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COMPARING DIFFERENT STRATEGIES FOR DATA ANALYSIS. APPLICATIONS TO THE SEARCH FOR PERSONALITY CORRELATES OF LIFE SATISFACTION

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The aim of this methodological article was to compare different statistical strategies suitable for analyzing the same database, on the relationships between life satisfaction, and personality and attitude variables. The sample was composed of 1080 adult participants, equally subdivided on the basis of gender, family status, and geographical residence. To search for variables which better discriminate and/or predict life satisfaction, different approaches, both exploratory and confirmatory, were used, including multidimensional scaling, causal analysis (Structural Equations Modeling), Discriminant analysis, and different regression techniques. Similarities and differences in results are discussed.

Key words: Life satisfaction; Big Five factors; Multidimensional scaling; Structural Equations Modeling; Discriminant analysis.

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PREMISE
DATA ANALYSIS AS A DECISION-MAKING PROCESS

The choice of the proper strategy for data analysis is often a challenge for empirical researchers. A preliminary choice is between exploratory and confirmatory strategies (e.g., Thompson, 2007; Tukey, 1977). The former use an inductive approach, avoid preconceptions in examining data, and is open to further questions. In the latter, the approach is deductive, specific answers are expected for specific questions, and hypotheses are determined at the beginning. Multidimensional scaling is an example of exploratory analysis; Regression analyses and Structural Equations Modeling are examples of confirmatory analyses.

Advantages and shortcomings of these approaches may be summarized as follows: exploratory analyses use flexible ways to generate hypotheses and to promote a deeper understanding of processes; yet they often require subjective judgements and do not provide definitive answers. On the other hand, confirmatory analyses permit the testing of hypotheses and production of precise estimates. They rely on well-established theories and models; but, at the same time, are often driven by preconceived ideas and therefore unexpected or alternative results are difficult to detect.

Within each approach, a secondary choice is the use of correlations among variables or differences between groups. It is well-known that analyses of correlations and analyses of differ-

ences essentially answer the same question; many indices of correlation may be converted into indices of differences (e.g., *r* vs. *t*) and vice versa, producing the same effect interpretable as *d* (Cohen, 1988).

A design based on correlation, alternative to the comparison between groups, partially makes up for the impossibility of randomly selecting participants, frequent in experimental applied psychology, or to pair or match the groups as in the strictly experimental model. Once a large enough (though not random) sample is collected, the characteristics of the sampled participants may be correlated with the variables selected for the research, and these relations can supply information about the incidence of variables not controlled by the randomization of the sample. The well-known shortcoming of this procedure is that correlation estimates the degree of covariation, not of the influence of a variable on another. The causal relation has to be inferred logically, on the basis of specific hypotheses about the nature of the variables at hand.

Moreover, the correlation (or the difference) found between two variables could be due to other super-ordinate variables not included in the hypothesis, or could be mediated by other variables not directly taken into account. Only analyses including "latent" variables can be used to test hypotheses pertaining to variables not directly observed in the research.

So, an exploratory approach may trigger the need of a confirmative one. But can the theoretical background of the research support "strong" causal hypotheses and the prevision of proper latent variables? Sometimes, a previous exploratory study is necessary to identify the most likely mediation, among a pool of potential mediating variables. These will subsequently be included in a causal model.

Transversal to the others is the choice between parametric or nonparametric approaches. This problem was very clearly posed by Siegel's pioneering book (revised edition, Siegel & Castellan, 1988) but has often been underestimated by researchers. For almost all the strategies of data analysis, both alternatives are available. The matrix used for exploratory or causal analyses may result from either parametric or nonparametric correlations.

Decisions about the above summarized choice depend on several factors, such as the general theoretical background, the model deducted from the theory, the specific hypotheses formulated, the number and quality of variables, the number of participants in the sample, the reliability of measures, and their location on a scale of measurement based on equivalent intervals, ranks, or simply categories.

When data have been collected and the database is ready to be imported into a statistical software, the researcher has to cope with the problem of selecting the method of analysis most suitable for data and work hypotheses.

A preliminary comparison between different approaches may be useful to assist the choice for the definitive analysis. The aim is not to use a "try-and-see" strategy, or to make "hypotheses suggested by data" (Tukey, 1980), but to test strengths and limits for each approach, and to make the final decision on a solid empirical, as well as theoretical, basis.

