PUBLIC MANAGER REQUIREMENTS OF SKILLS AND TRAINING: IMPORTANCE RANK ANALYSIS USING COMPOSITE INDICATORS

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Abstract *To reconceptualize the role and profile of public managers, a survey has been designed and performed in collaboration with the National Association of the Municipalities of Italy (Veneto region). Public managers and in particular municipal directors were asked to rate the importance of various requirements of skills and training for their job. The aim of the paper is to understand how municipal directors rank requirements of skills and training from the least to the most important one. Preference ratings are combined using composite indicators. The outcome of a composite indicator depends on normalization, aggregation and weighting of partial indicators. Therefore the robustness of results is under question. To address this issue, an uncertainty analysis on the ranking of skill and training requirements has been performed. Three uncertainty factors have been considered: normalization, aggregation and weighting. It is shown that the uncertainty analysis allows a better understanding of the problem.*

Keywords: *public manager, composite indicator, ordered categorical variable, Monte Carlo computation.*

1. INTRODUCTION

A survey has been designed and performed in collaboration with the National Association of the Municipalities of Italy (Veneto region) to study perception and expectation of the role of the municipalities with regard to the local area, to reconceptualize the role and profile of public managers and to study municipal directors as far as requirements in terms of competencies for skills and training are concerned (Boccuzzo and Bolzan, 2014; Bolzan, 2010). In the United Kingdom, the term "competence" was adopted to indicate the set of conditions and means to give a good professional performance (Horton et al., 2002). Such a set includes

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knowledge, abilities and personal traits. The study of competencies includes the perception that each working individual has of himself/herself in relation to the organization, to the other organizational actors, and to the goal or mission of the institution. Noordegraaf (2000) stated that competent public managers are "professional sense–makers" who know how to perceive political cues, stimuli and triggers, which can relate to new or existing issues, solve problems and go ahead with policies. Boyatzis (1982) defined competencies as an underlying characteristic of an individual, which is causally related to effective or superior performance in a job or a situation. This definition replaces the concept of job description as the carrying out of designated tasks; the new concept puts emphasis on the relationship between competencies and performance.

The aim of the paper is to understand how municipal directors rank requirements of skills and training from the least to the most important one. Preference ratings are combined using composite indicators. Composite indicators can be used to assess variables that are difficult to directly observe or measure (Fayers and Hand, 2002; Marozzi, 2012). They are used very often in medicine and psychology to assess for example quality of life, mood states, intelligence (Marozzi, 2009). In marketing they may be used for assessing customer satisfaction and in finance for ranking investment alternatives. The context where composite indicators are most widely used is country performance comparison in economic openness, globalization, competitiveness, development, security, education, health, human rights, environment, corruption and financial risk (OECD, 2008). Their purposes are to rank countries according to complex phenomena, inform policy makers, international commitments, investors and citizens about trends and changes in country rankings across time. They are designed by public institutions as well as by profit and non profit private organizations. Recently, composite indicators have been used to assess the trust in European public institutions (Marozzi, 2014).

Section 2 discusses composite indicator computation, that is normalization, aggregation and weighting of partial indicators. In Section 3 we address the robustness of a composite indicator using uncertainty analysis. Ranking of skills and training requirements given by municipal directors are analyzed in Section 4. Final remarks are given in Section 5.

2. A GENERAL FRAMEWORK FOR COMPOSITE INDICATORS

A rather general framework to compute composite indicators is reported in Marozzi (2015). We use this framework to analyze a data set about the importance given by municipal directors in Veneto (Italy) to various skill and training requirements.

$K = 160$ municipal directors were asked to rate the importance of needs of skill and training for their job in a ten point scale, where 1 denotes minimal importance and 10 maximum importance. $J = 26$ requirements of skills and 26 requirements of training were considered. Let ${}^{S}X_{jk}$ and ${}^{T}X_{jk}$ denote the importance given by municipal director k to skill j and training requirement j respectively, $k = 1,...,K$, $j = 1,...,J$. The central question is: how do municipal directors rank requirements for skills and training from the least to the most important one? Their preference ratings are combined using composite indicators.

A rather general procedure to compute a composite indicator is based on two steps

1. normalization
2. weighting and aggregation.

STEP 1

Even if the preference ratings are expressed in the same scale, they may have different dispersion and therefore they should be normalized before performing the aggregation step. X_{jk}, where the superscript S (T) has been removed, is transformed to

$$ {}_{b}\beta(X_{jk}) = {}_{b}\gamma_{jk}, \quad b = 1,...,B $$

where B denotes the number of normalization methods. We consider $B = 4$ with

- $b = 1$,
$$ {}_{1}\beta(X_{jk}) = \frac{X_{jk}}{\max_{j=1,...,J}(X_{jk})} = {}_{1}\gamma_{jk} $$
which we prefer to linear scaling in the min–max range because ${}_{1}\beta(X_{jk})$ does not produce zero values which are not compatible with the multiplicative aggregation rule. Note that ${}_{1}\beta(X_{jk})$ is not really different than X_{jk} itself because it is likely that $\max_{j}(X_{jk}) = 10 \ \forall k$;

- $b = 2$,
$$ {}_{2}\beta(X_{jk}) = \frac{X_{jk} - M(X_{jk}, j = 1,...,J)}{SD(X_{jk}, j = 1,...,J)} = {}_{2}\gamma_{jk} $$
where $M(X_{jk}, j = 1,...,J)$ and $SD(X_{jk}, j = 1,...,J)$ denote respectively the mean and the standard deviation of $X_{jk}, j = 1,...,J$;

