Building a composite score of general practitioners’ intrinsic motivation: a comparison of methods

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Abstract

Objective. Pay-for-performance programmes have been widely implemented in primary care, but few studies have investigated their potential adverse effects on the intrinsic motivation of general practitioners (GPs) even though intrinsic motivation may be a key determinant of quality in health care. Our aim was to compare methods for developing a composite score of GPs’ intrinsic motivation and to select one that is most consistent with self-reported data.

Study design. A postal survey.

Setting. French GPs practicing in private practice.

Main Measures. Using a set of variables selected to characterize the dimensions of intrinsic motivation, three alternative composite scores were calculated based on a multiple correspondence analysis (MCA), a confirmatory factor analysis (CFA) and a two-parameter logistic model (2-PLM). Weighted kappa coefficients were used to evaluate variation in GPs’ ranks according to each method.

Results. The three methods produced similar results on both the estimation of the indicators’ weights and the order of GP rank lists. All weighted kappa coefficients were >0.80. The CFA and 2-PLM produced the most similar results.

Conclusions. There was little difference regarding the three methods’ results, validating our measure of GPs’ intrinsic motivation. The 2-PLM appeared theoretically and empirically more robust for establishing the intrinsic motivation score.

Code JEL. C38, C43, I18.

Keywords: composite indicator, confirmatory factor analysis, general practitioners, intrinsic motivation, item response theory, multiple correspondence analysis

Introduction

As pay-for-performance schemes have been introduced in primary care, concerns have been raised about their effectiveness in changing practice and their impact on patient outcomes [1]. Some observers question the consequences of such incentives on general practitioners (GPs) and particularly the potential undesirable effects of extrinsic incentives on intrinsic motivation [2, 3]. The crowding-out theory posits that enhancing extrinsic motivation through monetary rewards may decrease intrinsic motivation leading to negative impacts on both work engagement and quality of care [4]. Motivational crowding out was first recognized in the educational context by psychologists [5] and has been studied also by economists and sociologists [6].

Motivational crowding out may significantly reduce the efficiency of any pay-for-performance system, yet few studies have examined the theory in the context of medical practice and, a fortiori, in the context of GPs [7]. Measurement of intrinsic motivation is challenging. Indeed, intrinsic motivation is difficult to observe and may have more than 1 dimension (1D). Actually, there are two main conceptions of intrinsic motivation. Psychological theory posits that individuals derive pleasure from performing an activity that is considered intrinsically satisfying and rewarding [8]. Sociologists posit that individuals may experience intrinsic motivation from playing a social role in an organized system [9].

The aim of this study was to build a composite score to measure intrinsic motivation. A composite score is typically constructed from the aggregation of multiple variables using a specific algorithm using methods such as factor analysis, data envelopment analysis and analytic hierarchy process [10]. We assumed that the method for developing a composite for
intrinsic motivation would require the following features. First, the method should handle qualitative variables, which may better describe intrinsic motivation. Second, the method should enable investigation of the multi-dimensionality of our set of variables while accounting for measurement errors that are inherent to self-reported data. Based on these expectations, three methods were selected: the multiple correspondence analysis (MCA) method (used by Asselin and Vu [11] to construct a composite score of poverty), a derivative of confirmatory factor analysis (CFA) that accommodates categorical indicators [12, 13] and a two-parameter logistic model (2-PLM) based on item response theory (used previously to estimate intelligence and quality-of-life scores) [14]. Item response models such as the 2-PLM are extensions of generalized mixed logit models and are based on similar estimation techniques [15].

In this paper, we first constructed and validated a GP Intrinsic Motivation Composite Score (IMCS) through the comparison of the results of different statistical methods and then selected the most relevant and parsimonious scoring model.

Methods

Sample and data collection

A survey was conducted based on an auto-questionnaire of GPs working in community-based offices in southwestern France (Midi-Pyrénées). The questionnaire was designed to investigate GPs’ practice organization, working activities and satisfaction. The questions were developed in collaboration with GPs from the French General Practice Association (SFMG in French) and based on literature review [16, 17]. The sample included ~3000 GPs registered in the database of the regional union for private practitioners (Union Régionale des Médecins Libéraux). The target sample size was 450 respondents.