This article presents an example of comparison between different explorative and confirmative strategies for analyzing the same database, which was extracted from a wider research plan regarding the relationships between personal values and other personality and behavioral variables.

THE DATABASE
SEARCH FOR CORRELATES AND/OR PREDICTORS OF LIFE SATISFACTION

Subjective well-being, defined on the basis of hedonic outcomes (e.g., life satisfaction), has been studied in both social (Kahneman, Diener, & Schwarz, 1999) and clinical (Lent, 2004) psychology and is related to the concept of *life satisfaction*, namely to the overall evaluation of different activities and relationships that make one's own life worth living (Diener, 1984).

Other studies indicated that personality traits are the best predictors of well-being and life satisfaction (Steel, Schmidt, & Shultz, 2008); yet the effects have not always been consistent (DeNeve & Cooper, 1998), and the causal pathways that presumably link personality or affective attitudes to satisfaction are not well understood (Diener, 1996).

Personality factors may not represent separate and independent predictors of well-being (Judge & Ilies, 2002). It is therefore appropriate to consider mediators: e.g., *self-esteem*, that is the degree of global regard and acceptance of self (Harter, 1999); *optimism*, that is a positive view about future personal and social events (Carver & Scheier, 2002).

Cummins and Nistico (2002) suggested that well-being homeostasis may be controlled by positive cognitive biases pertaining to the self. Most relevant in this regard are the positive biases in relation to self-esteem, control, and optimism. Lent et al. (2005) presented findings indicating that life satisfaction — reciprocally related with domain-specific satisfaction — is predicted by social cognitive variables even after controlling for the effects of positive affectivity or extraversion. In adolescence, a higher level of global life satisfaction is related to good adaptive functioning (Gilman & Huebner, 2006). In a cross-cultural study, Kuppens, Realo, and Diener (2008) examined how the frequency of positive and negative emotions is related to life satisfaction, and demonstrated that the experience of positive emotions is more strongly related to life satisfaction than the absence of negative emotions. Yet, the cultural dimensions of individualism and self-expression moderated these relationships.

In our study, we hypothesized that personality variables would have an influence on life satisfaction. We also expected that this influence would be mediated by other variables which may be used within a causal model.

The hypothesis was simplified in line with the methodological aim of the study, which was to compare different techniques of data analysis starting from the same database, including a small subset of variables.

SAMPLE

The study sample was composed of 1080 adult participants, 540 males and 540 females, equally subdivided on the basis of marital status (for each gender, half were married, and half single) and geographical residence (one third of the sample was recruited respectively in Northern, Central, and Southern Italy). The sample was extracted with random criteria from a wider database collected to validate Schwartz's *Personal Values Questionnaire* in Italy.[1]

VARIABLES AND MEASURES

The variables analyzed in our study, selected from the project database, were four.

1) *Life satisfaction*. Two instruments were used, derived from the *Life Satisfaction Scale* originally developed by Diener, Emmons, Larsen, and Griffin (1985), and adapted by Caprara, Steca, Gerbino, Paciello, and Vecchio (2006), and by Caprara, Alessandri, Tisak, and Steca (2009). This domain-specific 6-item satisfaction scale asked participants to indicate the degree to which they felt satisfied with various aspects of their life (e.g., health, friendship). Responses were obtained on a 5-point scale ranging from 1 (*extremely unsatisfied*) to 5 (*extremely satisfied*). The second measure was a goal attainment scale — composed of six items — asking participants to indicate how well their goals were achieved in various aspects of their life (e.g., study, friendship). Participants responded on a 5-point scale ranging from 1 (*not at all*) to 5 (*completely*). A previous high-order factor analysis showed that the two scales could represent a single factor. As a consequence, they were used as a single measure.

2) *Self-esteem*. The Rosenberg (1965) scale, consisting of 10 items, requiring responses on a 4-point scale (1 = *completely disagree*, 4 = *completely agree*) was employed.

3) *Optimism*. A 6-items scale derived from *Life Orientation Test* (Scheier & Carver, 1985; Scheier, Carver, & Bridges, 1994) was used (e.g., "In uncertain times, I usually expect the best"). Responses were obtained on a 5-point scale (1 = *completely disagree*, 5 = *completely agree*).

