Stratum Representation for Importance-Performance Analysis

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Importance-performance analysis

Importance-Performance Analysis (IPA; Martilla & James, 1977) is a graphical method that represents the entities of a set over a Cartesian plane. The performance and the importance of the entities are represented on the abscissa and ordinate axes, respectively. Where the entities are aspects of a service, the position of the entities over the plane defined by the performance and importance axes allows the researcher to make inferences about the need to intervene in relation to aspects of the service that have a low performance and are relevant to customers.

The method may be rather naive from a statistical viewpoint. In general, it is sufficient to be able to define both the level of performance that discriminates between satisfactory and unsatisfactory levels and the level of importance that separates relevant from irrelevant aspects. The crossing of the two axes at the zero levels defines four quadrants, which assume the following meanings for a decision maker:

1) Quadrant 1—where both importance and performance are positive—indicates *keep up the good work* (Martilla & James, 1977).
2) Quadrant 2—where performance is relatively poor but topics are important to people—defines a critical zone *concentrate here* to improve performance and move to the first quadrant.
3) Quadrant 3—where performance is poor but unimportant to people—can be considered an *irrelevance* zone.
4) Quadrant 4—where importance is low even when performance is high—points to a *possible overkill* zone.

The meanings are clear for points that are far from the origin of the axes but become less clear as the points approach the origin. The way in which the origin is fixed is a matter of methodological concern, because the value of IPA lies in determining relative, rather than absolute, levels of importance.

Several authors have studied technical aspects of IPA methodology for defining the best method to fix the origin of the axes, and consequently the levels of importance and performance that discriminate between positive and negative situations (Guadagnolo, 1985; Alberty and Mihalik, 1989; Oh, 2001; O'Neill and Palmer, 2004).

In this paper, we introduce a third stratification variable of statistical units into the IPA general framework. In general, the stratification variable is a characteristic of the units, that could define subgroups that are interesting for the analyst. At the end of the paper, we discuss a basic application of the revised IPA model.

The model

Let us consider the orthogonal axes (*X*, *Y*) and a set of points with the coordinates (X_i, Y_i) (*i*=1, …, *p*). A point represents the joint performance (*X*) and importance (*Y*) of the i^{th} aspect. Determining the origin of the axes and, consequently, the position of the quadrants is crucial for the analysis. The performance-axis origin could be either the intermediate value of the measurement scale or some centrality measure of data distribution. For instance, in a 1 to 10 scale, it could be 5.5, which is the central value of the measurement scale, or it could be fixed at the mean or the median value of the observed data distribution (Mount, 1997).

The mean of the observed data represents the overall distribution and possesses good mathematical properties. For these reasons, in most cases it is adopted as the point that discriminates positive from negative performances. In the case of a skewed distribution, the median can be taken as the reference value, rather than the mean (Martilla & James, 1977).

Importance can either be explicitly evaluated by asking customers to assess the importance of each single aspect of the set, or it can be estimated with a statistical method. The relevance $\hat{y}_i$ of each aspect *i* in the assessment of the overall concept, Y_o, can be estimated from performance data obtained from customers. For example, to evaluate the quality of a service, customers can be asked to assess the quality of the service as a whole and of all its aspects. To try to understand the relevance of each aspect to the overall quality, the relationships between the performance data can then be analysed. The best way to indirectly estimate the importance is a matter of methodological debate. Several authors (Dolinsky and Caputo, 1991; Wittink and Bayer, 1994; Taylor, 1997; Matzler et al., 2003; Lowenstein, 1995) have suggested estimating importance by means of regression analysis:

$$\hat{y}_0 = \hat{\beta}_1 \; x_1 + \hat{\beta}_2 \; x_2 + ... + \hat{\beta}_p \; x_p , \qquad (1)$$

where y_0 denotes the observed performance on the whole concept, x_i (*i*=1, …, p) denotes the observed performance on i^{th} aspect (*i*=1, …, *p*) and $\hat{\beta}_i$ denotes the estimate of the regression coefficient between the observed evaluation of the whole concept and that of the i^{th} aspect. If the data are standardized (zero mean and unit variance), the estimated coefficients vary between –1 and 1 and are mutually comparable.

The basic idea for eliciting the items' importance through regression analysis is that, at the individual level, the whole concept performance, Y_0, can be considered as a combination of the assessments of the various aspects that comprise the concept.

This idea implies that all reasonable aspects of the concept are incorporated in the *p* items and that the overall concept is perceived by linearly combining the observational aspects. The first assumption requires that R^2, the measure of the explained deviance of Y_0, must be large, possibly 1. The second assumption relies on a large number of observed aspects.

