Proposal of a composite indicator of job quality based on a measure of weighted distances

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Abstract

In this paper, we propose a formulation of a composite indicator (CI) computed for individuals and based on elementary indicators that are measured using quantitative, ordinal and dichotomous scales. It is based on a measure of the distance from an ideal minimum. Moreover, we consider the correlation between indicators. This CI is applied to measure the job quality of young graduates. The results show that the CI has a balanced structure, both at the overall level and the level of dimensions. It is stable, but with the capacity to discriminate well between individuals and groups. The CI that we formulated is reliable and accurate.

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Keywords

- Composite indicator
- Generalised distance
- Correlation
- Job quality

Mathematics Subject Classification

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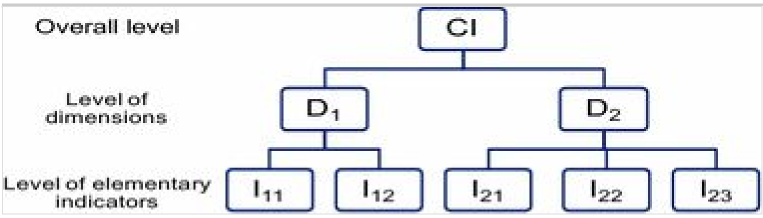
1. Introduction

Complex phenomena and concepts, such as the economic situation, health, standard of living and political participation, are difficult to measure statistically, both with regard to the choice of the method and the choice of the variables (Scippacercola 2011). This is a challenge for composite indicators (CIs). A CI is a combination of (1) elementary indicators that represent several aspects of the latent concept under description and (2) weights, which commonly represent the relative importance of each indicator (OECD 2008). The growing interest in CIs among academic circles, the media and policy-makers is justified for two main reasons. The first is that they can be used to illustrate complex issues in wide-ranging fields, and the second is that they provide a synthetic measure that can be utilised, for example, for policy analysis or benchmarking a country's performance (Saltelli 2007). Numerous choices are required in the CI-building phase, from the choice of the methodological approach to the issue to the definition of the theoretical framework (and consequently the definition of the elementary indicators) to the choice of the weighting and aggregating techniques (Nardo et al. 2005; Salzman 2004).

A complex phenomenon can be described by means of a hierarchical scheme. It is often a multidimensional concept comprised of various dimensions. In turn, each dimension is composed of several elementary indicators, which are represented by variables that can be directly measured (Fig. 1).

Fig. 1

Hierarchical structure of the composite indicator (*CI* composite indicator, *D* dimension, *I* elementary indicator)



Often, the intention of the researcher is to build rankings among countries or macro-units in general (Gupta et al. 1994). Because CIs usually involve variables (elementary indicators) in aggregate form, that is, at the national level, the nature of these variables is almost always quantitative (because CIs are a rate or a mean, for example). However, CIs may be adopted to measure phenomena at a micro-level, that is, to consider individuals or families. The problem in this case is that non-quantitative variables are frequently observed. Information on single individuals can be collected as a quantitative variable but also as a dichotomous or ordinal variable. While a considerable number techniques have been proposed for the aggregation of variables of the same nature in a CI (factor analysis for quantitative variables, e.g., in Susmilch and Johnsons (1975) or item response theory or rating scale models for ordinal variables, e.g., in Baker (1992) or Carpita and Golia (2012), respectively), less attention has been paid to the case of mixed data. The solutions that are often adopted are to either convert all of the variables to the same scale (such as dichotomous variables) or to quantify ordinal variables.

Moreover, in dealing with individuals, instead of countries, the correlation between elementary indicators may appear to be more marked. As explained in OECD (2008), it may happen that by combining variables with a high degree of correlation, an element of double-counting may be introduced into the index: if two collinear indicators are included in the composite index with a weight of w_1 and w_2, the unique dimension that the two indicators measure would have weight $w_1 + w_2$ in the composite. It is necessary to choose only those indicators that exhibit a low degree of correlation or to adjust their weights correspondingly, e.g., giving less weight to correlated indicators.

Our objective is to propose a new CI formulation in which the two issues introduced above, that is, dealing with mixed data and handling the correlation between variables, are considered.

It is worth remarking that we develop our proposal using the assumption of compensability given that the CI is based on linear additive aggregation. Compensability refers to the existence of trade-off, i.e., the possibility of offsetting the disadvantage of one criterion by a sufficiently large advantage via another criterion (Munda 2005). It is necessary to discuss whether or not compensability among the indicators should be permitted in the specific concept for which the CI was designed (OECD 2008). We are aware that compensability cannot be always acceptable, as in the case of sustainability (Munda 2005) or human development. Regarding this last case, since 2010, the Human Development Index has been based on a geometric aggregation instead of a linear one, as in the past. In this way, low achievement in one dimension is no longer linearly compensated for by high achievement in another dimension, because the geometric mean reduces the level of substitutability between dimensions (UNDP 2010).

We will propose the application of our composite indicator to job quality, where compensability is acceptable. To this end, we consider the mainstream economic approach to job quality, which supports the existence of compensating differentials in the labor market because workers with the same skills will be offered differing combinations of wages and working conditions, leading to the same job quality. Workers choose whatever combination best suits their preferences, such as working in a location farther away from home in exchange for a better wage or accepting a lower wage in exchange for an interesting and professional job (Ciavolino et al. 2014; Muñoz de Bustillo et al. 2011a).

