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Statistical analysis on the intellectual capital statement

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Abstract

Purpose – The intellectual capital (IC) can be divided into three categories, i.e. human, structural, and relationship capitals. The purpose of this paper is to investigate the correlation among those capitals to their indicators, particularly for intellectual capital statement made in Germany and intellectual capital statement made in Europe models.

Design/methodology/approach – In these two models, each capital has four, six, and five indicators, respectively. So totally, there are 15 indicators. Structural equation modeling and its sensitivity analysis are utilized for measuring the correlation among those capitals to their indicators.

Findings – Among those 15 indicators, 14 indicators have strong correlation with their respective capitals. Moreover, there exist strong correlation in a similar weight among those capitals, i.e. the correlations between human (HC) and structural capital (SC) is 0.88, SC and relationship capital (RC) is 0.87 and HC to RC is 0.81.

Originality/value – So far, the data collected from the IC projects are presented and analyzed through descriptive statistics and statistics summaries, e.g. mean and standard deviation. This paper offers other statistical tools for exposing valuable information such as the correlation among each capital to its indicators in IC model.

Keywords Intellectual capital, Mathematical modelling, Sensitivity analysis, Statistical analysis

Paper type Research paper

1. Introduction

Nowadays, intangible assets such as staff's skills, strategic and process quality, software, patents, brands, supplier and customer relationship provide a great involvement to the successes in many corporate, so as considered as valuable assets. These assets are delivering a fast-growing contribution to corporate competitiveness and usually are classified as intellectual capital (IC) (Hofman, 2005).

The IC is defined as intellectual resources that have been "formalized, captured, and leveraged" to produce higher value assets (Prusak, 1998). There are many models and classifications on intellectual resources in literature. Most of them could be term the Sveiby-Stewart-Edvinsson model (Bukh *et al.*, 2001). The model consists of human capital (HC), structural capital (SC), and customer (relationship) capital (RC). According to Sveiby (1997), the HC involves capacity to act in wide variety of situation to create both tangible and intangible assets. Stewart (1997) emphasized that the primary purpose of a HC is innovation of new products and services or of improving in business process.

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The combination of Sveiby and Stewart definitions of HC if given by Edvinsson and Malone (1997) who defined it as combinations of knowledge, skill, innovativeness, and ability of the company's individual employees. The SC, as said by Sveiby, Edvinssons, and Mallone consists of internal structure which includes patents, concepts, models, computer, and administrative systems. Steward mentioned it as knowledge that does not go home at night. The customer relationship is defined as an external structure includes relationship with customers and suppliers. It also encompasses brand names, trademarks, and the company's reputation or image (Sveiby, 1997; Stewart, 1997).

As it is intangible, measuring IC cannot be regarded as an easy process. Kannan and Aulbur (2004) provided a useful framework for comparing several main approaches to measure IC and reviewed the limitations of current measurement systems. Those approaches include intangible asset monitor by Sveiby (1997), balance scorecard by Kapplan and Norton (1996), Skandia value scheme by Edvinsson and Malone (1997) and knowledge capital score by Lev (2000).

In the intangible asset monitor measurement systems, Sveiby proposed to measure the components of IC using qualitative and quantitative indicators and communicate the results in an intellectual capital statement (ICS) (Mertins *et al.*, 2006). The ICS can be employed as a strategic management instrument to assess and develop the IC of an organization. Mouritsen *et al.* (2001) also stated that "ICS combines numbering, visualization and narration to account for organizational value creation," and such statements help to explain the conditions for future value creation rather than present financial results. Moreover, Mouritsen (2003) gave a reflection on the idea of representation of knowledge resources as it may be related to insights communicated in ICS. Bukh *et al.* (2001) showed, analytically, IC comprises three dimensions. The first dimension is an identity story. It is a grand narrative of innovation, flexibility, or knowledge that includes the justification of the identity story. The second one is a management model specifying the set of managerial activities that gives substance to the grand story in areas such as technology, organizational structure or employee development. The last one is a presentation model that identifies the objects that are committed to numbers in the ICS. Bukh *et al.* (2001) analyzed the development of ICS in 19 Danish firms, Pablos (2005) gave an interesting lesson on the IC reports in India, Mertins *et al.* (2006, 2009) presented the measuring IC in European small and medium-sized enterprise (SME).