- $b = 3$,
$$ {}_{3}\beta(X_{jk}) = \frac{X_{jk} - Med(X_{jk}, j = 1,...,J)}{MAD(X_{jk}, j = 1,...,J)} = {}_{3}\gamma_{jk} $$

where $Med(X_{jk}, j = 1, ..., J)$ and $MAD(X_{jk}, j = 1, ..., J)$ denote respectively the median and the median absolute deviation of $X_{jk}, j = 1, ..., J$. Both ${}_2\beta$ and ${}_3\beta$ transform the values to a common scale, ${}_3\beta$ uses statistics that are more robust against outliers than the mean and the standard deviation. Note that both ${}_2\beta$ and ${}_3\beta$ are not compatible with the multiplicative aggregation rule that is defined only for positive numbers;

- $b = 4$,

$$ {}_4\beta(X_{jk}) = \sum_{h=1}^{J} I(X_{jk} \geq X_{hk}) = {}_4\gamma_{jk} $$

that is the rank transformation. ${}_4\beta$, like ${}_3\beta$, is not affected by outliers. Respect to ${}_3\beta$, by using ${}_4\beta$ we loose information on levels since only relative positions are considered but ${}_4\beta$ is compatible with the multiplicative aggregation rule.

STEP 2

In the second step of the procedure, the normalized data are weighted and aggregated to obtain the composite indicator of requirement for skill (requirement for training) j importance, $j = 1, ..., J$

$$ {}_{dc}\delta({}_b\gamma_{jk}, {}_dw_k, k = 1, ..., K) = {}_{dcb}\psi_j, \quad c = 1, ..., C, \quad d = 1, ..., D $$

where C denotes the number of aggregation methods, ${}_dw_k$ denotes the weight assigned to the k–th sub–indicator with ${}_dw_k \geq 0, \forall k = 1, ..., K$ and $\sum_{k=1}^{K} {}_dw_k = 1$, D is the number of weighting schemes. We consider the additive and multiplicative rules of aggregation

- $c = 1$,

$$ {}_{d1}\delta({}_b\gamma_{jk}, {}_dw_k, k = 1, ..., K) = \sum_{k=1}^{K} {}_b\gamma_{jk} \cdot {}_dw_k = {}_{d1b}\psi_j, $$

this rule has been criticized for being fully compensatory: an increase of v% in one sub–indicator can compensate a decrease of z% in another sub–indicator where z depends on the ratio between the weights corresponding to the two sub–indicators. Therefore the weights are trade–off coefficients instead of importance coefficients. However, we use this rule because is much simpler than non fully compensatory aggregation rules, it can be always applied, it is readily comprehended by non statisticians and can compensate for possible inconsistencies in the data;

- $c = 2$,

$$_{d2}\delta({}_b\gamma_{jk}, {}_d w_k, k = 1, ..., K) = \prod_{k=1}^{K} {}_b\gamma_{jk}^{{}_d w_k} = {}_{d2b}\psi_j,$$

this rule is less compensatory than the additive one but also less readily comprehended and is not compatible with ${}_2\beta$ and ${}_3\beta$ normalization methods.

The selection of the weighting scheme is highly debated. Cox et al. (1992) emphasized that weighting schemes commonly encountered in the literature are either based on too complicated multivariate methods or have little practical meaning. However, sub–indicators are weighted equally in many composite indicators. In general, the selection of the weighting scheme is subjective and therefore questionable as it is the selection of normalization and aggregation. Each selection of (b, c, d) has its pros and cons, and leads to a different composite indicator of requirement for skill (requirement for training) j importance

$$_{dcb}\psi_j = {}_{dc}\delta\left({}_b\beta(X_{jk}), {}_d w_k, k = 1, ..., K\right), \quad j = 1, ..., J,$$

for example $(b, c, d) = (1, 1, d)$ leads to

$$_{d11}\psi_j = \sum_{k=1}^{K} \frac{X_{jk}}{\max_{j=1,...,J}(X_{jk})} {}_d w_k,$$

whereas $(b, c, d) = (4, 2, d)$ leads to

$$_{d24}\psi_j = \prod_{k=1}^{K} \sum_{h=1}^{J} I(X_{jk} \geq X_{hk})^{{}_d w_k}$$

and then potentially to a different importance ranking of requirements for skills and training. Therefore the robustness of importance ranking should be analyzed. The question is: are the importance rankings robust with respect to the selection of normalization, aggregation and weighting rules? This question is answered in the next section by performing uncertainty analysis.

3. UNCERTAINTY ANALYSIS

OECD (2008) emphasized two points in designing composite indicators, clear definition and computation, and robustness testing. These points can be addressed using uncertainty analysis, a Monte Carlo simulation based procedure applied to the equations defining the composite indicator (Saisana et al., 2005). The sources of uncertainty are:

a) normalization (Step 1);

b) aggregation (Step 2);

c) weighting (Step 2).