4) *Personality traits*. The *Big Five Questionnaire* (Italian version by Caprara, Barbaranelli, & Borgogni, 1993) was adopted. It consists of 60 items, 12 for each subscale measuring five factors: 1) Extraversion/energy, 2) Agreeableness/cooperativeness 3) Conscientiousness/responsibility, 4) Emotional stability/control of impulses and emotions, 5) Mind openness (to experience and culture). For each item participants responded on a 5-point scale ranging from 1 (*completely false*) to 5 (*completely true*).

The reliability indices (Cronbach's *alpha*) for each scale[2] were satisfactory, ranging from .66 to .84 (see Table 1).

DATA ANALYSIS

Descriptive Statistics

Means, standard deviations, and reliabilities for each variable, as well as Pearson correlations among variables are reported in Table 1. Due to the large number of participants in the sample, all the correlations are statistically significant, with many greater than .30, a "moderate effect size," according to Cohen (1988).

Exploratory Analysis: Multidimensional Scaling

The first analysis performed was exploratory, suitable to obtain a representation of the relations among variables in a geometric space.

TABLE 1
Descriptive statistics, correlations, and reliability coefficients (N = 1080).
Alpha coefficients in italics on the diagonal

		M	*SD*	1	2	3	4	5	6	7	8
1	Life satisfaction	3.50	0.50	*.75*							
2	Self-esteem	3.15	0.42	.51*	*.81*						
3	Optimism	3.52	0.72	.49*	.51*	*.74*					
4	Extraversion	3.09	0.46	.35*	.35*	.36*	*.66*				
5	Agreeableness	3.31	0.45	.31*	.08*	.34*	.09*	*.68*			
6	Conscientiousness	3.50	0.52	.36*	.32*	.19*	.35*	.30*	*.77*		
7	Emotional stability	2.93	0.64	.36*	.34*	.44*	.08*	.30*	.11*	*.84*	
8	Mind openness	3.39	0.57	.23*	.17*	.21*	.39*	.45*	.39*	.20*	*.77*

* $p < .05$.

Multidimensional scaling (MDS; Borg & Groenen, 1997; Cox & Cox, 2001; Davison, 1983) is an exploratory technique for multivariate data analysis, suitable to localize proximities in a dimensional space, and arrive at a configuration that best approximates them. The aim is to reduce the observed complexity of relations among variables explaining the distance matrix in terms of few latent dimensions. Interpretation of the space dimensions can help to understand the processes underlying the perceived nearness of variables represented in space. Thus MDS allows an insight in the underlying structure of relations between variables by providing a geometrical representation of such relations. Almost any measure of relation between pairs of variables can be translated into a proximity (correlation) or a dissimilarity (distance) measure, and used as an input for MDS.

In more technical terms, MDS uses a function minimization algorithm that evaluates different configurations with the goal of maximizing the goodness-of-fit. The "stress" measure evaluates how well a particular configuration reproduces the observed distance (or similarity) matrix: the smaller the stress value, the better the fit of the reproduced matrix to the observed one. The reproduced distances or similarities can be plotted against the observed ones, producing a scatter plot (*Shepard diagram*) showing the reproduced distances on the vertical (Y) axis versus the original similarities on the horizontal (X) one.

McCallum (1974) compared factor analysis and MDS, in terms of assumptions, aims, type of data, computational procedures, geometric representations of solutions, and meaning of results, concluding that the strongest relations between the techniques lie in the realm of individual differences models.

Kemmler et al. (2002) used MDS "to complement conventional descriptive and confirmatory methods in the validation and analysis of quality of life data" (p. 223). They concluded that "applications of MDS may give an impression of the broad range of possible uses of the technique. Compared with the most common method for data reduction, exploratory factor analysis, MDS has the advantage of allowing a more drastic reduction in dimensionality. Often the number of dimensions needed can be restricted to two, which is rarely possible in factor analysis" (pp. 231-232). But some shortcomings were underlined as well: "For a given MDS solution, there

is no straightforward method to make probabilistic statements about its precision" (p. 232); although Ramsay (1977) proposed an equation for the maximum likelihood estimation of the configuration.

In our analysis, Guttman's (1954) method was followed, using Lingoes and Roskam computation (Schiffman, Reynolds, & Young, 1981). The technique starts from the correlation matrix (data as similarities), minimizing the coefficient of stress (here named "alienation") to two dimensions. The value of "alienation" of the final configuration — i.e., how far the data depart from the model — after six iterations was .13, with a proportion of explained variance (RSQ) = .94.