So far, the data collected from the IC projects are presented through descriptive statistics and analyzed based on histograms, bar charts and statistics summaries such as, mean and standard deviation (Bukh *et al.*, 2001; Mertins *et al.*, 2009). In fact, those data are rich with information. They can expose valuable information such as the correlation among each capital to its indicators. Strong correlation may indicate strong dependency between each capital and its indicators, and vice versa. We therefore, interested to investigate this correlation and we used structural equation modeling (SEM) as the primary tool for this study.

The presentation of this paper will be organized as follows. In Section 2, we will present a glimpse of the ICS-Germany and intellectual capital statement made in Europe (InCaS). Methodologies for analyzing the ICS statistically will be delivered in Section 3. Section 4 will be occupied by the data analysis and results. Conclusion and a future research recommendation will be presented in the last section.

2. A glimpse of the ICS

In this section, we only describe the main stream of the ICS-Germany and InCaS (see detail on Federal, 2004; InCaS, 2008).

In 2004, a project consortium consisting of Competence Centre Knowledge Management at Fraunhofer Institute for Production Systems and Design Technology (IPK), Wissenskapital Edvinsson und Kivikas Entwicklungsunternehmen GmbH and Intangible Asset Management Consulting, developed "ICS – Made in Germany" (ICS-Germany). The results and the experiences of the project led to the German Guideline "Wissensbilanz – Made in Germany". Further, in 2008 the InCaS guideline (InCaS, 2008) was launched. InCaS was developed to improve the existing ICS-Germany and discovered unused innovation potentials. It was also designed to identify the common grounds as well as the culture differences among European countries (Mertins *et al.*, 2006).

The ICS-Germany and InCaS are intended to SMEs, as well as other forms of organization which have a comparable structure. The main target of those ICSs is SMEs since it is realized that the SMEs will be able to adapt quickly to the changes in economic environment. The IC of an organization can be divided into three categories (Alwert, 2006). They are HC, SC, and RC. HC that can be defined as "what a single employee brings into the value adding processes," consists of four indicators, i.e. professional competence, social competence, employee motivation, and leadership ability. SC is defined as "what happens among the people, how the people are connected within the company, and what stays when the employee leaves the company." This capital consists of six indicators, namely, corporate culture, internal cooperation and knowledge transfer, leadership instrument, information technology and explicit knowledge, product innovation, process optimization, and innovation. The last capital, RC is defined as "the relations of the company to external stake holders". The RC consists of five indicators, i.e. customer relationship, supplier relationship, public relationship, investor relationship, and relationship to the cooperation partners.

Overall, there are 15 indicators listed on the HC, SC and RC. For each indicator, guidelines in Federal (2004) and InCaS (2008) asked three fundamental questions on the quality, quantity, and systematic (QQS) of each SME. The questions are stated as follows:

(1) Is the quantity/volume of the influencing factor sufficient? Do we have enough resources to achieve our goals?

(2) Is the quality of the influencing factor sufficient? Do we have the right factor, and is the quality of that factor right in order to achieve our goals?

(3) How systematically are we on developing the influencing factor? Are there any definitions, regular measurements and any routines for caring and for improving the factor?

Moreover, to measure the QQS "quantitatively," the ICS gives four scaling, they are:

(1) *0 per cent*. The QQS cannot be sensibly identified or is not (yet) available.

(2) *30 per cent*. The QQS is partly sufficient.

(3) *60 per cent*. The QQS is mostly sufficient.

(4) *90 per cent*. The QQS is (always/absolutely) sufficient.

To comprehend this system, let us take one example from the InCaS (2008). In this example, the representatives of an SME who used InCaS guideline for measuring its IC, let us call them the participants, measured the QQS of every indicator on the ICS using the four scales (Table I). The second last column of Table I consists of mean values of the QQS measurement. Those mean values recap the current condition of the SME. Since the total achievement would be 100 per cent (perfect condition) then, the (100 – mean value) per cent exposes the potential improvement that can be accomplished. This information is given in the last column. So, we can say that, e.g. the SME had achieved its professional competence 63 per cent and potentially it can be improved by 37 per cent more. However, the ICS sets the maximum sufficiency that can be completed by an SME only 90 per cent. Hence, there is always a potential room for improvement for at least 10 per cent from the perfect condition of the respective SME.