In this work, we formulate a CI as a multivariate distance from a reference point, in which a solution is provided for the two main problems: different units of measurement and the correlation between indicators.

Linking the concept of distance with CIs is an original approach. Moreover, the concept of distance usually refers to quantitative variables, while we would like to extend it to qualitative variables as well in dealing with distance based on mixed data. Thus, the problem of using different units of measurement can be overcome by considering distance for mixed data to be the "new variable" when building the CI. Our conceptual assumption is that the CI pertains to a reference from which it is desirable to move away. When the worst possible subject is conceived as "a calamity to be left as far behind as possible" (UNESCO 1972), the CI gains the meaning of a development measure of a subject.

Some references to our approach, though not direct ones, can be identified. These include (a) data envelopment analysis, which bases the CI on the distance between an indicator and its maximum (Cherchye et al. 2006); (b) the taxonomic approach, which is also built on the distance from an ideal subject (Tasciotti 1973); and (c) Gower's distance, a weighted mean based on dissimilarity that attempts to aggregate variables measured with different scales (Cox and Cox 2000; Gower 1971).

In Sect. 2 we give a short overview about the concept and the measure of job quality. The concepts of distance and correlation are specified in the framework for our approach in Sect. 3. The mathematical formulation of the CI is then presented. Section 4 describes the data utilised in the analysis. Section 5 proposes a CI for job quality that can be applied to young graduates. Potential applications of the CI as an indicator of job quality are shown. Finally, there are some concluding remarks in Sect. 6, as well as suggestions for further research.

2. Job quality: concepts and measures

2.1. Theoretical approaches to job quality

The quality of working life is a key element of the quality of life, given that full-time workers spend almost 40 h a week on the job. This is the first reason for measuring job quality (Muñoz de Bustillo et al. 2011b). Secondly, the standard labour market usually focuses on quantity (e.g. employment rates), but there are ‘good’ and ‘bad’ jobs, and the performance of an economy also should be evaluated through the quality of its jobs.

Job quality is necessarily a multidimensional concept, because a ‘good’ job is assessed by the sum of multiple aspects affecting both the employment relation and work itself. We can identify three approaches to the definition, and consequently to the measure, of job quality (Muñoz de Bustillo et al. 2011b).

The first approach is completely subjective: job satisfaction mirrors job quality. In this case, job quality is measured by a unique indicator, based on the output, that is, the well-being of the worker at her/his job (Crandall 1976). The subjective quality of work has become a major subject of study and discussion in labour economics within a short time (Carpita and Golia 2012; Clark 2001, 2005; Gazioglu and Tansel 2006; Levy-Garboua et al. 2007). On the other hand, job satisfaction has been shown to be an inadequate indicator of job quality. Job satisfaction depends on the worker’s expectations and often has no apparent relevance to other objective indicators of job quality (De Bustillo Llorente and Fernandez Macias 2005). There are many other variables not related to job quality that affect the level of job satisfaction.

The second approach is subjective and based on what aspects make a good job according to workers’ opinions. Several indicators based on these aspects are considered in order to measure job quality.

Finally, the third approach is based on selecting the attributes of a good job following the economic and sociological tradition. The economic tradition is rich in approaches, although the dominant school focuses on wages. The sociological tradition includes the intrinsic qualities of work, such as skills and autonomy.

In our research, we will follow this last approach. We choose the dimension of job quality referring both to economic and sociological approaches, with special attention to the relevant dimensions in young graduates.

2.2. Measuring job quality

Several general aspects should be considered in the measure of job quality. The most important in our research are the following:

(a) Should we measure job quality at individual or aggregate level? In this paper, we measure job quality among young graduates; our interest is not related to a country, but to a sub-group of the population. Moreover, our aim is to compare job quality among several categories of graduates. Consequently, the approach is based on individual data.

(b) Composite indicator or system of indicators? A multidimensional concept can be described by a system of indicators (mainly elementary indicators) or by a composite indicator. Both approaches have pros and cons, but in our research the choice is taken for granted: a system of elementary indicators can refer only at aggregate level, not individual one.

(c) Which kind of indicators? Results vs. Procedures. The variables/indicators included in a job quality indicator should be based, when possible, on results (wage, career, working hours, …) and not on procedures (participation of workers, best practices, …), because procedures do not necessarily effect results. In our proposal, we use only variables related to results.

2.3. Methodological approach for the construction of a job quality indicator

For the sake of simplification, we can distinguish between the 'traditional' composite indicator approach and the multicriteria approach (OECD 2008), even if other proposals can be found in the literature. The first one is represented by the structure of Fig. 1 and has been widely adopted even by international organisations because of its simple structure. It is well known that the traditional structure contains critical steps: the standardisation of indicators, the evaluation of compensability and the aggregation procedure, and the choice of weights. Multicriteria approaches aim to overcome such criticisms, but the procedures and the results could be difficult to understand for an inexperienced audience.

Many indicators of job quality have been proposed by international agencies and academics; a great part of them derive from international or European databases (European Working Conditions Survey, European Community Household Panel, European Labour Force Survey, Statistics on Income and Living Conditions, ILO database, …). In most cases, the proposed indicator is at the aggregate level, and composite indicators based on individual data often originate from ad-hoc surveys, for example, the Subjective Quality of Working Life Index in the Czech Republic (Vinopal 2009), the DG Good Work Index in Germany (Mußmann 2009) and the Quality of Work in Flanders (Flanders Social and Economic Council 2009).