In collaboration with the union, an informative letter presenting the study was sent in the middle of March 2010, 2 weeks before the anonymous postal questionnaire was mailed. A reminder letter was sent to all GPs 3 weeks after the questionnaire. By the end of July, 438 questionnaires had been returned and 423 were usable. The sample was representative of the overall French GP population according to gender (72% are male vs. 72% in the French GPs population), age (the mean age is 52.1 vs. 50.1), participation in group practice (58% belong to a group vs. 54%) and individual net turnover (€71 364 vs. €71 690) [18].

Intrinsic motivation variables

Ten variables were preselected based on hypotheses regarding whether they at least partially revealed GPs’ intrinsic motivation (Table 1). The assumptions were based on literature review on the intrinsic motivation concept [4–9]. To obtain tractable variables, we harmonized the response scales by dichotomizing them: variables were coded 1 when the answer indicated intrinsic motivation (‘positive’ answer) and 0 otherwise. The relevant descriptive statistics are listed in Table 1. Two variables (1 and 2) were associated with the concept of enjoyment at work [8]; one variable (3) indicated a commitment to the results of medical practice. Six variables (4–8) represented activities that required time and for which payment was non-existent or relatively low; such variables were supposed to reveal intrinsic motivation and to improve the quality of care. Finally, the last two variables (9 and 10) illustrated physicians’ attitudes towards the environment (vis-à-vis ‘more informed’ patients and the public health insurance). According to the psychological approach, GPs who did not feel constrained by patients’ requests or public health insurance control were supposed to be more intrinsically motivated.

Analyses

Analysis of the structural validity of intrinsic motivation indicators. To examine the structural validity of the preselected variables assumed to represent all or a part of GPs’ intrinsic motivation, an MCA was performed. Based on the decomposition of the inertia of the data, this method consisted in extracting axes, each representing 1D, from a set of preselected variables [19]. Applied to our study, the purpose of the MCA was to select a

Table 1  Descriptive statistics of the intrinsic motivation variables (N = 423 GPs)

<table>
<thead>
<tr>
<th>Intrinsic motivation</th>
<th>N</th>
<th>%a</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Satisfaction with professional activity (often/sometimes-rarely-never)</td>
<td>245/168</td>
<td>57.9/39.7</td>
</tr>
<tr>
<td>(2) The job is considered personally rewarding (often/sometimes-rarely-never)</td>
<td>266/153</td>
<td>62.9/36.2</td>
</tr>
<tr>
<td>(3) Exchanges with GPs or specialists about patients’ situations (very often/often-sometimes-never)</td>
<td>82/341</td>
<td>19.4/80.6</td>
</tr>
<tr>
<td>(4) Teacher or tutor activities (yes/no)</td>
<td>83/340</td>
<td>19.6/80.4</td>
</tr>
<tr>
<td>(5) Participation in the continuity-of-care system (yes/no)</td>
<td>231/192</td>
<td>54.6/45.4</td>
</tr>
<tr>
<td>(6) Provision of alcohol or tobacco prevention (very often/often-sometimes-never)</td>
<td>63/360</td>
<td>14.9/85.1</td>
</tr>
<tr>
<td>(7) Participation in professional practice evaluation (yes/no)</td>
<td>176/247</td>
<td>41.6/58.4</td>
</tr>
<tr>
<td>(8) Involvement in a care network (yes/no)</td>
<td>132/291</td>
<td>68.8/31.1</td>
</tr>
<tr>
<td>(9) Feeling constrained by more informed patients (rarely-never/often-sometimes)</td>
<td>161/209</td>
<td>38.1/49.4</td>
</tr>
<tr>
<td>(10) Feeling constrained by health insurance (yes/no)</td>
<td>254/155</td>
<td>60.1/36.6</td>
</tr>
</tbody>
</table>

*aFor some variables, the total percentage does not equal 100% because of missing values.
measuring variables associated with one or more latent axes of intrinsic motivation. MCA also made it possible to determine whether there was a single construct underpinning these variables (the unidimensionality assumption). Once selected, the variables were labelled intrinsic motivation indicators.