3. Methodology

Basically, the investigation of the correlation among indicators which build the ICS-Germany and InCaS will be completed through SEM. However, due to data limitation we have, some of them are considered as missing, then we need to first, impute these missing data. We also need to detect outliers in the data since outliers may diffract our result(s). They should be cleaned from the data. We therefore need a sensitivity analysis (SA) for detecting those outliers.

3.1 Data imputation

Missing data can occur due to several facts in the field of research. In the case of measuring IC, it happened due to the diversity of the SMEs that involved in this project. Some of them do not have the same indicators as in the ICS guideline; they have their own indicators.

There are several methods for handling missing data. The simplest way is the listwise deletion. In this method, all subjects with any missing values are omitted from analysis. The disadvantage of using this approach is a possibility to loose power.

			QQS-overview				
IC type	ID	IC factor	Quantity (%)	Quality (%)	Systematic (%)	Mean value (%)	Improvement potential (%)
HC	HC1	Professional competence	50	80	60	63	37
	HC2	Social competence	N/A	40	40	40	60
	HC3	Employee motivation	75	50	30	52	48
SC	SC1	Corporate culture	N/A	85	20	53	47
	SC2	Internal co-operation and knowledge transfer	50	85	75	70	30
	SC3	Information technology and explicit knowledge	30	50	40	40	60
RC	RC1	Customer relationships	60	70	60	63	37
	RC2	Investor relationships	90	90	90	90	10

Notes: Low-mean value (high-improvement potential) indicates weakness; high-mean value (low-improvement potential) indicates strength
Source: InCaS (2008, p. 41)

Table I.
An example of QQS overview

Little and Rubin (2002) explained how to deal with missing data in detail. In this paper, we are only going to utilize the multiple imputation technique which was developed by King *et al.* (2001) and Honaker *et al.* (2005). This method has been implemented into R packages, Amelia II: A Program for Missing Data, and can be downloaded in R-Team (2008).

3.2 Structural equation modeling

SEM is defined as multiple-equation regression models in which the response variable in one regression equation can appear as an explanatory variable in another equation (Fox, 2008). SEM is more than a regression technique. It has an ability to test specified theory-based models including latent (unobservable) variables and multiple-related equations. The latent variables can be measured indirectly through their effects (called indicators), or sometimes through their observable causes. Moreover, two variables in SEM can effect one-another reciprocally, either directly, or indirectly through a feedback loop. For the detail explanation of SEM, we refer to Kline (2005). SEM can be modeled by two components, i.e. structural equation model and the measurement model(s) (Jöreskog and Sörborn, 1996).

3.2.1 The structural equation model. The structural equation model can be written as:

$$\boldsymbol{\eta} = \alpha + \mathbf{B}\boldsymbol{\eta} + \Gamma\xi + \boldsymbol{\zeta} \tag{1}$$

where $\boldsymbol{\eta}$ is a $m \times 1$ vector of endogenous latent variables, ξ is a $n \times 1$ exogenous latent variables which have mean $\boldsymbol{\kappa}$ and covariance matrix $\boldsymbol{\Psi}$. The $m \times 1$ vector $\boldsymbol{\zeta}$ is the error term which has zero mean and covariance matrix $\boldsymbol{\Psi}$, and $\mathrm{cov}(\boldsymbol{\zeta}, \boldsymbol{\zeta}') = 0$.

3.2.2 Measurement model. The measurement models for p endogenous observed variables, represented by vector $\mathbf{y}$, and q exogenous observed variables, contained in the vector $\mathbf{x}$, relate the observed (manifest) variables to the underlying factors (latent variables) and can be expressed as:

$$\mathbf{y} = \tau_{\mathbf{y}} + \Lambda_{\mathbf{y}}\boldsymbol{\eta} + \varepsilon, \quad E(\varepsilon) = 0, \ \ \mathrm{cov}(\varepsilon) = \Theta_{\varepsilon} \tag{2}$$

$$\mathbf{x} = \tau_{\mathbf{x}} + \Lambda_{\mathbf{x}}\xi + \delta, \quad E(\delta) = 0, \ \ \mathrm{cov}(\delta) = \Theta_{\delta} \tag{3}$$

respectively.