The proposed indicators vary in terms of aims, dimensions considered, variables and so on. In addition, our proposal is based on the ad-hoc longitudinal survey, specifically the 'Agorà' survey on the career outcomes of graduates from the University of ~~Padua~~Padova (Fabbris 2012).

For the purposes of our work, we determined job quality to be a multifaceted concept based on a limited number of dimensions that can be described using objective and subjective indicators. If the indicators were subjective, they were not considered to comprise job satisfaction, because that is shaped by the worker's expectations rather than merely the conditions of employment.

As explained in the introduction, we accept the hypothesis of compensability and follow a methodology based on the traditional approach for the construction of a job quality indicator. This research is aimed also at the dissemination of results to a wide and disparate audience, and consequently, we intend to join the accuracy of the methodology and ease of the procedure and results comprehension.

We analysed the quality of the jobs of graduates from ~~Padua~~Padova University three years after graduation. Given the particular population segment, some dimensions generally included in the job quality indexes are not considered here, because they are almost irrelevant in our context (e.g. job security).

3. Proposal of a new composite indicator

3.1. Distance

The term "distance" refers to a measurement between entities. Given two entities *r* and *s*, the distance between them has the following properties:

$$d_{rs} > 0 \text{ for every } r, s;$$

$$d_{rr} = 0 \text{ and } d_{ss} = 0 \text{ for every } r \text{ and } s;$$

$$d_{rs} = d_{sr} \text{ for every } r,\ s;$$

$$d_{rt} + d_{ts} > d_{rs} \text{ for every } r,\ s,\ t.$$

The last property is the triangle inequality. If it does not hold, then the measure is not a metric, and the measure is a dissimilarity.

Many formulations for measuring the distance between quantitative variables have been proposed in the literature. Other techniques aim to transform one kind of variable into another, e.g., optimal scaling (Kruskal 1964).

Our objective is to calculate a multidimensional distance between a subject and a theoretical "minimum" subject, that is, a subject that has the minimum values for each variable and is intended to represent the less desirable observable situation. The distance between two subjects is based on the composition of distances evaluated for each of the observed variables. The Euclidean distance is the most common distance between subjects. The statement that only variables with the same level of measurement can be compared and combined does not seem to be objectionable. However, the issue of how to define the distance is not trivial. In particular, in the field of social sciences, it is standard to use different scales of measurement.

One proposal for how to deal with different kinds of variables, inspired by Gower (1971), could be to consider a distance, d_{cmi}, between the c-th subject and its minimum, m, based on the i-th variable, which is defined according to the variable's typology:

- *Dichotomous variables* $d_{cmi} = 0$ if the c-th subject shares the same categorisation as its "minimum" for variable i, and $d_{cmi} = 1$ if it does not. The minimum is intended to represent the less desirable situation. Thus, attention should be paid to ensuring that the less desirable situation is coded as 0.

- *Quantitative variables* The distance is calculated as the absolute value of the difference between the variable observed for subject c and its minimum, m, standardised by the range R_i: $d_{cmi} = |(x_{ci} - x_{mi})|/R_i$.

- *Ordinal variables* We consider the ranks and the formulation to be similar to the quantitative case: $d_{cmi} = |(rk(x_{ci}) - 1)|/(Rk_i - 1)$, where $rk(x_{ci})$ is the rank of the c-th observation for the i-th ordinal variable and Rk_i is the maximum ranking position of the observations for variable i. The term "1" after Rk_i is inserted so that the distance varies between 0 and 1. In fact, it must be noted that the distance d_{cmi} always varies between 0 and 1 so that it is normalised.

Clearly, we do not consider categorical variables with more than two categories, because in this case, no measure of distance can be adopted.

3.2. General formulation of the composite indicator

A CI is usually formed by various dimensions, each one measured through different elementary indicators. This hierarchy must be taken into consideration in our formulation. Thus, the conceptual framework is defined at different levels, each level having its own weight. Two kinds of weights are defined: main weights, which load on the variables, and correlation weights, which account for the degree of correlation between variables. We use the term "main weights" instead of "importance weights" because in linear aggregation, the relative importance of variables also depends on the characteristics of their distribution, as well as their correlation structure (Paruolo et al. 2013).

How to aggregate the weights also depends on the functions involved in the various levels. If all of the functions are linear and each elementary indicator contributes by describing just one dimension, the weights can simply be multiplied. If the simplest situation of a two-leveled hierarchy (elementary indicators → dimensions → overall CI) is considered, then our formulation is as follows:

$$CI_c = \frac{\sum_{j=1}^{J} \frac{\lambda_j}{N_j} \left(\sum_{i=1}^{N_j} l_{ij} w_i d_{ij}^{cm} \right)}{\sum_{j=1}^{J} \frac{\lambda_j}{N_j} \left(\sum_{i=1}^{N_j} l_{ij} w_i \right)} \quad 1$$

where J is the number of dimensions, and j is the index for the dimension, N_j is the number of indicators forming the j-th dimension, and i is the index for the elementary indicators within each dimension, λ_j are main weights in the upper level of the structural hierarchy, representing the weight assigned to each dimension. $\lambda_j > 0$ and $\sum_{j=1}^{J} \lambda_j = 1$, l_{ij} are the main weights at the lower level for the elementary indicators. $l_{ij} > 0$ and $\sum_{i=1}^{N_j} l_{ij} = 1$, w_i are the correlation weights at the lower level for the elementary indicators (see Formula 2), d_{ij}^{cm} is the dissimilarity measure of subject c from the minimum m with respect to the variable i in the dimension l~~.~~ and $0 \leq d_{ij}^{cm} \leq 1$ ~~and the~~ . The term $1/N_j$ is necessary because, in this way, the impact of a dimension does not depend on the number of indicators describing it.