Figure 1 presents the Shepard Diagram, Table 2, the coordinates in the two dimensions, then plotted in Figure 2, that evidences the almost circular configuration of variables, that is "circumplex" according to Guttman's (1954) definition.

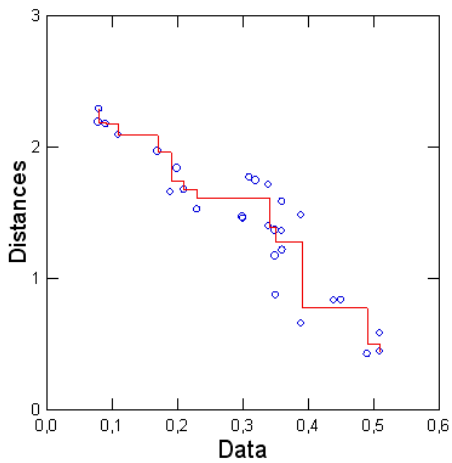


FIGURE 1
Shepard diagram for multidimensional scaling (N = 1086).

TABLE 2
Multidimensional scaling analysis. Coordinates in the two dimensions

Variables	Dimensions	
	1	2
Satisfaction	–0.50	0.25
Self-esteem	–0.90	0.43
Optimism	–0.71	–0.12
Extraversion	0.27	1.12
Agreeableness	0.75	–1.00
Consciousness	0.84	0.46
Emotional stability	–0.71	–0.95
Mind openness	0.96	–0.19

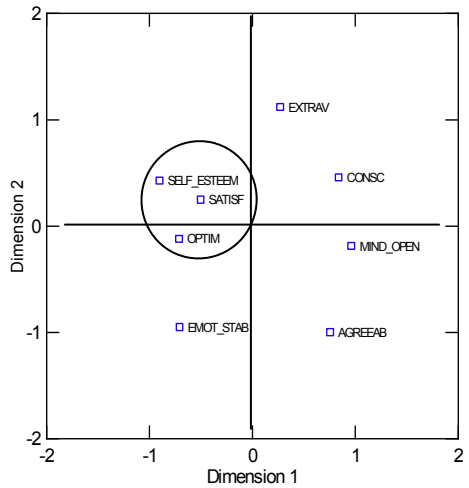


FIGURE 2
Multidimensional scaling analysis. Plot of variables in the two dimensions.

The variables most polarized on dimension 1 are *Mind openness Consciousness*, and *Agreeableness* opposite to *Self-esteem*, *Optimism*, and *Emotional stability*. The first dimension may be defined as opposing *out-directed* vs. *internal (self-centered)* traits.

Extraversion is located at the positive polarity of dimension 2, opposite to Emotional stability and Agreeableness, characterizing the dimension as contrasting *activity and energy* vs. *stability and sociability*.

The target variable *Satisfaction* is the most centered with respect to both axes (–.50/.25).

The crossing of the two dimensions in Figure 2 represents (clockwise in the four quadrants): 1) Satisfaction strictly linked to Self-esteem and Optimism (–.90 and –.71, respectively, on dimension 1; .43 and –.12 on dimension 2; see the ellipse in Figure 2); 2) Extraversion and Consciousness; 3) Mind openness and Agreeableness; 4) Emotional stability.