3.3 Sensitivity analysis

SA is a study of how the variation (uncertainty) in the output of a mathematical model can be apportioned, qualitatively or quantitatively, to different sources of variation in the input of a model (Saltelli *et al.*, 2004). SA can be used to simplify models, to investigate the robustness of the model predictions, to play what-if analysis exploring the impact of varying input assumptions and scenarios and as an element of quality assurance. It provides as well information on: factors that mostly contribute to the output variability, the region in the space of input factors for which the model output is either maximum or minimum or within predefined bounds, optimal – or instability – regions within the space of factors for use in a subsequent calibration study interaction between factors (Saltelli *et al.*, 2004). It is also a general statistical concept to evaluate the stability of estimators with respect to parameters and model assumptions, and to detect the presence of outlier(s) or peculiar observation(s) in the data set (Cook, 1986).

Basically, the SA can be categorized into two classes, the local SA, e.g. Cook (1986), Lee and Wang (1996) and the global SA, e.g. Sobol (2001), and Saltelli *et al.* (2008). In this work, we will apply the local influences SA for the SEM, which was developed by Lee and Wang (1996).

Let $X_1, X_2, \ldots X_n$ be a random sample of $p \times 1$ random observations which are drawn from a population with mean 0 and covariance matrix $\boldsymbol{\Sigma}_0$, and assume that n is greater than p. In general, a covariance structure is defined by $\boldsymbol{\Sigma} = \boldsymbol{\Sigma}(\boldsymbol{\theta})$, where every element $\sigma_{ij}(\boldsymbol{\theta})$ of $\boldsymbol{\Sigma} = \boldsymbol{\Sigma}(\boldsymbol{\theta})$ is twice differentiable function of a $q \times 1$ parameter vector $\boldsymbol{\theta}$, which varies in an open set Θ in the parameter space. It is also assume that:

- $\boldsymbol{\Sigma}(\boldsymbol{\theta})$ is identified;
- there exist a $\boldsymbol{\theta}_0 \in \Theta$ such that $\boldsymbol{\Sigma}(\boldsymbol{\theta}) = \boldsymbol{\theta}_0$; and
- $\boldsymbol{\Sigma}(\boldsymbol{\theta})$ is locally regular at $\boldsymbol{\theta}_0$.

An estimate $\hat{\boldsymbol{\theta}}$ of $\boldsymbol{\theta}_0$ is obtained by minimizing a discrepancy function $G(\boldsymbol{\theta}) = G(\mathbf{S};\boldsymbol{\Sigma})$, where $\mathbf{S} = (S_{ij})$ is the sample covariance matrix.

In the following, for any symmetric matrix $\mathbf{A}$, vecs($\mathbf{A}$) will represent the $p^* = p(p+1) = 2$ by 1 column vector formed by stacking the lower triangular elements of $\mathbf{A}$, row by row sequentially; and vec($\mathbf{A}$) is the p^2 by 1 vector similarly formed by stacking all elements of $\mathbf{A}$.

Consider the general nonlinear model:

$$\mathbf{y}_i = \sigma(\boldsymbol{\theta}) + \boldsymbol{\varepsilon}_i, \quad i = 1, 2, \ldots, n \tag{4}$$

where:

$\sigma(\boldsymbol{\theta})$ general function of an unknown parameter vector $\boldsymbol{\theta}$;

$\mathbf{y}_i$ an observed random vector from the sample; and

$\boldsymbol{\varepsilon}_i$ a random error vector.

The GLS estimation of $\boldsymbol{\theta}$ is obtained by minimizing the following GLS function:

$$G(\boldsymbol{\theta}) = n^{-1}\sum_{i=1}^{n}[\mathbf{y}_i - \sigma(\boldsymbol{\theta})]'\mathbf{V}[\mathbf{y}_i - \sigma(\boldsymbol{\theta})] \tag{5}$$

where:

$\mathbf{V}$ an appropriate positive definite weight matrix.

$\mathbf{V} = 2^{-1}n\boldsymbol{K}_p^-(S^{-1}\otimes S^{-1})\boldsymbol{K}_p^-$, where $\boldsymbol{K}_p$ is the $p^2 \times p^*$ matrix such that vecs($\mathbf{A}$) = $\boldsymbol{K}_p'$ vec($\mathbf{A}$) with $\boldsymbol{K}_p^- = (\boldsymbol{K}_p'\boldsymbol{K}_p)^{-1}\boldsymbol{K}_p'$ (Browne, 1974).

