality of life despite the mild clinical symptoms found in patients n. 129 and 3118) or with very low values in some indicators (such as the combination of very severe clinical symptoms, low subjective quality of life, low satisfaction with services and low service utilization found in patients n. 3366 and 1239 or the dissatisfaction with services found in patients n. 3450, 1338, 1672) provided highly relevant and easily understandable clinical information that should be targeted in the review of cases taking place at regular intervals in the South-Verona community-based psychiatric service.

In summary, a well-chosen sequence of graphical displays constitutes a more powerful tool to explore data than a long sequel of numerical tables because they '*induce the viewer to think about substance rather than methodology . . . , make large data sets coherent . . . , encourage the eye to compare different pieces of data, . . . reveal the data at several levels of detail, from a broad overview to the fine structure*' (Tufte, 1983). The need for guidelines to statistical analysis and informative displays of data has recently been emphasized (McGuigan, 1995; Hand and Sham, 1995) and graphical methods are in line with these requirements.

In future years, one major area of application of graphical methods will certainly be the evaluation of treatment outcome. A better understanding of the effects of various treatments on a wide number of indicators is the preliminary step for formulating a minimal, but reliable, set of indicators to be used on a routine basis. At the current stage of scientific knowledge, outcome studies in many clinical sciences, including quality research and epidemiological psychiatry, can take great advantage of the graphical approach in order to increase their impact in everyday clinical practice and to monitor and evaluate services.

Acknowledgements

This study was supported by the Istituto Superiore di Sanità (ISS), Roma, with a grant (No. 96/QT/26) to Professor M. Tansella.

References

Andrews DF. Plots of high-dimensional data. Biometrics 1972; 28: 125–36.

Biggeri A, Rucci P, Ruggeri M, Tansella M. Multidimensional assessment of outcome. The analysis of conditional independence as a new statistical tool to describe the correlation among variables. In Thornicroft G and Tansella M. (eds) Mental Health Outcome Measures. Berlin: Springer-Verlag; 1996: 207–16.

Cairn J. Measuring health outcomes. British Medical Journal 1996; 6: 313–16.

Chambers JM, Cleveland WS, Kleiner B, Tukey PA. Graphical Methods for Data Analysis. Monterey: Wadsworth; 1983.

Chernoff H. The use of faces to represent points in k-dimensional space graphically. Journal of the American Statistical Association 1973; 68: 361–8.

Cleveland WS, McGill R. Graphical perception: theory, experimentation, and application to the development of graphical methods. Journal of the American Statistical Association 1984; 79: 531–54.

Cox DR, Wermuth N. Multivariate Dependencies. Models, Analysis and Interpretation. London: Chapman & Hall, 1996.

Dunn G. Longitudinal records of anxiety and depression in general practice: the Second National Morbidity Survey. Psychological Medicine 1983; 13: 897–906.

Dunn G. Patterns of psychiatric diagnosis in general practice: the Second National Morbidity Survey. Psychological Medicine 1986; 16: 573–81.

Edlifsen LE and Jones SD. Reference Guide to GAUSS. Washington: Applied Technical Systems, 1993.

Ellwood PM. Outcomes management: a technology of patient experience. New England Journal of Medicine 1988; 318: 1549–56.

Epstein AM. The outcomes movement: will it take us where we want to go? New England Journal of Medicine 1991; 3233: 266–70.

Endicott J and Spitzer RL. The Global Assessment Scale. A procedure for measuring overall severity of psychiatric disturbance. Archives of General Psychiatry 1986; 33: 766–71.

Everitt BS. Exploring multivariate data graphically: a brief review with examples. Journal of Applied Statistics 1994; 21: 63–94.

Fienberg SE. Graphical methods in statistics. The American Statistician 1979; 33: 165–78.

George LK. Definition, classification, and measurement of mental health services. In: Taube D, Mechanic AA, Adimann CA. Eds. The Future of Mental Health Services Research. DHHS Publ. No. (ADM) 89-1600. Washington: National Institute of Mental Health, 1989.

Gibbons RD, Hedeker D, Elkin I, Waternaux C, Kraemer HC, et al. Some conceptual and statistical issues in analysis of longitudinal psychiatric data. Archives of General Psychiatry 1993; 50: 739–50.

Hadorn DC, Uebersax J. Large-scale health outcomes evaluation: how should quality of life be measured? Part I - calibration of a brief questionnaire and a search for preference subgroups. Journal of Clinical Epidemiology 1995; 48: 607–18.