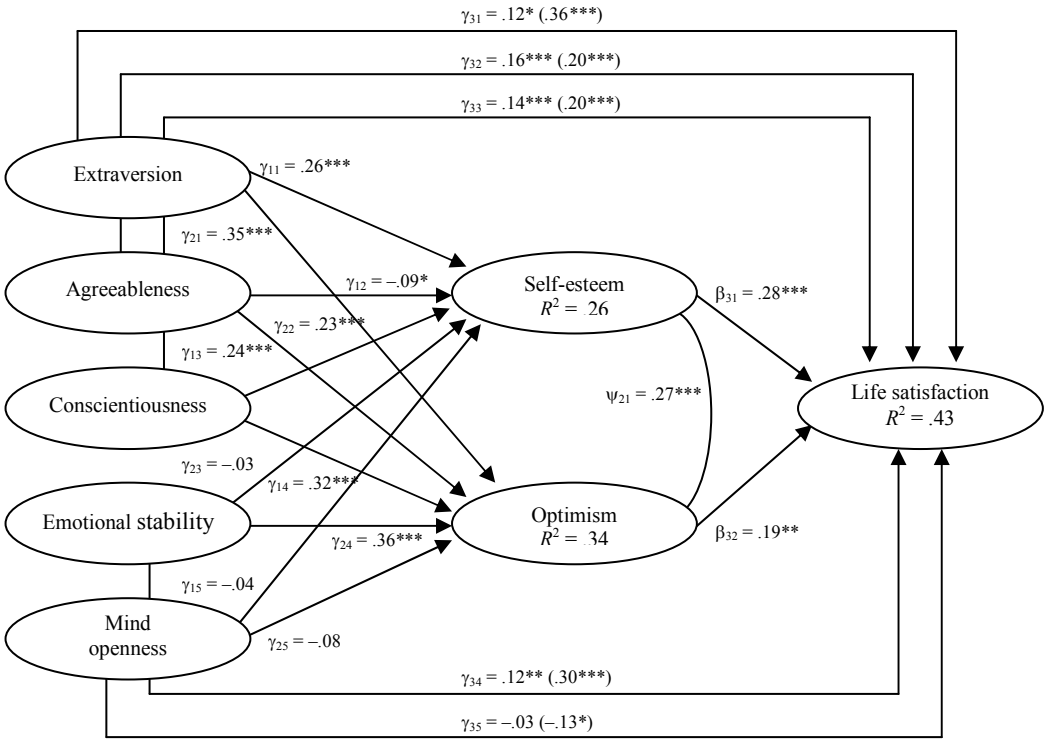
Causal Analysis: Structural Equations Modeling

In contrast with the exploratory aims of the MDS, a causal analysis with latent variables was performed through Structural Equations Modeling (Jöreskog & Sörbom, 1996/2001; Kline, 2005), considering *Life satisfaction* as dependent variable, the *Big Five factors variables* as predictors, and *Self-esteem* and *Optimism* (i.e., the variables closer to *Life satisfaction* in MDS) as mediators.

To test mediation, the procedure proposed by Baron & Kenny (1986) was followed, which establishes four criteria: 1) the independent variable should correlate with the dependent variable; 2) the independent variable should correlate with the mediator; 3) the mediator affects the dependent variable when controlling the effects of the independent variable; 4) the mediator completely mediates the relationship between independent and dependent variables if the effect of the initial variable on the outcome variable is zero; the mediator partially mediates the relationship if the effect of the initial variable on the outcome variable is still significant.

To test the model, two aggregated indicators were obtained for each variable by randomly splitting the respective items (partial disaggregation model, according to Bagozzi & Heatherton, 1994).

The testing of the model is reported in Figure 3.



Note. χ^2 (76) = 267.30, $p < .001$; CFI = .98; SRMR = .031.
*$p < .05$. ** $p < .01$. ***$p < .001$.

FIGURE 3
Structural Equations Modeling. Mediation effects of Optimism and Self-esteem on the relationship between personality and life satisfaction.
Effects of independent variables without considering the mediator are reported in parentheses.

The model has a good general fit: χ^2 (76) = 267.30, $p < .001$; CFI = .98; SRMR = .031. Although χ^2 was significant, CFI and SRMR satisfied the criteria that require CFI to be greater than or equal to .95 and SRMR to be smaller than or equal to .08; see Hu & Bentler, 1999.

The relationship between the personality factors and the two mediators, Self-esteem and Optimism, can be defined as follows: *Extraversion/Energy*, *Emotional stability*, and *Agreeableness* were significantly linked with both *Self-esteem* and *Optimism*; *Consciousness* was linked only with *Self-esteem*; *Mind openness* was correlated with neither *Self-esteem* nor *Optimism*.

The mediators, *Self-esteem* and *Optimism*, were linked with each other (ψ = .27), and both significantly predicted *Life satisfaction* (βs are .28 for *Self-esteem*, 19 for *Optimism*), when effects of independent variables were controlled.