To apply the above nonlinear regression model to structural equation models, let $\bar{\mathbf{x}}$ and $\mathbf{S}$ be the sample mean vector and the sample covariance matrix based on a random sample $\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_n$ from a distribution with mean vector $\mathbf{0}$ and covariance matrix $\boldsymbol{\Sigma}(\boldsymbol{\theta})$, $\mathbf{s} = \text{vecs}[(\mathbf{x}_i - \bar{\mathbf{x}})(\mathbf{x}_i - \bar{\mathbf{x}})']$, $\boldsymbol{\Sigma}(\boldsymbol{\theta}) = \text{vecs}(\boldsymbol{\Sigma}(\boldsymbol{\theta}))$.

Now, by taking $\omega_0 = (1, \ldots, 1)$ and introduce a perturbation $\omega = (\omega_1, \ldots, \omega_n)'$ to the case weights if $G(\boldsymbol{\theta})$ of the form in equation (7). Let:

$$G(\boldsymbol{\theta}|\omega) = \frac{1}{n}\sum_{i=1}^{n}\omega_i(\mathbf{y}_i - \sigma(\boldsymbol{\theta}))'\mathbf{V}(\mathbf{y}_i - \sigma(\boldsymbol{\theta})) \tag{6}$$

$\hat{\boldsymbol{\theta}}$ and $\hat{\boldsymbol{\theta}}_\omega$ be the minimizer of $G(\boldsymbol{\theta})$ and $G(\boldsymbol{\theta}|\omega)$, respectively. It can be shown that:

$$B = \left.\frac{\partial^2 G(\boldsymbol{\theta}|\omega)}{\partial \boldsymbol{\theta} \partial \omega}\right|_{(\boldsymbol{\theta},\omega)=(\hat{\boldsymbol{\theta}},\omega_0)} = -\frac{2}{n}[\Delta'\mathbf{V}\hat{\varepsilon}_1, \Delta'\mathbf{V}\hat{\varepsilon}_2, \ldots, \Delta'\mathbf{V}\hat{\varepsilon}_n] \tag{7}$$

$$\ddot{G} = \left.\frac{\partial^2 G(\boldsymbol{\theta})}{\partial \boldsymbol{\theta} \partial \boldsymbol{\theta}'}\right|_{(\boldsymbol{\theta},\omega)=(\hat{\boldsymbol{\theta}},\omega_0)} = 2\Delta'\mathbf{V}\Delta - 2[(\bar{y} - \sigma(\boldsymbol{\theta}))'\mathbf{V}\otimes\mathbf{I}_q]\nabla \tag{8}$$

where $\mathbf{I}_q$ is a $q \times q$ identity matrix, $\hat{\varepsilon}_i = \mathbf{y}_i - \sigma(\boldsymbol{\theta})$:

$$\Delta = \frac{\partial \sigma(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \quad \text{and} \quad \nabla = \frac{\partial}{\partial \boldsymbol{\theta}'}\left(\frac{\partial \sigma(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}}\right) \tag{9}$$

both evaluated at $\hat{\boldsymbol{\theta}}$. Then, the matrix $\mathbf{A}$ will be equal to:

$$\mathbf{A} = B'\ddot{G}^{-1}B = \frac{2}{n^2}\, T'F^{-1}T \tag{10}$$

where $T = -2^{-1}nB$ and $F = 2^{-1}\ddot{G}$.

Now, using equation (12), the Cook's (1986) influence curvature along direction h, with $\|h\| = 1$, C_h, can be deduced as:

$$C_h = |h'\mathbf{A}h| \tag{11}$$

The influence curvature C_h is a measurement for sensitivity of $\boldsymbol{\omega}$ along the direction h. In practice, the maximum value of $C_{\max}$ of C_h and the corresponding direction $\mathbf{h}_{\max}$ are most useful. The vector $\mathbf{h}_{\max}$ indicates how to perturb the postulated model to obtain the greatest local change. If the i th element of $\mathbf{h}_{\max}$ is found to be relatively large, then it indicates that perturbations in the weight ω_i of the i-th case may lead to significant changes and hence ω_i is relatively influential to the results of the analysis. Moreover, it can be seen that $C_{\max} = \lambda_{\max}$, where $\lambda_{\max}$ is the largest eigenvalue of matrix $\mathbf{A}$ and $\mathbf{h}_{\max}$ is the corresponding eigenvector.