The CI for the unit c is the weighted arithmetic mean of the dissimilarities between the value of the elementary indicators calculated in c and their minimum. This is a generalization of the Gower distance when a hierarchical structure for variables is observed.

Note that correlation weights are absent at the upper level (dimensions). This choice is justified by two theoretical factors: (a) In the construction of a CI, the dimensions should be conceived of as concepts that are very poorly correlated because they are built to explain different aspects of the general concept, and (b) the correlation between dimensions is not available at the beginning of the process; eventually, it can be calculated a posteriori, when the dimensions have been constructed, and this seems to be a forcing procedure.

The minimum to be considered for every indicator depends on the choice between the theoretical and sample minimum. This choice is relevant only for quantitative variables given that the theoretical and sample minimums for dichotomous and ordinal variables are the same (zero for dichotomous variables and the lowest rank for ordinal ones). We suggest that the choice of quantitative variables should be based on the considered phenomenon;

sometimes, a theoretical minimum makes sense, and at other times, one does not. For instance, no theoretical minimum has been universally established in the case of wages, so we will use the minimum observed in the sample.

3.2.1. Main weights

To address the issue of the main weights, we consider Decancq and Lugo's (2013) three types of approaches: data-driven, normative, and hybrid. Data-driven weights are a function of how the dimensions analysed are distributed in the sample or population; they are not explicitly based on any value judgment. Normative weights, on the other hand, are set based on value judgments (e.g., expert opinions), while hybrid weights take advantage of both data-driven and normative approaches.

In order to weigh the job-quality dimensions, we adopted a hybrid approach (Carpita and Vezzoli 2012; Decancq and Lugo 2013; Vezzoli 2011) in which the opinions of individuals are elaborated upon using statistical methods that consider information about value judgments, as well as data. We considered such approach the better choice for the indicator proposed in this article as compared with data-driven and normative approaches because young graduates experience their jobs first-hand and have all the information and knowledge required to assess the quality of their jobs.

Among the hybrid approaches, we chose the hedonic approach, which is based on the implicit opinions of the graduates. Weights were obtained by regressing a measure of overall satisfaction on a set of variables representing the three dimensions of the concept. We asked respondents to express their level of job satisfaction (using a 1–10 scale) for their jobs as a whole and with reference to a set of specific job characteristics. The job characteristics listed were ascribed to the three job-quality dimensions of the JQCI: the economic dimension referred to the level of satisfaction with contractual stability and wages, the professional dimension referred to satisfaction with the opportunity for professional development and career prospects, and the work-life balance dimension referred to satisfaction with working time flexibility and with the distance between the home and workplace. The weights are the regression coefficients obtained via an ordinal logistic regression model, where the dependent variable is the level of overall job satisfaction and the explanatory variables are the level of satisfaction with the individual job attributes. In order to obtain the weights for each dimension, we calculated the arithmetic mean of the standardized regression coefficients of the job attributes included in each dimension and rescaled to sum to one.

Weights were validated in two ways. The first validation refers to the robustness of estimates. ~~w~~We proceeded with a bootstrap procedure: a sampling of 70 % of observations was replicated 1000 times, and we observed the distribution, mean and median of the estimates of the regression coefficients.

The second validation is the comparison of the obtained weights with the results presented in Boccuzzo and Gianecchini (2015). In their~~,~~ paper, the authors consider a subjective approach based on value judgments expressed by a group of individuals. The individuals considered in order to compute the weights were a representative sample of graduates from the same cohorts of the Agorà survey, but who had not been interviewed before. The sample of the new cross-sectional survey, carried out during the period between July and October 2010, consisted of 380 employed graduates and 332 unemployed graduates.

During the survey, the employed respondents were required to describe, through an open question, the five most important job characteristics that determine their job satisfaction. The answers were read by the two authors independently and were assigned to one of the three dimensions of job quality considered (the detailed process is described in the original article). The weights were calculated as the proportion of responses assigned to a dimension compared with the total number of responses allocated to the three dimensions.

3.2.2. Correlation weights

We propose defining the correlation weight of each i-th indicator as a function of the correlation coefficients r_{il} between that indicator and all of the other indicators (indexed by l):

$$w_i = \frac{1}{N-1} \sum_{l \neq i}^{N} (1 - |r_{il}|) \tag{2}$$

where $N = \sum_{j=1}^{J} N_j$ is the total number of elementary indicators. $0 \leq w_i \leq 1$.

The type of correlation we have considered depends on the pair of variables:

- *Two quantitative variables:* Bravais–Pearson correlation coefficient~~,~~.

- *Two ordinal variables:* Spearman's rank correlation coefficient.
- *Two dichotomous variabless:* Phi coefficient (Fleiss et al. 2003).
- *One quantitative and one dichotomous variable:* Point-biserial correlation coefficient (Das Gupta 1960).
- *One quantitative and one ordinal variable:* Jaspen's coefficient of multiserial correlation (Jaspen 1946).
- *One ordinal and one dichotomous variable:* Rank-biserial correlation coefficient (Glass 1966).