The mediation analysis showed that *Self-esteem* partially mediated the relationship between *Extraversion* ($Z = 3.70$, $p < .001$),[3] *Consciousness* ($Z = 3.80$, $p < .001$), *Emotional stability*

(Z = 4.42, p < .001), and *Life satisfaction*. *Optimism* partially mediated the relationship between *Extraversion* (Z = 2.76, p < .01), *Agreeableness* (Z = 2.61, p < .01), *Emotional stability* (Z = 2.94, p < .01), and *Life satisfaction*. The mediation effect of *Self-esteem* on the relationship between *Agreeableness* and *Life satisfaction* was not significant (Z = 1.86, ns). Finally, *Mind openness* directly influenced *Life satisfaction.*

Analysis of Differences: Discriminant Analysis

The third strategy focuses on dissimilarities rather than correlations. To study differences between groups divided according to the "life satisfaction" target-variable, we used *Discriminant Analysis* (Klecka, 1980; McLachlan, 2004). This well-known technique provides linear or quadratic functions of the variables that best separate cases into two or more predefined groups, and can also explore which variables are most useful for discriminating among those groups. The variables in the linear function can be selected in a forward or backward stepwise procedure, entering the variable that contributes most to the separation of the groups, or removing the variable that is the least useful.

Discriminant analysis is related to both multivariate analysis of variance and multiple regression.[4] Cases are grouped in cells just as in a one-way multivariate analysis of variance and predictor variables form an equation like that for multiple regression. In *Wilks' lambda* discriminant analysis, the same statistic used in multivariate ANOVA is employed to evaluate the equality of group centroids (Wilkinson, 1990), testing whether the model as a whole is significant.

We performed Discriminant Analysis to determine the most useful variables in differentiating the *very high satisfaction* and *very low satisfaction* subgroups. Following the warnings on the dichotomization of continuous variables (McCallum, Zhang, Preacher, & Rucker 2002), these extreme groups were selected using the first and fourth quartiles (i.e., cut-offs at 25° and 75° percentiles) of the distribution of the scores of the *life satisfaction* variable. The groups were composed of 299 participants each, thus the total sample was of 598 participants (289 males, 309 females).

The variables used as predictors of Life satisfaction were the same as those for the other, already reported, analyses: *self-esteem*; *optimism*; the Big Five factors (*extraversion*, *agreeableness*, *consciousness*, *emotional stability*, *mind openness*).

The Wilks' Lambda index to test homogeneity among groups (*df* 7, 1, 596) was .66 (approximated F ratio = 44.00, p < .001 with 7 and 590 *df*).

The incidence of each of the variables on the discriminant function is ranked in Table 3.

If a backward stepwise method is used (alpha = .10), the variable *Mind openness* should be removed.

The eigenvalue for the canonical variable was high enough (.52). Canonical correlations between the "satisfaction" variable and the groups (represented as dummy variables) were quite high: .59.

Discriminant analysis classifies each case into the specific group having the largest value of its classification function. The overall percentage of correct classifications was quite high (78%). The percentages were similar for both groups, with some slight prevalence for the "less satisfaction" group (80%) compared with the other group (77%).

TABLE 3
Discriminant analysis: *F*-to-remove and tolerance values

Rank	Variables	*F*-to-remove	Tolerance
I	Self-esteem	50.60	.83
II	Consciousness	15.47	.84
III	Optimism	14.19	.83
IV	Emotional stability	13.33	.88
V	Agreeableness	11.74	.83
VI	Extraversion	1.79	.84
VII	Mind openness	0.13	.79

The best discriminating variable in the classification of groups based on satisfaction levels was *Self-esteem* (highest level of *F*), followed by *Consciousness*, *Optimism*, *Emotional stability*, and *Agreeableness*. Less relevant for the discrimination was *Extraversion*. The variable *Openness to experience* was not significant.

Analysis of Predictors: Multiple and Logistic Regression

We compared the results of discriminant analysis with those obtained using regression analysis, on the same subset of variables and participants. Both linear (least-square) and logistic regression were performed.

The results of multiple regression, on satisfaction as dependent variable, are shown in Table 4.

TABLE 4
Multiple regression analysis

Rank	Variables (Predictors)	Stand. Coeffic.	Tolerance	$p \leq$
I	Self-esteem	.30	.71	.001
II	Emotional Stability	.17	.79	.001
III	Optimism	.16	.71	.001
IV	Agreeableness	.14	.77	.001
V	Consciousness	.14	.76	.001
VI	Extraversion	.08	.79	.03
VII	Mind openness	.02	.74	.65

Note. For each predictor of life satisfaction, standard coefficient, tolerance and probability are reported. $F = 56.73$ ($p < .001$). Multiple $R = 0.63$; Multiple $R^2 = 0.40$; Standard error of estimate = 0.51; A.I.C. (Akaike information criterion) = 901.88; B.I.C. (Bayesian information criterion) = 941.42.