**Strategies for constructing the Intrinsic Motivation Composite Score.** We assumed that a positive response to one or more of the indicators was intrinsically motivated at some point that we wished to measure. Thus, a numerical value was associated with each GP and placed him/her somewhere on the intrinsic motivation scale. We used three different models to compute an IMCS, enabling us to rank doctors on a latent intrinsic motivation continuum.

**Multiple correspondence analysis: IMCS1.** The IMCS1 was computed using the binary indicators as active variables. The contributions of the categories coded 1 (and thus positively associated with the intrinsic motivation concept) were used as indicator weights to construct IMCS1. These weights were standardized so that their sum was equal to 1 and so that the final score lied between 0 and 1. Thus, IMCS1 was calculated using the following formula:

\[
\text{IMCS}_1 = \sum_{i=1}^{p} \frac{c_i}{T_i} I_i
\]

where \( c_i = (n_i/np)(a_i)^2 / \mu \) was the contribution of the category \( i \) to the first axis of the MCA (we considered only the first axis of the MCA because, as revealed in the section Results, there was only 1D in our data), \( n_i \) is the number of GPs in category \( i \), \( a_i \) is the coordinate of category \( i \) on the first axis of the MCA, \( n \) is the total number of GPs, \( p \) is the total number of categories and \( \mu \) is the inertia of the first axis. \( T_i \) was the sum of the contributions of all categories coded 1 to the first axis of the MCA and \( I_i \) was the dummy variable equal to one if the GP was in category \( i \). The MCA was computed using SPAD® software (Version 7.4).

**Addressing missing data: three indicators had missing values: satisfaction with professional activity, feeling of being humanly rewarded from the activity and feeling of being constrained by more informed patients. We imputed values for non-respondents with the average value for matched respondents, i.e. GPs who had a similar overall pattern of answers on non-respondents with the average value for matched respondents.** We imputed values for humanly rewarded from the activity and feeling of being constrained by more informed patients. We imputed values for these variables (the unidimensionality assumption) of indicator weights to construct IMCS1. These weights were associated with the intrinsic motivation concept (IMCS2). Using CFA, the model was used to derive weights for the indicators according to the extent to which they were correlated with a latent factor. The \( p \)-dimensional vector of dichotomous variables was denoted by \( n \). It was assumed that underlying each variable \( n_i \), there was a latent variable \( \xi^*_i \), called the response strength [13] such that

\[
\eta_i = \begin{cases} 1, & \text{if } \xi^*_i \geq \tau_i \\ 0, & \text{if } \xi^*_i < \tau_i \end{cases}
\]

where the parameter \( \tau_i \) was interpreted as a threshold value for \( \xi^*_i \). We also assumed that

\[
\xi^* = \Lambda \xi + \varepsilon
\]

where \( \Lambda \) was a \( p \times k \)-dimensional matrix of factor loadings, \( \xi \) was the \( k \)-dimensional latent variable vector of the factors and \( \varepsilon \) was a \( p \)-dimensional vector of residuals that was uncorrelated with \( \xi \) and had zero expectation [13]. We obtained the following covariance matrix:

\[
V' (\xi^*) = \Lambda \Phi \Lambda' + \Psi \frac{1}{2}
\]

where \( \Phi \) was the covariance matrix of the factors, and \( \Psi \) denoted the covariance matrix of \( \varepsilon \), which was assumed to be diagonal. The model thus contained three parameter arrays to be estimated: \( \tau_i \), \( \Lambda \) and \( \Phi \); the threshold vector \( \tau \) was estimated based on the proportions of positive responses to each of the selected indicators, and the arrays \( \Lambda \) and \( \Phi \) were estimated using robust weighted least-squares estimation techniques to adjust the tetrachoric correlations [20]. The estimates of the different parameters and of IMCS2 were obtained using M-PLUS® software (6.12).