Uncertainty analysis is applied to test whether the importance ranking is robust or volatile with respect to index design. Index design depends on three sources of uncertainty that are assessed probabilistically by assigning to them proper distribution functions. More precisely, the sources of uncertainty are translated in input factors $U_e, e = 1,...,E = 3$ that are scalar for $e = 1,2$ and vectorial for $e = 3$. Input factors are then sampled from the distributions, discrete for the scalar input factors and continuous for the vectorial input factor, assigned to them. Let ε be a continuous random variable uniformly distributed in $[0,1]$. For input factors $U_e, e = 1,2$ the general disposal rule is as rolling a fair dice with F_e faces, that is

$$U_e = \begin{cases} 1 & \text{if} \quad \varepsilon \in \left[0, \frac{1}{F_e}\right) \\ \vdots & \quad\ \vdots \\ f & \text{if} \quad \varepsilon \in \left[\frac{f-1}{F_e}, \frac{f}{F_e}\right) \\ \vdots & \quad\ \vdots \\ F_e & \text{if} \quad \varepsilon \in \left[\frac{F_e-1}{F_e}, 1\right] \end{cases};$$

where f is a natural number, $F_1 = B$ and $F_2 = C$.

In case there are some incompatibilities between the methods corresponding to the various input factors, the disposal rule of input factor $e = 2$ should be conditioned on input factor $e = 1$. In our case the disposal rules are

- normalization input factor

$$U_1 = \begin{cases} 1 \text{ ie select } {}_1\beta & \text{if} \quad \varepsilon \in \left[0, \frac{1}{4}\right) \\ 2 \text{ ie select } {}_2\beta & \text{if} \quad \varepsilon \in \left[\frac{1}{4}, \frac{1}{2}\right) \\ 3 \text{ ie select } {}_3\beta & \text{if} \quad \varepsilon \in \left[\frac{1}{2}, \frac{3}{4}\right) \\ 4 \text{ ie select } {}_4\beta & \text{if} \quad \varepsilon \in \left[\frac{3}{4}, 1\right] \end{cases};$$

- aggregation input factor

$$U_2|U_1 = \begin{cases} U_2|(U_1 = 1 \cup 4) & = \begin{cases} 1 \text{ ie select } {}_1\delta & \text{if} \quad \varepsilon \in \left[0, \frac{1}{2}\right) \\ 2 \text{ ie select } {}_2\delta & \text{if} \quad \varepsilon \in \left[\frac{1}{2}, 1\right] \end{cases} \\ U_2|(U_1 = 2 \cup 3) & = 1 \text{ ie select } {}_1\delta \quad \text{if} \quad \varepsilon \in [0,1] \end{cases}.$$

Input factor $U_3 = (U_{31}, ..., U_{3K})$, is the vector of length K of the not normalized weights. We assign to each not normalized weight an uniform distribution in the interval $[p, q]$ with $p > 0$. Therefore the normalized weights are restricted to take values between

$$U'_{3min} = \frac{p}{p + (K-1)q}$$

when one not normalized weight is equal to p and the other ones are equal to q and

$$U'_{3max} = \frac{q}{q + (K-1)p}$$

when one not normalized weight is equal to q and the other ones are equal to p. Marozzi (2015) suggests to select p and q so that

$$\max\left(\frac{U_{3max}}{U_{3min}}\right) \leq \omega,$$

with $\omega > 1$, where for example $\omega = 3$ means that the maximum theoretical normalized weight cannot exceed three times the minimum theoretical normalized weight. The corresponding values of p and q are given by Marozzi (2015). See Lago and Pesarin (2000) for a different approach on weightselection.The weights are then rescaled as

$$w_k = \frac{U_{3k}}{\sum_{k=1}^{K} U_{3k}}, k = 1, ..., K$$

so that they lay between 0 and 1 and their sum is 1. We assign different weights to municipal directors to simulate different authoritativeness profiles. Giving different weights is also a way to assess that eg "quite important" may mean "6" for a certain public manager whereas "7" for another one due to the quite elusive meaning of the different levels of importance from 1 (minimal importance) to 10 (maximum importance).

After we have defined the sample input space, we sample it and generate L combinations of the three sources of uncertainty. A different composite indicator ${}_l\psi = ({}_l\psi_j, j = 1, ..., J)$ corresponds to each combination $l = 1, ..., L$. The J requirements for skills and training may be ranked from the most to the least important one according to ${}_l\psi$. Let ${}_l\boldsymbol{R} = ({}_lR_j, j = 1, ..., J)$ be the rank vector. Considering all L combinations of input factors we obtain for each skill and training requirement a vector of L ranks ${}_j\boldsymbol{R} = ({}_lR_j, l = 1, ..., L)$, $j = 1, ..., J$ which is an estimate of the uncertainty distribution of the rank of need for skills and training j. The median of ${}_j\boldsymbol{R}$ may be interpreted as a summary measure of requirement j

rank uncertainty distribution and the interval defined by the 5–th and 95–th percentiles of the rank distribution reflects its robustness with respect to the design of the composite indicator. By looking at the uncertainty interval corresponding to each j, we can understand whether a particular index design may or may not provide a biased picture of the importance of the requirements. In fact, the wider the uncertainty interval for requirement j, the less robust requirement j importance rank against the design of the composite indicator.

4. APPLICATION

In this section we apply the framework for composite indicator computation and robustness testing to the data set about requirements for skills and training (Bolzan, 2010). Table 1 lists these requirements.