Self-esteem was confirmed as the variable most influencing satisfaction, followed by *Emotional stability* (more relevant in this analysis), *Optimism,* and *Agreeableness.* Less influencing

were *Consciousness* and *Extraversion*. *Mind openness* was not significant, as it resulted in other analyses.

Logistic Regression, a widely used alternative to linear regression when the assumptions for the latter are not met (Hilbe, 2009; Menard, 1995), is also an alternative to Discriminant Analysis. It may be preferable when data are not normally distributed or group sizes are very unequal, but it has less statistical power.

Results of this analysis applied for comparative purposes are shown in Table 5.

TABLE 5
Logistic regression analysis: parameter estimates and probabilities

Rank	Variables (Predictors)	Estimate	*Z*	$p \leq$
I	Self-esteem	–1.88	–6.55	.001
II	Consciousness	–0.86	–3.85	.001
III	Agreeableness	–0.84	–3.25	.001
IV	Emotional stability	–0.70	–3.89	.001
V	Optimism	–0.64	–3.85	.001
VI	Extraversion	–0.36	–1.41	.16
VII	Mind openness	–0.11	–0.57	.58

Note. A.I.C. (Akaike information criterion) = 590.48; B.I.C. (Bayesian information criterion) = 625.63.

The results, apart from the variables confirmed as most influencing (*Self-esteem*) and least influencing (*Extraversion* and *Mind openness*), showed *Consciousness* as the second best predictor, as in discriminant analysis. *Optimism* seems less relevant in this analysis.

The reduction of the A.I.C. and B.I.C. indices (Akaike and Bayesian information criteria), when compared with linear regression, is worth noticing.

Analysis of Predictors: Regression with Structural Equation Model

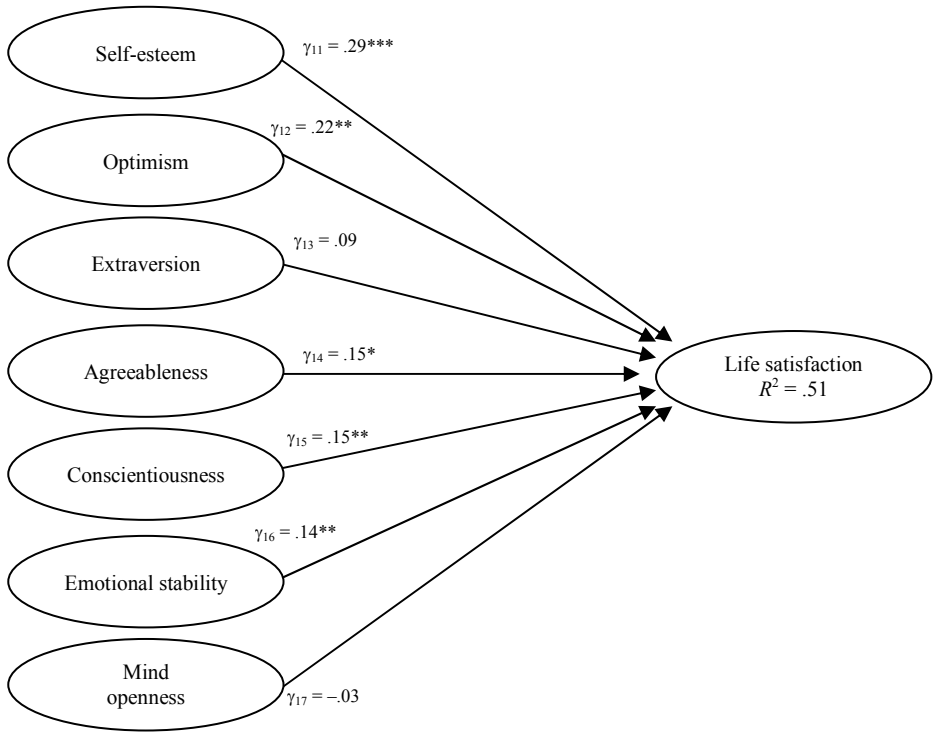
Finally, the regression parameters were estimated using structural equations modeling, on the same subset of variables and participants of discriminant analysis and multiple and logistic regression.

Figure 4 shows that *Self-esteem* was the most influential variable, followed by *Optimism, Consciousness, Agreeableness*, and *Emotional stability*. *Extraversion* and *Mind openness* were not significant, such as in the logistic regression.