Hand D and Sham P. Improving the quality of statistics in psychiatric research. British Journal of Psychiatry 1995; 167: 689–91.

Jenkins R. Toward a system of outcome indicators for mental health care. British Journal of Psychiatry 1990; 157: 500–14.

Knudsen HC, Thornicroft M. Mental Health Service Evaluation. Cambridge: Cambridge University Press, 1996.

Lukoff D, Nuechterlein K, Ventura J. Manual for expanded Brief Psychiatric Rating Scale (BPRS). Schizophrenia Bulletin 1986; 4: 594–602.

McGuigan SM. The use of statistics in the British Journal of Psychiatry. British Journal of Psychiatry 1995; 167: 683–8.

Morley S, Adams M. Some simple statistical tests for exploring single-case time-series data. British Journal of Clinical Psychology 1989; 28: 1–18.

Oliver JP. The social care directive: development of a quality of life profile for use in community services for the mentally ill. Social Work and Social Science Review 1991; 3: 4–45.

Powsner SM, Tufte ER. Graphical summary of patient status. Lancet 1994; 344: 386–9.

Ruggeri M, Biggeri A, Rucci P, Tansella M. Multivariate analysis of outcome of mental health using graphical chain models. The South-Verona Outcome Project 1. Psychological Medicine 1998; 28 (in press).

Ruggeri M, Dall'Agnola R. The development and use of the Verona Expectations for Care Scale (VECS) and the Verona Service Satisfaction Scale (VSSS) for measuring expectations and satisfaction with community-based psychiatric services in patients, relatives and professionals. Psychological Medicine 1993; 23: 511–23.

Ruggeri M, Dall'Agnola R, Agostini C, Bisoffi G. Acceptability, sensitivity and content validity of VECS and VSSS in measuring expectations and satisfaction in psychiatric patients and their relatives. Social Psychiatry and Psychiatric Epidemiology 1994; 29: 265–76.

Ruggeri M, Tansella M. Evaluating outcome in mental health care. Current Opinion in Psychiatry 1995; 8: 116–21.

Ruggeri M, Tansella M. Individual Patient Outcomes. In Knudsen HC, Thornicroft G (eds) Mental Health Service Evaluation. Cambridge: Cambridge University Press, 1996.

Sasieni PD, Royston P. Dotplots. Applied Statistics 1996; 45: 219–34.

Spitzer WO. The future of epidemiology. Journal of Clinical Epidemiology 1996; 49: 705–9.

Statistical Sciences, Inc. S-PLUS for Windows User's Manual, Version 3.1. Seattle: Statistical Sciences Incorporation, 1993.

Sytema S, Giel R, ten Horn GHMM, Balestrieri M. The reliability of diagnostic coding in psychiatric case registers. Psychological Medicine 1989; 9: 999–1006.

Tansella M (ed.). Community-Based Psychiatry. Long-Term Patterns of Care in South-Verona, Psychological Medicine Monograph Supplement 19, Cambridge: Cambridge University Press, 1991.

Tansella M, Ruggeri M. Monitoring and evaluating a mental health service: the epidemiological approach. In Peckam M, Smith R (eds) Scientific Basis of Health Services. London: British Medical Journal Publishing Group 1996: 160–9.

Thornicroft G, Tansella M (eds) Mental Health Outcome Measures. Heidelberg: Springer Verlag, 1996.

Tufte ER The Visual Display of Quantitative Information. Connecticut: Graphics Press Cheshire, 1983.

Tukey J. Exploratory Data Analysis. Cambridge: Addison Wesley, 1977.

Wegman EJ. Hyperdimensional data analysis using parallel coordinates. Journal of the American Statistical Association 1990; 85: 664–75.

Wilkinson L. Graphical displays. Statistical Methods in Medical Research 1992; 1: 3–25.

Wing JK. The cycle of planning and evaluation. In Wilkinson G, Freeman H (eds) Mental Health Services in Britain: the Way Forward. London: Gaskell Books 1986: 35–48.

World Health Organization. Disability Assessment Schedule (DAS-II). Geneva: WHO, 1988.

World Health Organization. The ICD-10 Classification of Mental and Behavioural Disorders: Clinical Descriptions and Diagnostic Guidelines. Geneva: World Health Organization, 1992.

Correspondence to Dr Mirella Ruggeri, Servizio di Psicologia Medica, Istituto di Psichiatria, Ospedale Policlinico, 37134 Verona, Italy.
Telephone: +39-45-80-74441.
Fax: +39-45-58 58 71.
Email: MRuggeri@Borgoroma.univr.it.