**Two-parameter logistic model: IMCS3.** The 2-PLM was defined such that

\[
\logit p_{ij} = \alpha_j + \delta_i + \varepsilon_{ij}
\]

where \( \logit p_{ij} \) was the log odds ratio associated with the probability of doctor \( j \) responding positively to indicator \( i \); \( \varepsilon_{ij} \) and \( \theta_j \) were two random residuals such that \( \varepsilon_{ij} \) corresponded to the residual for indicator \( i \) of doctor \( j \) (within-doctor variability) and \( \theta_j \) to the residual of doctor \( j \) (between-doctor variability). Hence, \( \theta_j \) (IMCS3) was the realization of a random variable \( \theta_j \), denoting GPs’ intrinsic motivation, which was assumed to be normally distributed in our sample of French GPs. The parameters \( \delta_i \) and \( \alpha_j \) were the difficulty and discrimination parameters, respectively, of indicator \( i \). According to item response theory models, the difficulty parameter was associated with the proportion of doctors who responded negatively to indicator \( i \); the higher this rate, the greater was \( \delta_i \). The discrimination parameter of indicator \( i \) described the extent to which the probability of responding positively to this indicator was correlated with \( \theta_j \); thus, more discriminating indicators provided greater information about a respondent than less discriminating indicators. The estimates of \( \delta_i \), \( \alpha_j \) and \( \theta_j \) were computed through marginal maximum likelihood using PROC NLMIXED of SAS® software (9.3).

**A comparison of the three IMCSs**

By plotting the scores previously calculated based on the results of each scoring method, we were able to inspect
differences in scores between GPs and for a specific GP between scores obtained by the three methods (we provide a representation for the first 30 GPs). We used Cohen weighted kappa coefficients [21] to evaluate the variation in GPs’ rankings according to the three aggregation methods. Prior to computing the kappa coefficients, GPs were classified according to the quartiles of each IMCS distribution. As a complementary method to investigate the differences between the scoring method results, we compared the percentage of GPs that were classified in the first group (the least intrinsically motivated quartile of doctors) and the fourth group (the most intrinsically motivated quartile of doctors) under all methods.

Results

The identification of intrinsic motivation indicators

Based on the MCA performed on the original ten preselected variables of intrinsic motivation, we identified eight indicators to construct the IMCSs (Table 2 presents a summary of this selection). According to the Benzecri correction for eigenvalues [22], the first axis preserved 80% of the total inertia in the data and, thus, constituted the main dimension generated by eight of the indicators. Two variables (‘participation in the continuity of care system’ and ‘feeling constrained by the public health insurance’) were dropped because they did not contribute to the first axis and were not positively correlated with the others.

Table 2 A summary of the selected intrinsic motivation indicators and estimation of the weights of indicators based on the MCA (N = 423 GPs)

<table>
<thead>
<tr>
<th>Intrinsic motivation indicators</th>
<th>Modality associated with intrinsic motivation</th>
<th>Standardized weight on the MCA</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Satisfaction with professional activity</td>
<td>Often</td>
<td>0.19</td>
</tr>
<tr>
<td>(2) The job is considered professionally rewarding</td>
<td>Often</td>
<td>0.16</td>
</tr>
<tr>
<td>(3) Exchanges with GPs or specialists about a patients’ situation</td>
<td>Very often</td>
<td>0.13</td>
</tr>
<tr>
<td>(4) Teacher or tutor activities</td>
<td>Yes</td>
<td>0.19</td>
</tr>
<tr>
<td>(5) Provision of alcohol or tobacco prevention</td>
<td>Very often</td>
<td>0.03</td>
</tr>
<tr>
<td>(6) Participation in professional practice evaluation</td>
<td>Yes</td>
<td>0.10</td>
</tr>
<tr>
<td>(7) Involvement in a care network</td>
<td>Yes</td>
<td>0.11</td>
</tr>
<tr>
<td>(8) Feeling constrained by more informed patients</td>
<td>Rarely-never</td>
<td>0.08</td>
</tr>
</tbody>
</table>