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In order to show that the correlation weights are truly effective in reducing the impact of the highly correlated indicators with respect to the other indicators, let us consider the following example. For the sake of simplicity, we define a CI with only one dimension composed of three quantitative variables; $J = 1$, $N_1 = 3$. The main weights are equal (1/3), and the correlation coefficients are $r_{12} = 0.3$, $r_{13} = 0.7$ and $r_{23} = 0.7$, so $w_1 = 0.5$, $w_2 = 0.5$ and $w_3 = 0.3$. The distances are, in the first case, $d_{11} = 0.1$, $d_{21} = 0.5$, $d_{31} = 0.9$ and, in the second case, $d_{11} = 0.9$, $d_{21} = 0.5$, $d_{31} = 0.1$.

As we can see from Table 1, in the first case, the CI equals 0.438, and in the second case, it equals 0.562. The difference is considerable, and it is mainly due to the first addend, where the correlation weight is high (0.5) and multiplies a low distance the first time and a high distance the second time. If correlation weights were absent, the CI would be 0.5.

Table 1

Example of the effectiveness of correlation weights

	d_{11}	d_{21}	d_{31}	Addend 1	Addend 2	Addend 3	CI
Case 1	0.1	0.5	0.9	0.03846	0.19231	0.20769	0.438
Case 2	0.9	0.5	0.1	0.34615	0.19231	0.02308	0.562

4. Data

The study was conducted on a sample of Italian graduates in 2007 and 2008.

The data belong to the Agorà longitudinal survey on the career outcomes of graduates from the University of ~~Padua~~Padova (Fabbris 2012). Respondents were interviewed 6, 12 and 36 months after graduating, using a computer-assisted telephone interview technique. Workers were required to provide information on their current job, job search activities, the perception of skill and educational mismatch and an evaluation of their educational programme.

Two thousand eight hundred and eighty five people were interviewed 36 months after graduation. Of this number, only employed personnel with a regular contract (2330) were considered for our research.

5. The job quality indicator: dimensions, elementary indicators and weights

The CI that we propose is composed of three dimensions (Boccuzzo and Gianecchini 2015): economic, professional and work-life balance. The economic dimension concerns factors relating to the economic exchange between the worker and the employer, which are generally included in the formal employment contract. The professional dimension relates to the characteristics of the job, which influence the worker's human capital accumulation by enhancing his or her employability. The work-life balance dimension involves aspects that affect the worker's personal life and work relationships.

Each dimension is comprised of several elementary indicators. Table 2 shows the original variables used for the construction of the elementary indicators and the hierarchical structure of the job quality indicator (JQI).

Table 2

Variables used in the construction of the CI as an indicator of job quality

Dimension	**Elementary indicator**	**Description**
Economic	Hourly wage	*Quantitative* Monthly net salary/monthly working hours
	Contractual stability	*Ordinal* Permanent job, open-ended job, self-employment and other, e.g., temporary work
Professional	Horizontal educational match	Level of coherence between the respondent's field of education and the job *Ordinal* 0 (not at all) to 9 (a lot)

Dimension	Elementary indicator	Description
	Vertical educational match	A university degree is required for the job *Ordinal* To perform your current job, (i) the university degree that you hold is specifically required, (ii) a graduate from a different major could obtain similar results, (iii) a university degree is not necessary (a high school degree could suffice), (iv) a qualification lower than high school could suffice
	Skill match	In doing the job, the skills learned at university are utilized *Ordinal* To what degree can you exploit your professional skills at work? (i) not at all, (ii) not much, (iii) quite, (iv) very much
	Career advancement opportunities	Career advancement opportunities in the next two years *Dichotomous* (1 = yes, 0 = no)
	Teamwork	The job requires working in a team with other colleagues *Dichotomous* (1 = yes, 0 = no)
	Responsibility level	The job requires coordinating and controlling other people Dichotomous (1 = yes, 0 = no)
Work-life balance	Working hours	*Quantitative* 1-(weekly working hours normalized between 0 and 1)
	Home-work distance	The worker lives in the same geographical area in which he or she works *Ordinal* The residence province, the residence region, abroad or in an Italian region (different from the residence region)

Two kind of weights are used at different levels of the CI hierarchy with regard to the aggregation of the elementary indicators (only correlation weights were used) and dimensions (only main weights were used) in the overall CI.

The main weights are shown in Table 3.

Table 3

Main weights for the three dimensions that compose the JQI

Dimension	Economic	Professional	Work-life balance
Main weight	0.241	0.602	0.158

The weight of the professional dimension of the JQI is the highest (0.602) of the three dimensions, followed by the economic (0.241) and work-life balance (0.158) dimensions. Considering that only ~~23 %~~23% of the respondents had their own families (and only ~~7 %~~7% had children), it is reasonable to assume that the work-life balance dimension would have been the least relevant to the sample as a whole. The bootstrap validation gives the same weights obtained by the simple ordinal logistic regression, whereas the weights obtained by Boccuzzo and Gianecchini (2015) are 0.637, 0.242 and 0.121 for the professional, economic and work-life balance dimension respectively. Given that they are obtained with different method and sample, we retain that our results are satisfactory.