The aim is to rank the requirements from the most to the least important, according to municipal directors of Veneto (Italy) region, using this general composite indicator

$$_{dcb}\psi_j = {}_{dc}\delta\left({}_b\beta({}^aX_{ij}), {}_dw_k, k = 1, ..., K\right),$$

$j = 1, ..., J$, where $J = 26$, $K = 160$, $a \in \{S, T\}$. The uncertainty analysis presented in Section 3 is applied to test whether importance ranking is robust or volatile with respect to normalization, aggregation and weighting method selection. For the weights, we set $\omega = 3$ which means that the ratio between the maximum weight and the minimum one cannot exceed 3. $L = 20000$ combinations of the input factors have been considered. The results are displayed in Figure 1 as 5%–95% uncertainty interval of the median (shown as a large dot) of the rank of the requirements for skills (Figure 1, top) and training (Figure 1, bottom) from the most to the least important one.

To perform a more complete study, we stratified the municipal directors according to municipality population (more or less than 10000 inhabitants with groups of municipal directors denoted respectively as "small" and "large") and length of service (at least, or less than, 8 years, with groups denoted respectively as "less" and "more"). The results are displayed in Figures 2–8.

Figures 1–8 show that uncertainty intervals are wider for training requirements than for skill requirements and therefore the importance ranking for skill requirements is more robust than the importance ranking for training requirements.

Table 1: List of requirements for skills and training.

Code		Requirement for skills (S) and training (T)
S1	T1	Technical know–how linked to role specificity
S2	T2	Basic knowledge of cross–sector themes(eg informatics, statistics, quality control)
S3	T3	Knowledge of administrative procedures
S4	T4	Good knowledge of the aims of the local authority for which the manager works
S5	T5	Having a mind suited to administration
S6	T6	Ability to organize planning
S7	T7	Ability for management control
S8	T8	Sense of accountability
S9	T9	Ability to communicate with the political world
S10	T10	Ability to communicate with the local population
S11	T11	Ability to motivate staff
S12	T12	Ability to build teams and integrate others' skills
S13	T13	Ability to enhance acquired knowledge
S14	T14	Ability for conflict management
S15	T15	Decision–making ability
S16	T16	Having a mind suited to government
S17	T17	Loyalty in relationships
S18	T18	Ability to inspire trust
S19	T19	Having a sense of duty
S20	T20	Ability to work independently of political influence
S21	T21	Authoritative, rather than authoritarian, sense of leadership
S22	T22	Ability to obtain results from work colleagues
S23	T23	Ability to give reasons for choices
S24	T24	Ability to evaluate situations case by case, not ideologically
S25	T25	Creative ability (open to innovation, ability to see solutions)
S26	T26	Ability to interpret the local area's needs and resources