If regression analysis is applied, the mean of the estimated betas may be assumed as the value that discriminates between low and high important aspects for customers.

If criticalities differ among subgroups of customers, we can condition the IPA analysis on the subgroups, so that a targeted importance-performance relationship can help the policymaker to intervene in a more cogent fashion. Let Z_g (*g*=1, …, *G*) be the dichotomous variable that denotes the *g*-th group of customers, so that Z_g=1 if customers belong to group *g* and 0 otherwise.

Our purpose is to estimate the equation (1) by conditioning on Z_g, i.e.,

$$\hat{y}_0 = f(x_1, x_2, ... x_p | Z_g) , \qquad (2)$$

and positioning the *p* points on the plane defined for the whole set of customers. This approach is repeated to estimate the betas for all of the relevant subgroups.

Therefore, it is possible to establish the relative position of subgroup *g* with respect to the whole population. Further, it is possible to determine critical aspects of the subgroups that are satisfactory to the whole population and to identify satisfactory positions for some subgroups even if the situation is critical for the population as a whole.

The estimation of subgroup betas is a common practice for statisticians. We only need regressing the aspects' performance assessments on the whole concept assessment for customers belonging to the *g*-th group after data standardization. Customer stratification before IPA is also a common practice for researchers (for example, Koh et al., 2009). However, two problems arise when comparing the estimates for the population with those for the *G* strata that make up the population:

(i) If, for comparison purposes, we want to overlap the planes of different strata, how should the *g*-th group betas—estimated with model (2)—be rescaled if the betas' mean does not coincide with that of the whole population?

(ii) If the *g*-th group points are placed on the same plane as the overall population, how should differences among the groups and between a subgroup and the population as a whole be graphically represented?

Rescaling the estimates of betas of subgroups

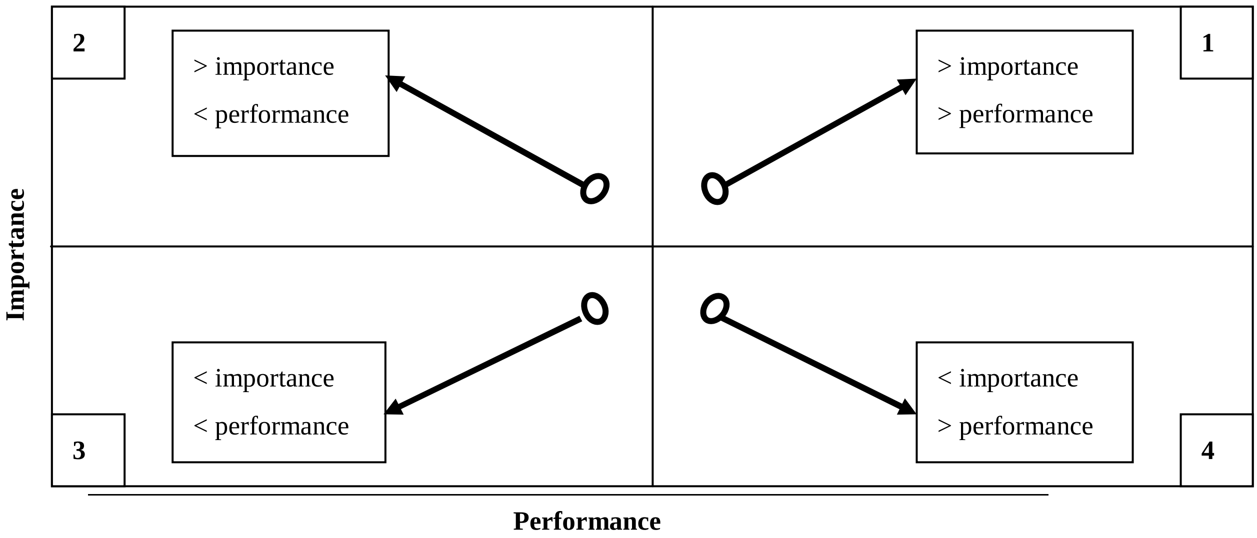
Let us suppose the coordinates of *p* points, which represent the items for the population at large, are centred on the performance (X-axis) and beta (Y-axis) means, i.e., $\tilde{x}_i = x_i - \bar{x}$, where $\bar{x}$ is the mean value of the *p* items' performance assessments and $\tilde{y}_i = \hat{\beta}_i - \bar{\beta}$, where the $\bar{\beta}$ is the mean value of the estimated standardized betas.