The correlation weights are calculated as in Formula (2). Highly correlated variables have low correlation weights because their original contribution to explaining the CI is small. This is the case with "coherence between degree and work", which is strictly linked with the "usefulness of the degree" and "possibility of enhancing skills" indicators. The variables less correlated with others are working hours, hourly wage and distance between home and work.

5.1. Results

The CI of job quality has an empirical distribution, which was symmetric and centered around 0.54 (thus, almost in the middle of its theoretical range). The minimum value was 0.13, and the maximum was 0.88.

The dimensions (Table 4) are quite centred, with the economic dimension showing the lowest mean score (0.45) and the work-life balance dimension showing the highest (0.61). There was a mean score of 0.56 for the professional dimension.

Table 4

Distribution of the JQI and its dimensions

Variable	Mean	SD	Min	Lower quartile	Median	Upper quartile	Max
JQI	0.54	0.31	0.13	0.45	0.54	0.63	0.88
Economic dimension	0.45	0.20	0.01	0.33	0.53	0.62	1.00
Profess. dimension	0.56	0.19	0.00	0.43	0.56	0.69	1.00
Work-life balance dimension	0.61	0.16	0.00	0.48	0.61	0.75	1.00

Max Maximum, *Min* minimum, *SD* standard deviation

The lowest mean score for the economic dimension suggests that wage and contractual conditions were critical aspects of job quality for young graduates.

The three dimensions are slightly correlated or uncorrelated (Table 5), confirming the fact that each dimension describes a different aspect of job quality.

Table 5

Correlation coefficients among dimensions that form the JQI

Economic-professional	Economic-work life balance	Professional-work life balance
0.207	−0.084	−0.170

5.2. Validation

The CI is considered to be reliable if it is shown to be stable. To test its reliability, we proceeded with two trials. First, the original sample was divided into two random subsamples of equal size (without replacement) and then into three random subsamples, again of equal size and without replacement. The value of the CI and its dimensions were calculated in each subsample separately. Both the main and the correlation weights were re-calculated for each random subsample. The results showed that the three dimensions were stable with respect to the subsamples.

Moreover, the CI appeared to measure what it was intended to measure (accuracy). It can be assumed that generally, job seekers' job quality is lower than that of people who wish to remain in their current position. In fact, those who are unsatisfied with their job will attempt to change it as many times as are necessary to find a position that best suits their expectations (De Bustillo Llorente and Fernandez Macias 2005). If this assumption can be verified by our CI, then we can say that our CI effectively measures job quality. We tested its accuracy by calculating job quality and the influence of its dimensions on subgroups of individuals for whom the level of job quality (relative to the other subgroups) was already known. We used the information (detected in the Agorà survey questionnaire) on the intention to change jobs and possible reasons for this choice to select such subgroups.

In particular, two questions were considered: the first one detects the intention of changing jobs via the fact of having searched—or not—a new job in the six months preceding the interview. The average of the CI has been calculated via stratifying based on the levels of this dichotomous variable; the results confirm the assumption because the mean of the job seekers is 0.50 and the mean of those people not intentioned in changing jobs is 0.56 (Table 6).

Table 6

Mean of the CI in two sub-samples: intention or not to change job

Intention to change job	Mean	SD	Min	Max	N° subjects
Yes	0.50	0.12	0.13	0.84	320
No	0.56	0.13	0.18	0.88	1596

Workers three years after graduation, University of ~~Padua~~Padova, 2007–2008. The p value of the two-sample *t* test for unbalanced data is < 0.0001. There were 414 missing values out of 2330 subjects

The data regarding the motivations for an eventual change of job are available (Table 7). The possible answers to this question coincide with the three dimensions of our CI. We are interested in the 775 respondents who declared a reason for changing jobs.

Table 7

Frequency of answers to the question about the motivation to change jobs

Motivation to change job	Frequency	Percentage
Never thought to change	1360	64.30
Change to improve pay and working conditions	326	15.41
Change to improve the business/the use of skills	260	12.29
Change for a better work environment/for the distance from home	86	4.07
Other reason	83	3.92
Total	2115	100
Two hundred and fifteen missing values. Workers three years after graduation, University of ~~Padua~~Padova, 2007–2008		

If the main reason for changing work is linked to the professional aspect of CI, the professional dimension would be the best predictor. The same reasoning is valid for the other dimensions.

Thus, the validity of the dimensions has been tested by three regression models, where the three dimensions of the JQI are the response variables and the motivations for a desired work change are the explanatory ones. Three motivations for leaving are available: economic/contractual, activity and inadequate use of competences, and distance from home and work environment. The first motivation should be the best predictor of the economic dimension, the second one of the professional dimension and the third one of the work-life balance dimension. This is confirmed (Table 8), even if economic/contractual motivation is also a significant predictor of the professional dimension and the use of competences is also a significant predictor of the economic dimension.

Table 8

Validity of the dimensions of the JQI, tested by three regression models

Motivation for leaving (ref. none) (*independent variables*)	CI's Dimension (*dependent variable*)				
	Y = economic		Y = professional		Y = wo balanc
	EST.	SD	EST.	SD	EST.