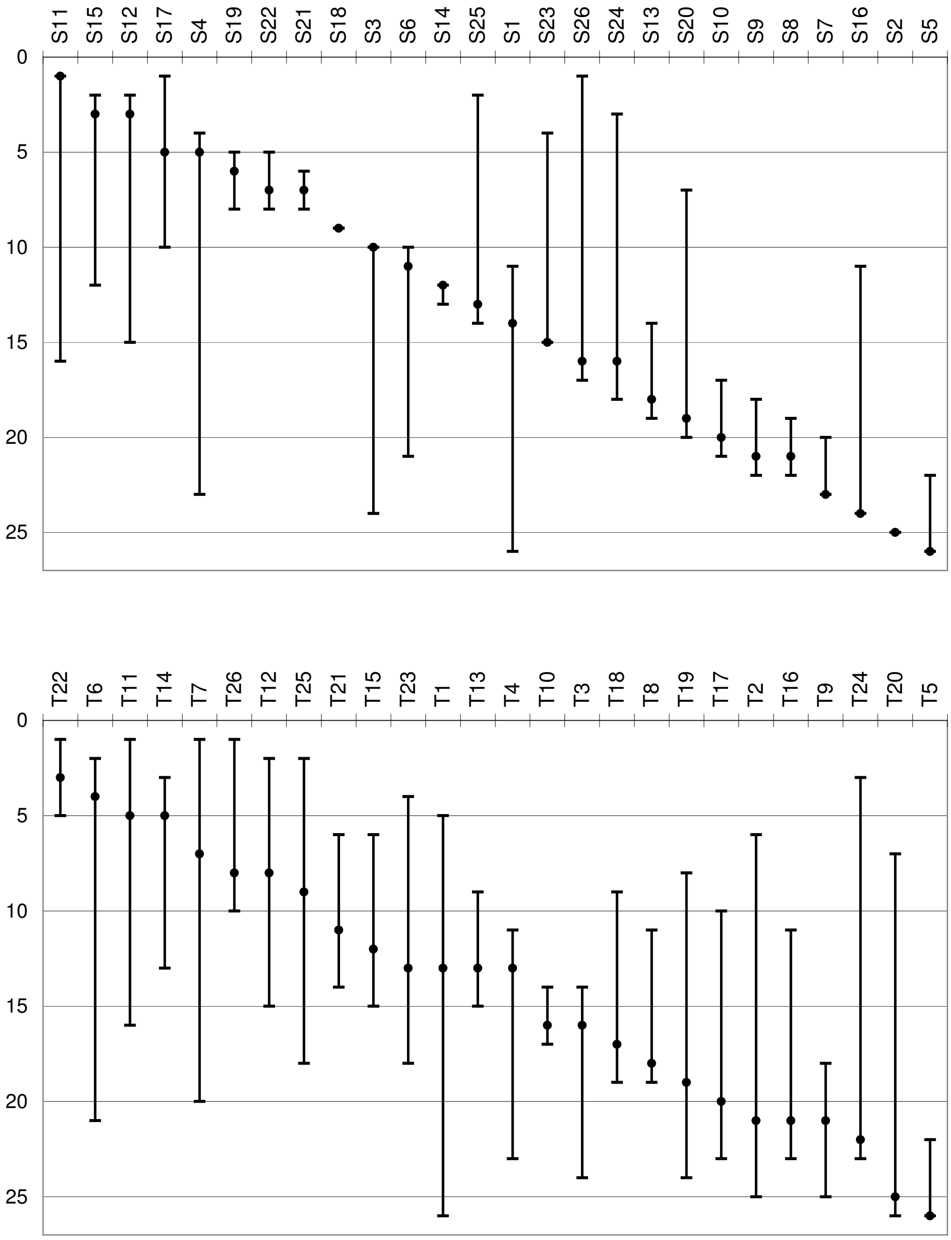

Figure 1: Importance ranking of the requirements for skill (S) and training (T) for all municipal directors, 5% – 95% uncertainty interval (the median is shown as a large dot).

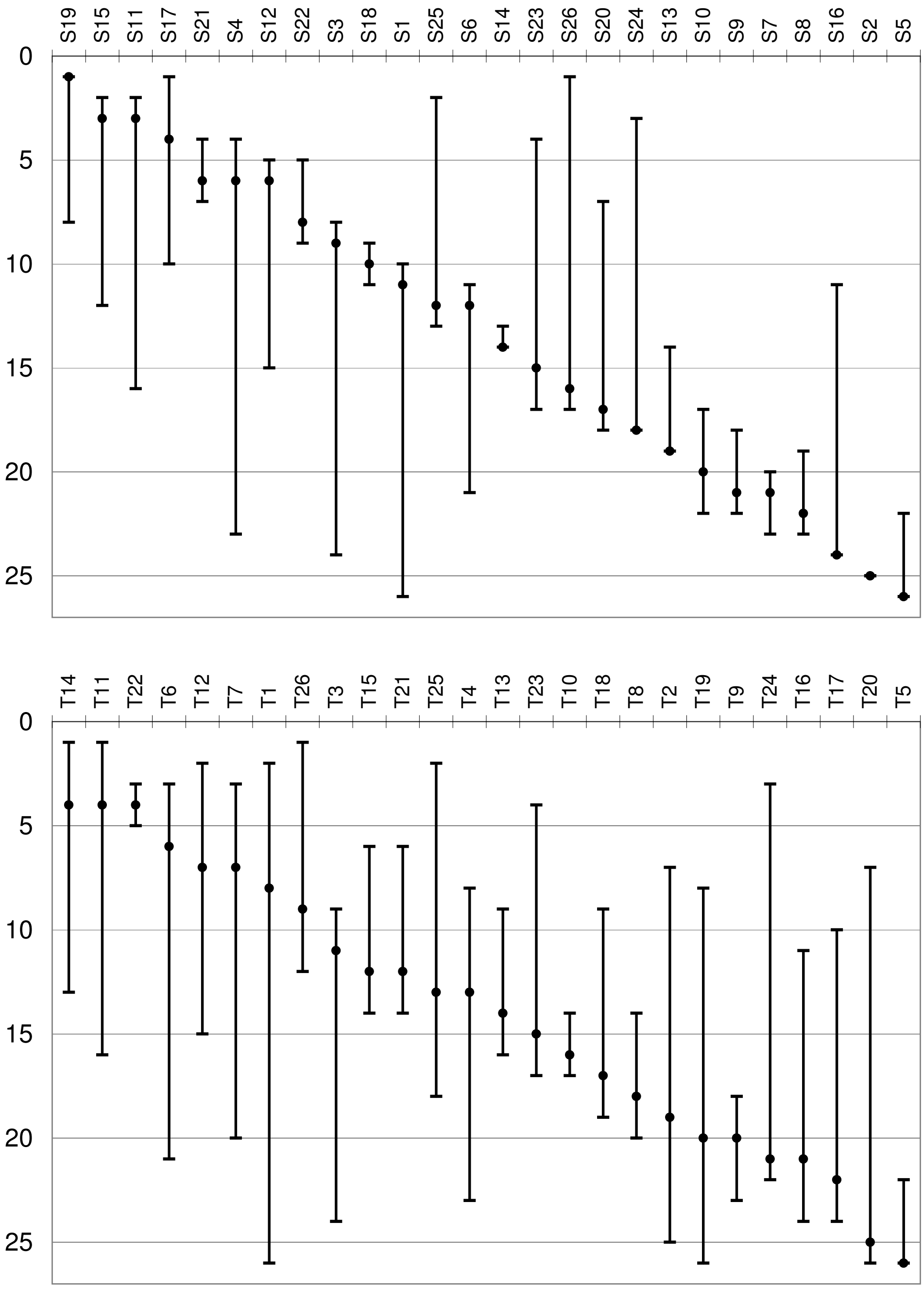

Figure 2: Importance ranking of the requirements for skill (S) and training (T) for municipal directors of small municipalities, 5% – 95% uncertainty interval (the median is shown as a large dot).