Table 3 The estimation results of the CFA and 2-PLM (N = 423 GPs)

| Indicator                                                                 | CFA                  | 2-PLM                  |
|                                                                          | Threshold (SE) | Factor loading (SE) | Difficulty parameter (SE) | Discrimination parameter (SE) |
| The job is considered personally rewarding                               | −0.35 (0.06) | 2.34 (0.53) | −0.27 (0.09) | 4.51 (1.42) |
| Satisfaction with professional activity                                   | −0.24 (0.06) | 2.35 (0.53) | −0.19 (0.07) | 4.45 (1.50) |
| Not feeling constrained by more informed patients                         | 0.16 (0.07)  | 0.84 (0.27) | 0.36 (0.20)  | 0.77 (0.30)  |
| Participation in professional practice evaluation                        | 0.21 (0.06)  | 0.90 (0.26) | 0.47 (0.21)  | 0.76 (0.28)  |
| Involvement in a care network                                             | 0.49 (0.06)  | 0.82 (0.26) | 1.20 (0.47)  | 0.69 (0.27)  |
| Teacher or tutor activities                                              | 0.86 (0.07)  | 1.15 (0.31) | 1.40 (0.46)  | 1.13 (0.40)  |
| Exchanges with GPs or specialists about patients’ situations             | 0.86 (0.07)  | 1.00        | 1.56 (0.15)  | 1.00         |
| Provision of alcohol or tobacco prevention                               | 1.04 (0.08)  | 0.51 (0.26) | 3.58 (2.00)  | 0.50 (0.29)  |
threshold of 0.08). Nevertheless, the chi-squared statistic was statistically significant \( \chi^2 = 66.4, p = 0.001 \) meaning that the one-factor model did not explain all the variability of the indicators.

The results of the two-parameter logistic model (2-PLM) are displayed in Table 3. The estimates of the difficulty parameters were comparable with the thresholds obtained in the CFA, as the eight indicators retained the same positions on the ‘difficulty’ scale. The most discriminating indicators were the ‘feeling of being humanly rewarded by the activity’ \( \alpha_1 = 4.51 \) and ‘satisfaction from the activity’ \( \alpha_2 = 4.45 \). The indicators ‘teaching activity’ and ‘exchanges with GPs’ were the third and fourth most discriminating indicators, respectively. In contrast, all other indicators had low discrimination parameters but were still significant at the 5% level.

Descriptive statistics comparing the three IMCSs are presented in Table 4. IMCS1 (derived from MCA) and IMCS3 (derived from 2-PLM) were theoretically distributed from 0 to 1. The IMCS1 ranged from a minimum of 0 for the least intrinsically motivated GP to a maximum of 0.99; half of the GPs had an IMCS1 of >0.38, which was also the mean of the distribution. IMCS3 had a lower variability (sd = 0.11 vs. sd = 0.24 for IMCS1); it ranged from a minimum of 0.32 to a maximum of 0.77, and the median was 0.49 (mean = 0.49). IMCS2 was not distributed from 0 to 1, and GPs could have negative scores: the minimum value was -0.43, and the maximum was 0.64; half of the GPs had a score of >0.06 (mean = -0.01). The three IMCSs had rather flat distributions (negative kurtosis coefficients), and IMCS3 had the flattest (\( K = -0.020 \)). IMCS1 distribution was positively skewed (\( S = 0.23 \)), whereas IMCS2 and IMCS3 distributions were not (\( S = 0.04 \)).

GP’s ranks were calculated based on the results of each scoring method (Fig. 1 provides a representation of the ranks of the first 30 GPs). According to Fig. 1, the three algorithms provided similar ranking results. The results of Cohen’s kappa coefficients are displayed in Table 5. All coefficients were >0.80, indicating a high or very high level of agreement between the different algorithms. The highest coefficient was obtained when comparing IMCS2 and IMCS3 (\( K_w = 0.96 \)), confirming that CFA and 2-PLM provided the most similar results. Eighty-four per cent of GPs were classified by all the three methods in the first group (the least intrinsically motivated quartile of doctors) and 86% in the fourth group (the most intrinsically motivated quartile of doctors).