Motivation for leaving (ref. none) (*independent variables*)	CI's Dimension (*dependent variable*)				
	Y = economic		Y = professional		Y = wo balanc
	EST.	SD	EST.	SD	EST.
X1 = Economic/contractual	**−0.0429*** **	**0.0124**	−0.0362**	0.0117	0.0005
X2 = Activity and use of competences	0.036**	0.0137	**−0.0977**** **	**0.0128**	−0.003
X3 = Distance from home and work environment	0.0292	0.0224	0.0005	0.0211	**−0.094**
X4 = Other	0.0314	0.0228	−0.0089	0.0214	−0.033
Intercept	0.4547****	0.0055	0.5849****	0.0051	0.6096
N = 2115. Workers three years after graduation, University of ~~Padua~~Padova, 2007–20					
p value: * ≤0.05; ** ≤0.01; *** ≤0.001; **** ≤0.0001					

AQ3

Therefore, the results of the JQI confirmed our expectations.

5.3. Applications of the job quality indicator

A JQI for young graduates could offer an informative basis for policy-making purposes and predicting employees' organizational behaviors.

To offer an informative basis for policy-making, we conducted a descriptive analysis that considered the mean score of the JQI and its dimensions according to the characteristics of graduates and their companies. Then, we conducted a multivariate analysis in order to identify the determinants of job quality using a stepwise linear regression with logit (JCI) as the dependent variable. The dependent variable is normally distributed, as verified by normality tests. The descriptive and multivariate analyses identified the groups of graduates who experienced the best and worst job quality. The characteristics of the companies that offered high-quality jobs were identified through these analyses.

The JQI was significantly higher for males than for females (0.56 versus 0.52, p value <0.0001, Table 9), and the economic and professional dimensions were higher for males, whereas the work-life balance dimension was higher for females.

Table 9

JCI and its dimensions: values according to company and graduate characteristics

	Mean	SD	*p* value*	Dimensions		
				Economic	Professional	Work-life balance
Gender						
Male	0.56	0.13	<0.0001	0.47	0.60	0.58
Female	0.52	0.13		0.42	0.53	0.63
Age						
≤24	0.51	0.13	0.0017	0.40	0.53	0.62
25–26	0.54	0.13		0.43	0.56	0.60
≥27	0.55	0.13		0.47	0.56	0.61
Final high school grade						
60–75	0.52	0.13	0.0008	0.44	0.64	0.53
76–90	0.54	0.13		0.44	0.61	0.56
91–100	0.55	0.12		0.45	0.58	0.58
University degree level						
Bachelor's degree	0.52	0.10	<0.0001	0.42	0.53	0.62
Master's degree	0.55	0.13		0.46	0.58	0.59
Five-year master's degree**	0.58	0.10		0.49	0.60	0.66
Final university grade						
66–90	0.54	0.10	0.521	0.46	0.56	0.62
91–100	0.54	0.12		0.44	0.56	0.60

SD standard deviation

* *p* value: Significance of *t* test when comparing the indicator mean between the two groups (for example, male versus female) and analysis of variance (ANOVA) test when comparing three or more groups (for example, the disciplinary area). Because the JQI lies in (0–1), the *t* test and ANOVA refer to log [(JQI)/(1 − JQI)], which is normally distributed

** Five-year tertiary education programme directed at obtaining a Master's degree

	Mean	SD	*p* value*	Dimensions		
				Economic	Professional	Work-life balance
101–110	0.54	0.13		0.44	0.56	0.61
Disciplinary field						
Humanities	0.51	0.13	<0.0001	0.41	0.51	0.65
Life Sciences	0.54	0.12		0.45	0.55	0.62
Socio-economic	0.54	0.13		0.47	0.56	0.60
Technical-scientific	0.57	0.13		0.47	0.62	0.56
Company size						
≤9	0.51	0.13	<0.0001	0.39	0.52	0.65
10–19	0.53	0.13		0.43	0.55	0.63
≥20	0.56	0.10		0.48	0.58	0.58
Sector						
Private sector	0.54	0.12	0.751	0.45	0.54	0.66
Public sector	0.54	0.13		0.44	0.56	0.60

SD standard deviation

* *p* value: Significance of *t* test when comparing the indicator mean between the two groups (for example, male versus female) and analysis of variance (ANOVA) test when comparing three or more groups (for example, the disciplinary area). Because the JQI lies in (0–1), the *t* test and ANOVA refer to log [(JQI)/(1 − JQI)], which is normally distributed

** Five-year tertiary education programme directed at obtaining a Master's degree

The JQI increases with age (p value 0.0017), primarily because of the contribution of the economic dimension. Of the oldest graduates, 52.6 % worked while studying and had maintained the same job since graduation.

The five-year Master's graduates had the highest JQI (0.58). While they were just a small group in the sample (6.8 %), most (70 %) were adult students with a stable job that they had held at university and maintained after graduating. The JQI comparison of Bachelor's and Master's degree graduates showed a significant difference (0.52 and 0.55, respectively), and the professional dimension was significantly higher for Master's graduates (0.58 for Master's graduates versus 0.52 for Bachelor's graduates).

Graduates from the technical-scientific discipline had the highest JCI due to the contribution of the professional dimension. Graduates in socio-economic and technical-scientific disciplines benefitted from the best economic dimension, while the work-life dimension was the highest for graduates in the humanities. These results were confirmed via the multivariate analysis, which showed that obtaining a degree in the socio-economic or technical-scientific disciplines was a significant predictor of job quality (as compared with graduates in the humanities). Because the value of the JQI for graduates in the life sciences group was influenced by the fact that 65 % of this group had completed a 5-year Master's degree, the variable related to life science was not statistically significant in the multivariate analysis.