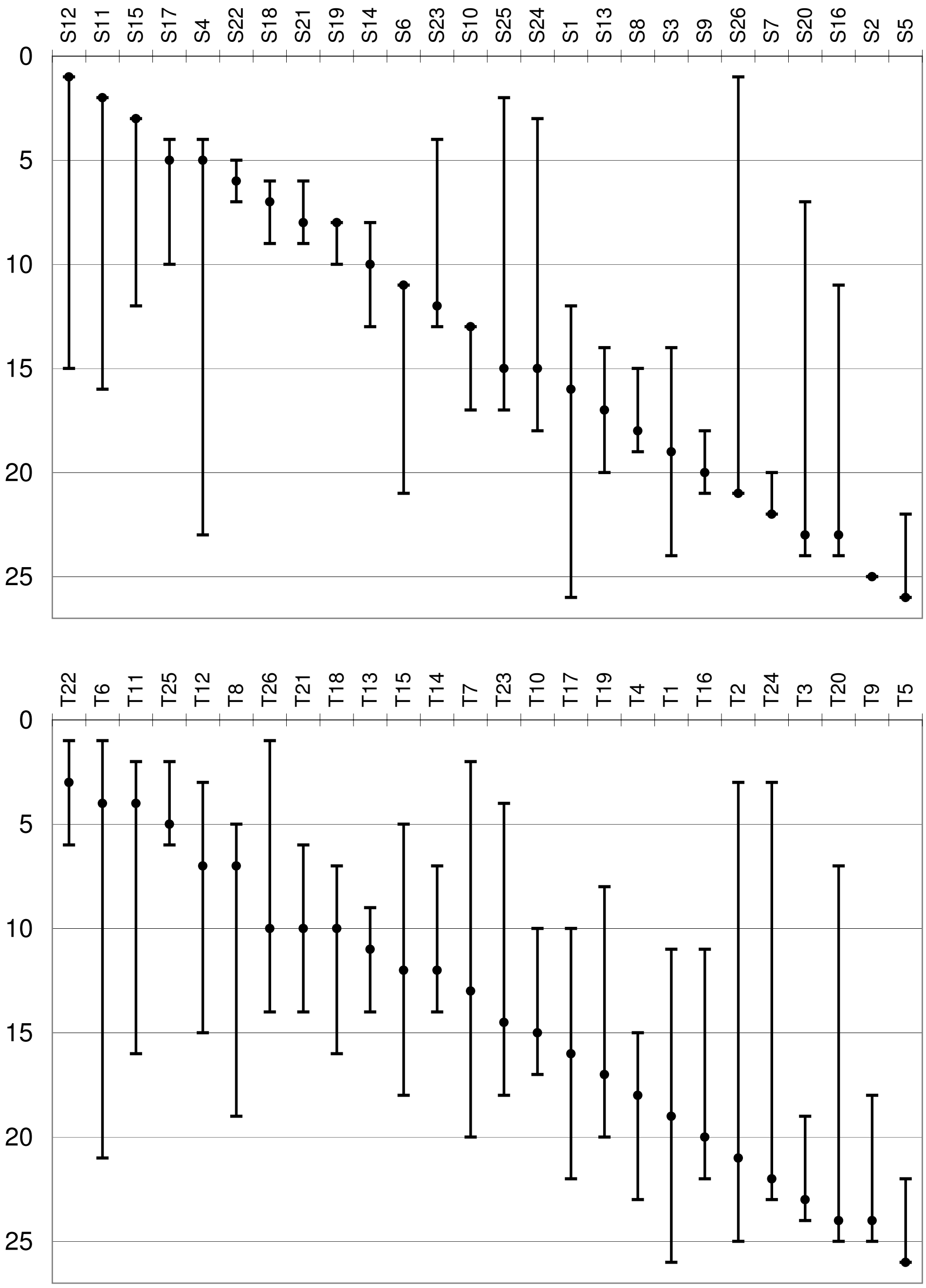

Figure 3: Importance ranking of the requirements for skill (S) and training (T) for municipal directors of large municipalities, 5% – 95% uncertainty interval (the median is shown as a large dot).