### Discussion

The goal of our study was to identify the best way to construct a composite score of GPs’ intrinsic motivation (IMCS) by comparing the results of different statistical methods. Among ten

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**Table 4** The IMCS distribution statistics (N = 423 GPs)

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median (Q1; Q4)</th>
<th>SD</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>IMCS1</td>
<td>0.38</td>
<td>0.38 (0.18; 0.56)</td>
<td>0.24</td>
<td>0.228</td>
<td>-0.635</td>
</tr>
<tr>
<td>IMCS2</td>
<td>-0.01</td>
<td>0.06 (-0.27; 0.18)</td>
<td>0.26</td>
<td>0.002</td>
<td>-0.925</td>
</tr>
<tr>
<td>IMCS3</td>
<td>0.49</td>
<td>0.49 (0.38; 0.58)</td>
<td>0.11</td>
<td>0.016</td>
<td>-1.020</td>
</tr>
</tbody>
</table>

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**Figure 1** Bar chart of 30 GPs’ ranking according to the three IMCSs.
preselected variables, we identified eight indicators related to the intrinsic motivation of doctors that were well correlated on a single dimension of the latent concept. In spite of the use of different algorithms to estimate the IMCSs, the three methods led to similar results concerning both the estimation of indicator weights and GPs’ rankings. Indeed, in all of the analyses, the two most weighted or discriminant variables were ‘satisfaction from the activity’ and the ‘feeling of being humanly rewarded by the activity’. The high Cohen’s weighted kappa coefficients obtained when comparing the different IMCSs indicated a high correlation in GPs’ rankings under each method, and especially between CFA and 2-PLM. The consistency and convergence of the results across methods suggests that the selected intrinsic motivation indicators represent a valid construct.

Theoretically, MCA and CFA methodologies differ in their handling of correlation patterns between non-continuous variables. In MCA, an active variable (or its categories) contributes to the construction of an axis through its inertia relative to the centre of gravity of the data. CFA extracts factors based on decomposition of the variance-covariance matrix of observed variables using maximum likelihood estimation techniques [23]. With dichotomous variables, the traditional sample variance-covariance matrix generated by the CFA is replaced with the tetrachoric correlations matrix, i.e., the correlations between the latent variables underlying each of the observed binary indicators. The estimations based on the tetrachoric correlations matrix lead to more robust results compared with using the usual Pearson variance-covariance matrix [20].

CFA and 2-PLM differ in the way each method models the relationship between a dichotomous variable and a latent continuous factor. CFA uses a linear model of the relationship between the observed variables and the latent variable, and the factor loadings are estimated by factor analysing the tetrachoric correlation matrix. In 2-PLM, both observed and latent variables are connected through a logit link function and the model’s parameters are estimated using marginal maximum likelihood estimation.

Compared with CFA and 2-PLM, MCA’s weakness is that it is not based on a specified model and does not account for measurement errors. In addition, the scoring method based on MCA is less effective regarding the treatment of missing responses because it is necessary to impute these values, in contrast to CFA or 2-PLM (and, more generally, for any model based on item response theory).

Multiple considerations lead to our conclusion that 2-PLM is the best method for computing the IMCSs. First, this model is based on estimation techniques that effectively address missing values [14, 24]. Second, 2-PLM has been used increasingly to measure latent variables based on categorical variables [25]. Finally, our empirical results show that 2-PLM provided the highest Cohen’s kappa coefficients, suggesting that it is the most conciliatory method.

The initial MCA, run to identify the intrinsic motivation indicators among preselected variables, provides a strong argument in favour of the selection of a 1D set of indicators: the first axis preserves >90% of total inertia in the data according to the Benzecri correction. The results are confirmed by CFA’s goodness-of-fit statistics, showing an acceptable one-factor model (CFI = 0.92, RMSEA = 0.074). However, the significant chi-squared statistic leads to a caveat concerning the model’s ability to account for all of the correlation structures in the data. As a consequence, some variables are less correlated with the estimated latent attribute. This result reveals a possible lack of precision in our indicators. In addition, a limit of our methods is that we cannot determine how much of the concept of intrinsic motivation our indicators represent; our data like the literature do not allow us to answer this question.

Using our results, future studies could examine intrinsic motivation by designing additional and better calibrated questions to construct a standardized questionnaire to measure the intrinsic motivation among GPs. For instance, preventive services are often a lower priority in practice relative to management of acute problems. Collecting specific information on actions taken to improve patients’ health status and on the time spent in carrying out such activities might provide strong additional measures of intrinsic motivation. Most importantly, we believe the measure we have developed may be used to test the impact on intrinsic motivation of new performance-based payments and other extrinsic incentives.

References