Both gender and discipline remained significant in the multivariate analysis. Despite a high association between gender and discipline (49 % of women were enrolled in liberal arts courses, as compared to 12.5 % of men, and 19.4 % of women were enrolled in sciences courses, as compared to 60.6 % of men), the lower quality of women's jobs could not be attributed to their choice of discipline entirely, because women have a comparative disadvantage in respect to job quality, even when they are compared to men in the same discipline (Table 10).

Table 10

Significant explanatory variables of the JCI, resulting from stepwise linear regression

Variable	Estimate	SD	Significance
Intercept	−0.1847	0.1237	0.1354
Personal characteristics			
Age	0.1114	0.0025	<0.0001
Gender (reference: male)			
Female	−0.1359	0.0253	<0.0001
School and academic background			
Final high school grade	0.0026	0.0009	0.0059
Because the JQI lies in (0–1), the dependent variable is log [(JQI)/(1 − JQI)], which is normally distributed			

Variable	Estimate	SD	Significance
University degree level (reference: five-year Master's degree)			
Bachelor's degree	−0.3812	0.0504	<0.0001
Master's degree	−0.3133	0.0519	<0.0001
Disciplinary field (reference: Humanities)			
Life sciences	0.0107	0.0371	0.7725
Socio-economic	0.1063	0.0309	0.0006
Technical-scientific	0.1706	0.0326	<0.0001
Job characteristics			
Company size	0.0550	0.0077	<0.0001
Because the JQI lies in (0–1), the dependent variable is log [(JQI)/(1 − JQI)], which is normally distributed			

It was interesting to note that the final university grades did not influence job quality, probably because they relate strictly to the faculty. The lowest average grade was 96.3 for Statistics, and the highest was 108.3 for Psychology. By contrast, graduates with enhanced high school performance possessed better jobs. The final high school grade represented a proxy for the human capital of the graduate.

Graduates with the highest-quality jobs tended to be employed by bigger companies because the JQI rose with the size of the firm [p value <0.0001 (ANOVA test)], from 0.51 for the smallest companies (≤9 employees) to 0.56 for the largest ones (≥20 employees). The work-life balance dimension reflected an inverse trend, decreasing as the firm size increased (from 0.65 to 0.58). Company size was the only organisation-related characteristic that significantly predicted job quality in the multivariate analysis (Table 10).

Finally, to predict employees' behaviour within their organisations, graduate workers' turnover intention was considered to be a relevant outcome for testing the predictive capacity of the JQI at the organisational level (e.g., Dychtwald et al. 2013). We used the question "In the last 12 months, have you searched for a new job, even if you are already employed?" to measure the intention to leave one's job. Together with the JQI, we considered other individual (gender, age, university degree level, the disciplinary field and work experience while studying) and organisational variables (industry, sector and company size) as predictors. Because intention to leave is a dichotomous dependent variable (1 = yes, 0 = no), we adopted a log-binomial regression that belongs to the generalised linear models family and is characterised by a logarithmic link function and a binomial distribution. The log-binomial regression allows the relative risk to be estimated as a function of more explanatory variables.[1] We selected explanatory variables using a stepwise technique. The results highlighted the fact that the only significant explanatory variable was the JQI, and this result suggests that the JQI, which is influenced by the features of both the person in the job and the job's working conditions, encompasses such features. Therefore, it is not necessary to take them into account when investigating the reasons for the intention to leave a job.

6. Conclusion

A new formulation of CI has been proposed to measure complex phenomena at the micro-level, that is, when dealing with individuals. Information about single individuals can be collected as quantitative, ordinal or dichotomous variables. Thus, one of the main characteristics of the original proposal was to consider variables of different natures. Other features of our CI took into account the correlation between variables and expressed the overall measure in the form of distance from an ideal minimum while simultaneously maintaining the hierarchical form of the CI.

The usefulness of this approach is that it can be used at both the macro- and at micro-levels to measure a wide range of complex phenomena, for example, to express development measures for various subjects, i.e., job quality. It can not only be used to rank aims but also in rating, i.e., in stating where a subject is positioned in the range (0–1) of the CI. As much attention as possible should be paid to maintaining both the original nature of the variables and their relationships, as well as the original nature of the multidimensional phenomenon. Finally, the formulation of our CI can be considered a form of weighted mean, as well as an easily understandable concept for non-technical people. This further expands its applicability.

Having applied our formulation of CI to job quality among graduate workers, the results show that the CI has a balanced structure, both at the overall level and at the level of dimensions. It was stable while simultaneously discriminating well between individuals and groups. It was both reliable and accurate.

In our opinion, the main weakness of this new theoretical formulation of CIs is that ordinal variables are taken as ranks. This representation is not faithful to the original nature of ordinal variables, although it is used by the large majority of proposed CIs in the literature. Other proposals regarding ordinal variables are available in the literature, but they are not compatible with the hierarchical structure of CIs (e.g., the POSet method) and do not allow the use of mixed data (e.g., multidimensional scaling). Such considerations should be accounted for as an open issue, although they are inserted in the theoretical framework of a new CI formulation.

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[1] We did not adopt the more popular logistic regression model, because it estimates odds ratios in order to approximate the relative risk of rare events. Because 17 % of the respondents in our sample planned to search for a new job, we could not consider the event to be rare.