To position the elicited performance and the estimated importance of the *p* items concerning the *g*-th group over the population's Cartesian plane, a consistent axis origin needs to be determined for the *g*-th group. The position of every point of the *g*-th group can be compared with that of the same point of the overall population by equating the mean values of the importance estimates for the g-th group. For item *i* (*i*=1, …, *p*), the importance coordinate is rescaled with reference to the *g*-th subgroup mean, i.e., ${}_g\tilde{y}_i = {}_g\hat{\beta}_i - {}_g\bar{\beta}$ where ${}_g\bar{\beta}$ is the mean value of the estimated betas for the statistical units of the *g*-th group's. The performance origin of the *g*-th group is the same as that of the overall population.

Graphical representation of the deviation of a group from the population

We suggest representing the deviations from a population point as arrows connecting this point with the coordinate points representing the subgroups (Figure 1).

Figure 1: Types of arrows connecting the population and subgroup points



The direction of the arrows indicates the type of deviation of a subgroup from the population as a whole:

- Case 1 indicates that the *g*-th subgroup is more positive than the remaining population for that aspect and and confers a larger importance on it.
- Case 3 is symmetric to case 1) because the perceived performance is lower but the annexed

importance is lower also.

- Case 2 indicates that the g-th subgroup is in greater difficulty than the general population because the subgroup perceives the performance to be poorer but assigns the aspect greater importance.
- Case 4, in contrast, perceives an improved performance compared with the general population, but the *g*-th group assigns this aspect reduced significance.

If G=2, it is easy to show that the arrows of the two groups go in opposite directions. This allows determining if either the importance or the performance, or both aspects of an item, differ in the two groups, and in which direction. If the deviation from the population average differs significantly, or, that is the same, the two group averages differ to each other, the group-related points stand far away from the population central point. The graphical method does not differ, but it may be complicated if the number of groups is larger than two. In addition, the number of arrows that cross the plane is pG, and the number of points that have to be analysed is $p(G+1)$. Therefore, G must remain low.

An application: critical aspects of graduates' job quality

We applied the modified IPA method to data on job quality collected from a random sample of 2,926 graduates of Padua University, Italy, 12 months after graduation (for detailed information on survey methodology, see Fabbris, 2010). Job quality was observed on the whole and on 11 aspects representing social, economic, professional and physical location viewpoints.

In Table 1, we present the performance means of the whole sample and of the three categories of graduates who worked during their studies and retained the same employment following graduation (SJ), graduates who worked during their studies but changed jobs within 12 months after graduation (NJ) and those who commenced their first job after receiving their university degree (FJ). The figures in Table 2 show the standardized betas and their deviation from the group mean. Figure 2 shows the arrows of the three categories from points referring to the whole population of graduates.

Table 1: Average performances of the whole set of graduates and of those who maintained the job they had during their studies (SJ), changed their job (NJ) or commenced a new job (FJ) – Measurement scale 1÷10

	SJ	NJ	FJ	All graduates
Stability	7.30	6.67	6.75	6.84
Skill attainment	7.37	7.72	7.63	7.56
Reputation	6.69	6.75	6.81	6.76
Cultural interests	7.10	7.23	7.29	7.22
Social utility	7.30	7.15	7.14	7.17
Autonomy	7.93	7.66	7.66	7.71
Flexibility	7.10	6.95	7.06	7.04
Time out	6.49	6.41	6.32	6.37
Location	7.33	7.50	7.28	7.32
Salary	6.28	6.41	6.52	6.43
Career	6.18	6.34	6.49	6.38