These results provide very similar coefficients to those obtained with the causal model performed on the complete sample when the effects of the mediators are controlled (Figure 3).

DISCUSSION

The methodological aim of this article was to compare different statistical strategies suitable for analyzing the same database, with respect to the relationships between personality and attitude variables and life satisfaction.



Note. χ^2 (76) = 176.63, p < .001; CFI = .98; SRMR = .030.
* p < .05. ** p < .01. ***p < .001.

FIGURE 4
Regression with Structural Equations Modeling.

The exploratory analysis firstly performed by means of multidimensional scaling verified the central position of the target variable (*life satisfaction*) in a dimensional space; the most proximal variables were *self-esteem* and *optimism*, that were therefore chosen as mediators for a causal analysis.

This result is in agreement with the most recent views about "positive orientation toward life," a construct in which *satisfaction* — as a core variable — is strictly connected with *self-esteem* (positive orientation toward the past and the present) and *optimism* (positive orientation toward the future), forming a basic tendency to consider and value the positive aspects of life, the future, and the self (Caprara, 2009).

The causal analysis tested by means of structural equations appears to be the most explicative of the matrix of correlations among the considered variables. It allows confirming, thanks to its goodness of fit, the model that explains the relations between *personality factors* (predictors) and *Life satisfaction* (dependent variable) as mediated by *Self-esteem* and *Optimism*.

Self-esteem appears to be a relatively stronger mediator of the link between *Emotional stability*, *Extraversion*, and *Conscientiousness* and the dependent variable *Life satisfaction*. *Emotional stability*, *Extraversion*, and *Agreeableness* seem to be mediated by *Optimism*. While the effect of *Emotional stability* is confirmed in the other analyses, the effects of *Extraversion* are only significant in the mediation model.

Mind openness is not significantly involved in any relationship with satisfaction and other mediating variables, but it is a direct predictor of satisfaction, with an inverse relationship (i.e., more open mind, less satisfaction).

The central role played by *Self-esteem*, and the absence of influence on the part of *Mind openness*, are also confirmed by the discriminant and different regression analyses, using the extreme groups of the sample divided according to *Life satisfaction* as dependent variable. These analyses were aimed to present an ordered rank of influence of the predictors, without taking into account any possible mediation effects. The general results are not substantially different using the whole sample or the extreme groups divided according to *Life satisfaction* as dependent variable.

While a substantial agreement among the different techniques exists on the main predictor (*Self-esteem*), and on the absence of influence on the part of *Mind openness*, each technique outlines a different ranking in the influence of the other variables. The differences among the multiple regression analyses confirm the difficulty to consider the regression coefficients as a reliable measure of the importance of the predictors: e.g., Azen & Budescu (2003, 2006) proposed a "dominance analysis" to compare predictors in multiple regression models. Our study suggests that a causal analysis taking into account mediation effects may be useful to assess the relative importance of predictors.

In conclusion, the exploratory approach was useful to select the potential mediating variables, in our case, *Self-esteem* and *Optimism*, successfully included in the causal model.

This model seemed to be explicative of the relations among the considered variables, more than the linear regression models. The variable *Extraversion*, less relevant in the Discriminant Analysis, is only significant in the model which includes *Optimism* as mediator.

Though taking into account Cohen's (1990) suggestion to prefer the simplest type of analysis to test the hypothesis of interest, the preliminary trial of both explorative and confirmative approaches is useful to better explain the relations among variables, to suggest further analyses, and to obtain more articulated and meaningful results in the final hypotheses testing.

NOTES

1. The national research project was coordinated by G.V. Caprara (University of Roma "La Sapienza") and P. Steca, (State University of Milano). The research group of the University of Catania participated in the project addressing methodological issues in particular.
2. Vassar, Ridge & Hill (2008), in considering life satisfaction studies, stressed the importance of reassessing reliabilities on the specific sample involved in the research, without inducing them from previous studies. Reliability coefficients for the data in hand should be estimated to ensure the validity of the research.
3. *Z* were calculated using the formula proposed by Baron & Kenny (1986).
4. It is well known that the mathematical basis for regression analysis is based on the *General Linear Model*, a general method of examining the statistical relations among variables. Both Regression and Analysis of Variance are derived from this model, so the assumptions for the two techniques are basically the same (Cohen, Cohen, West, & Aiken, 2003).

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