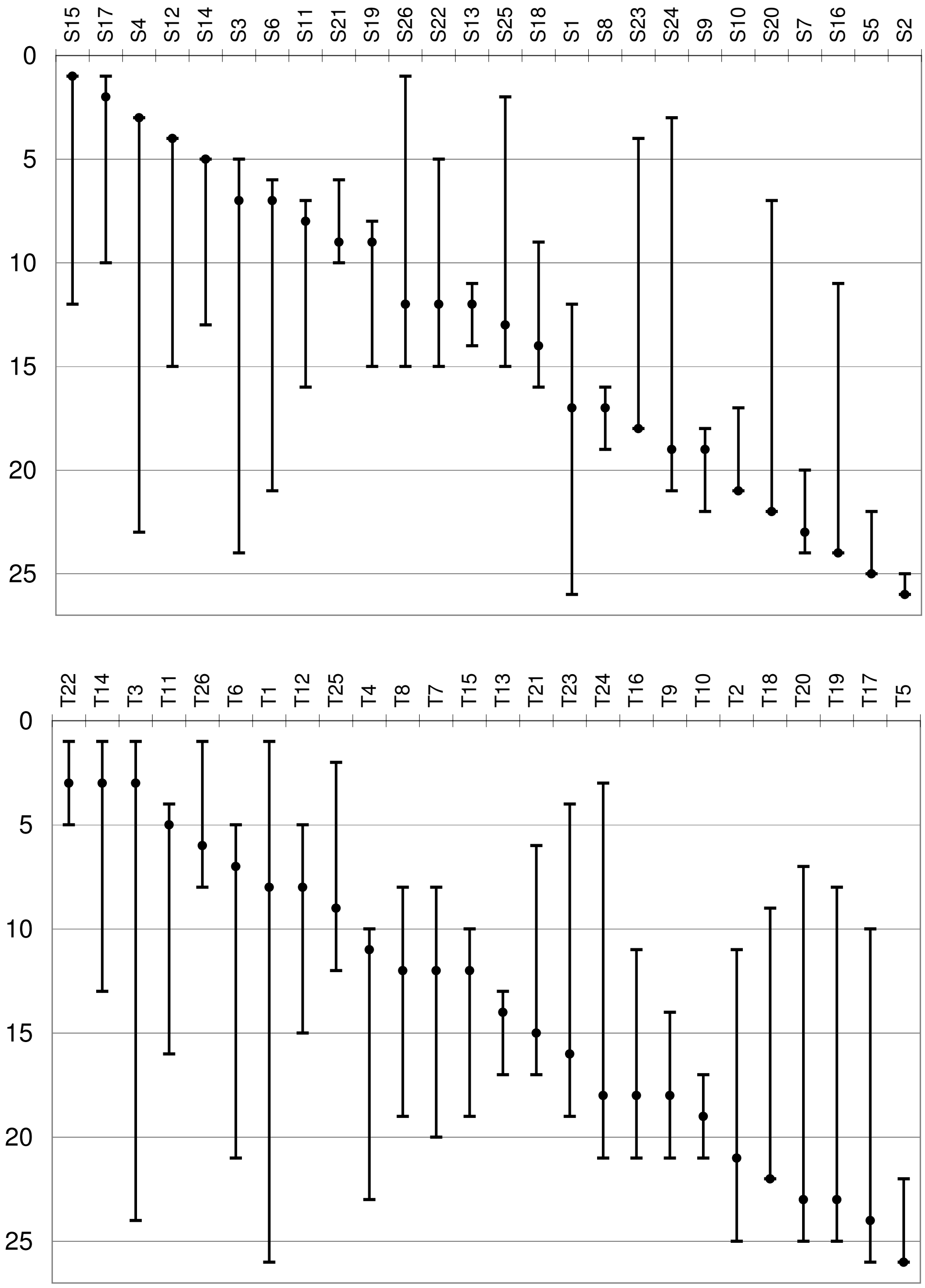

Figure 4: Importance ranking of the requirements for skill (S) and training (T) for municipal directors with less service, 5% – 95% uncertainty interval (the median is shown as a large dot).