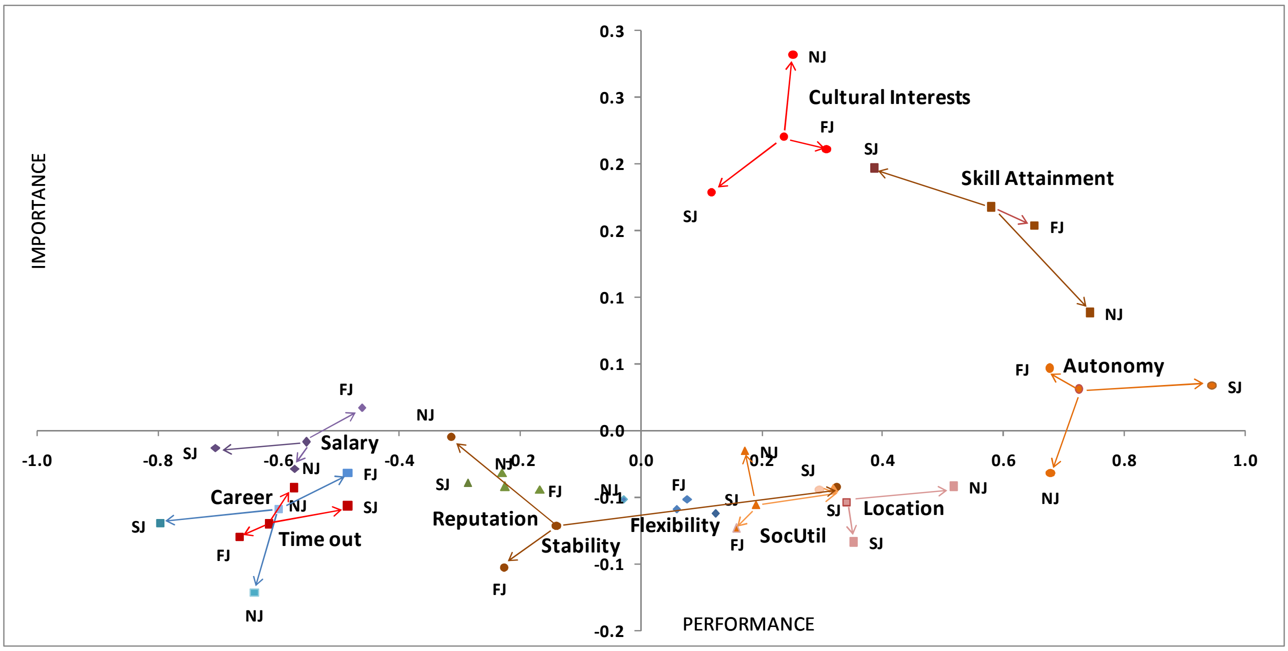
The results showed that none of the considered aspects were particularly critical and that cultural, professional and self-empowerment aspects fulfilled the graduates' expectations.

However, there were differences between the subgroups. Salary expectation was a critical issue for graduates who started work straight after graduation, whereas contract stability was the main concern for those who changed employment after graduation.

Table 2: Estimation of importance levels of the whole set of graduates and of those who maintained the job they had during their studies (SJ), changed their job (NJ) or started a new job (FJ)

	SJ (n=542)		*NJ (n=326)*		*FJ (n=1,406)*		*All (n=2,369)*	
	b_i	Y_i	b_i	Y_i	b_i	Y_i	b_i	Y_i
Stability	0.063	-0.042	0.107	-0.005	-0.007	-0.072	0.029	-0.072
Skill attainment	0.302	0.197	0.200	0.088	0.250	0.168	0.268	0.168
Reputation	0.066	-0.039	0.079	-0.032	0.052	-0.042	0.059	-0.042
Cultural interests	0.284	0.179	0.393	0.282	0.307	0.220	0.321	0.220
Social utility	0.062	-0.043	0.096	-0.015	0.023	-0.056	0.045	-0.056
Autonomy	0.139	0.034	0.080	-0.032	0.143	0.031	0.132	0.031
Flexibility	0.043	-0.062	0.060	-0.052	0.044	-0.059	0.041	-0.059
Time out	0.049	-0.056	0.069	-0.043	0.016	-0.070	0.030	-0.070
Location	0.022	-0.084	0.070	-0.042	0.052	-0.054	0.047	-0.054
Salary	0.092	-0.013	0.083	-0.029	0.113	-0.008	0.092	-0.008
Career	0.035	-0.070	-0.010	-0.121	0.065	-0.059	0.042	-0.059
Mean	0.105	0.000	0.112	0.000	0.096	0.000	0.100	0.000

Figure 2: Types of arrows connecting the population and subgroup points



This application is merely illustrative. Not only could we examine different characteristics of graduates, we could also combine together two or more Z-variables to represent salient groups. This would make it possible to detect interactions between group characteristics that determine different performance and importance for aspects. For example, if we hypothesise an interaction between gender and work practice, it is possible to combine the categories of the two variables into a new suitable set of categories. A simpler approach would be to define the same work practices for males and females. More refined combinations could be based on conjecture because males are more likely to work before graduation.

Concluding remarks

The criterion we suggest to modify the IPA model attaches a third analytical dimension to importance and performance so that the interpretation of the critical aspects of a service (or the job) can be improved. The modification we suggest makes it possible to easily detect the peculiarity of subgroups with respect to performance and importance, to deduce potential causes of criticalities and to suggest more finalised interventions to decision makers.

The application we discussed, although simple, shows that separating the study population into appropriate categories can enrich IPA and that even nontechnical people can understand the analytical results.

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