4. Data analysis

On data analysis, we used two data sets of the QQS assessment which were collected from ICS-Germany and InCaS' projects (Mertins *et al.*, 2009). So far, there are 42 German SMEs kleine und mittelstaendische Unternehmen – KMU which were listed in the ICS-Germany's project. Additionally, 25 SMEs from five European countries, i.e. France, Germany, Poland, Slovenia, and Spain were participated in the InCaS projects. These data sets are provided by the Fraunhaufer – IPK – Berlin.

However, among those 42 KMU's QQS data assessment, we only used 32 data, the other ten data employed different indicators from the standard which are listed in Section 2. The IC allows flexibility in formulating the influencing indicators which construct the human, structural, and relationship capitals, for adapting to the unique condition of SME. So totally, we only have 57 QQS data assessments.

We used the mean values of those 57 QQS data assessments, because these mean values already recapped the current condition of the SMEs. Their assessments were done by the participants of each SME with a help of a professional moderator and bias in the data were also avoided using a specific trick as it is mention above. Moreover, the participants of each SME should follow a training given by a professional trainer in order to understand the IC concept and how to measure it. Thus, we can say that validity and independency of each data are reliable.

So far, we have 15 variables represent the IC factors for 57 SMEs, i.e. the data dimension is 57×15. However, some SMEs did not assess corporate culture, investor relationship, or others in the data set. Since the formulation of SEM in Section 3.2 needs a complete data set for calculating the covariance matrices and the available data are limited, so we could not use the listwise deletion, i.e. deleted the data from SMEs which were not complete. We then should regard the uncompleted data as missing values and apply the data imputation technique, which is explained in Section 3.1, to predict those data. As the final data preparation, we normalized the data such that each variable will have mean zero and variance one.

We utilized R-programming to perform data preparation, data imputation, estimate the parameters in SEM and its SA. In addition, we also used two packages, namely, Amelia for data imputation and sem for the structural equation model. While for the SA, it has to be programmed specifically, since it depends on the structure of the IC-model.

The ICS-Germany and InCaS model together with the estimated factor loadings and the error variances for each variable can be seen in Figure 1. As an example, the factor