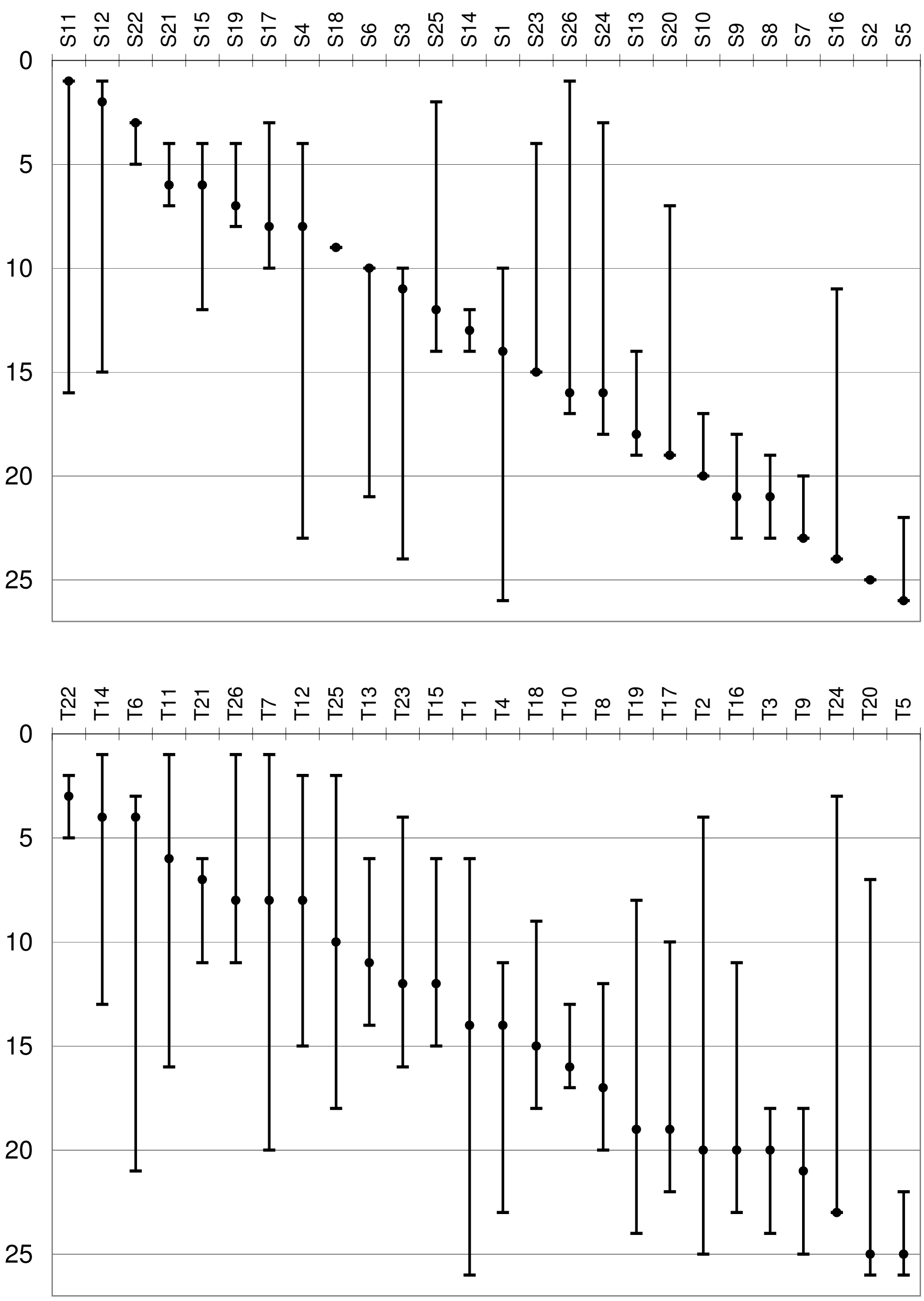

Figure 5: Importance ranking of the requirements for skill (S) and training (T) for municipal directors with more service, 5% – 95% uncertainty interval (the median is shown as a large dot).

A possible reason for this difference between training and skills is that public managers in assessing the importance of skills requirements look at themselves and make a sort of self assessment (what one is able to do is also necessary); whereas in assessing training requirements they think about the other public managers and in this case the assessment is less certain than for skill requirements. Even if the uncertainty intervals are quite wide, with some exceptions, the median importance rank is a good indicator because quite all the wide intervals are very skewed respect to the median (shown as a large dot in the figures).

Table 2: Most and the least important requirements for skill and training.

director	most important requirements		least important requirements	
group	for skills	for training	for skills	for training
all	S11 S15 S12	T22 T6 T11	S5 S2 S16	T5 T20 T24
small municipalities	S19 S15 S11	T14 T11 T22	S5 S2 S16	T5 T20 T17
large municipalities	S12 S11 S15	T22 T6 T11	S5 S2 S16	T5 T9 T20
less service	S15 S17 S4	T22 T14 T3	S2 S5 S16	T5 T17 T19
more service	S11 S12 S22	T22 T14 T6	S5 S2 S16	T5 T20 T24

Table 2 reports the most and the least important requirements for skill and training for the various strata of municipal directors. The most important skill requirements are “Ability to motivate staff”, “Decision–making ability” and “Ability to build teams and integrate others’ skills”; whereas the least important ones are “Having a mind suited to administration”, “Basic knowledge of cross-sector themes (eg informatics, statistics, quality control)” and “Having a mind suited to government”. The most important training requirements are “Ability to obtain results from work colleagues”, “Ability to organize planning” and “Ability to motivate staff”; whereas the least important ones are “Having a mind suited to administration”, “Ability to work independently of political influence” and “Ability to evaluate situations case by case, not ideologically”. These results show that municipal directors are aware of the end of an era in Italian public administration when they were assessed for length of service or for closeness to politicians, they play a new role and are aware of being assessed for their achievements.

It is interesting to compute the Spearman correlation coefficient between the median importance rankings given by the various groups of municipal directors as well as the correlation between training and skill requirement importance rankings. Table 3 shows that the importance rankings are similar for the various groups of municipal directors. More precisely, the most correlated importance rankings refer to the requirements for skills with a correlation coefficient of 0.861 respectively between directors of small and large municipalities, and of 0.837 between directors with less service and directors with more service. The correlations referring to the requirements for training are lower being respectively 0.690 and 0.741. It is interesting to note that the correlations between the requirements for skills and training are moderate: the largest of such correlations refers to directors of large municipalities (0.568) whereas the smallest one refers to directors of small municipalities (0.412). Note also that the correlation between directors with less service (0.469) is smaller than the correlation between directors with more service (0.543).

Table 3: Spearman correlation coefficients between median importance rankings.

groups		Spearman rho
S small municipalities	S large municipalities	0.861
T small municipalities	T large municipalities	0.690
S less service	S more service	0.837
T less service	T more service	0.741
S all	T all	0.494
S small municipalities	T small municipalities	0.412
S large municipalities	T large municipalities	0.568
S less service	T less service	0.469
S more service	T more service	0.543

5. CONCLUSION

A general framework for composite indicator computation has been applied to analyze data about the importance of various requirements of skills and training for the position of municipal director. The most important requirements for skill and training are respectively “Ability to motivate staff” and “Ability to obtain results from work colleagues”, whereas the least important one is “Having a mind suited to administration” for both. The analysis has been repeated on the strata of municipal directors obtained by considering municipality number of inhabitants and director length of service. It is shown that the various strata of directors are rather concordant in assessing the importance of skill and training requirements. In general the most important skill requirements refer to internal aspects of the organization, whereas the most important training requirements refer also to external aspects. It is shown that municipal directors are aware of Italian public administration now being oriented toward *new public management* (Hood and Lodge, 2004; Wright, 2001). The robustness of the results has been addressed using uncertainty analysis.

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