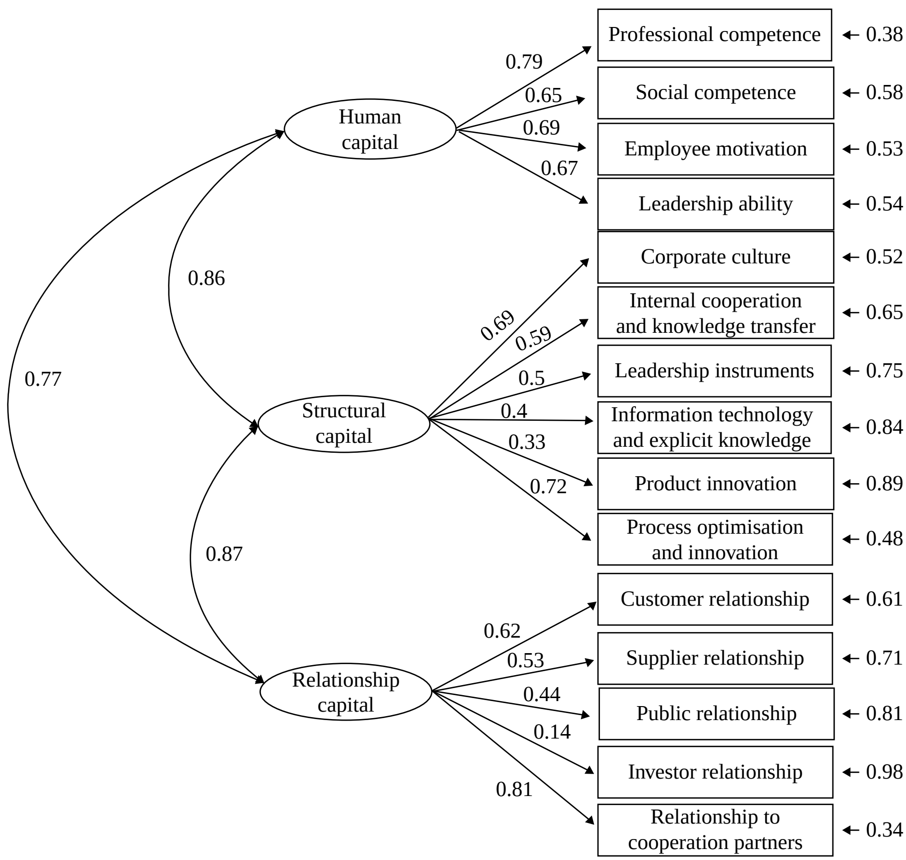
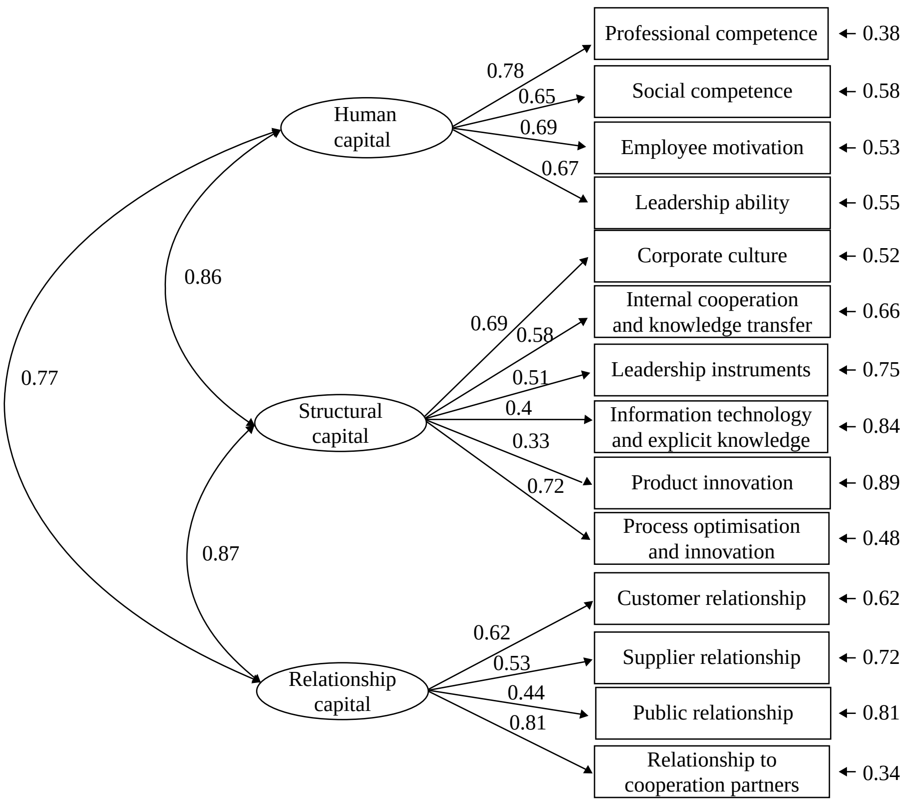


Figure 1.
The structural equation model of the IC

loading between HC and the professional competence is very strong, that is, 0.79 with variance of residual equal to 0.38. Since the data were normalized, then the factor loading will also indicate the correlation between those variables. In words, we can say that the professional competence is an influential indicator for measuring the HC. On the other hand, the factor loading between the RC and the investor relationship is only 0.14. Comparing to the others, it is the smallest one and therefore indicates weak influence to the RC. The statistical hypothesis test reports that the *p*-value of this loading factor equals to 0.36 (>5 per cent significant level, $\alpha = 0.05$). It can be concluded this factor loading is not significant and can be omitted from the analysis. The estimated parameters of Model 2, i.e. Model 1 without investor relationship, are only slightly altered (Figure 2). However, the performance of Model 2 is better than Model 1. It shows through the decreasing of the root mean square error approximation (RMSEA) from 0.093825 in Model 1 to be 0.081943 in Model 2. If the RMSEA $\leq$0.05 the model can be specified as a close fit model; if $0.05 < \text{RMSEA} \leq 0.08$ then the model can be said as a good fit model, otherwise if the value of RMSEA is in between 0.08 and 0.10 then it can be said as a marginal fit model (McCallum *et al.*, 1996). Hence, Model 2 is a good fit model, than the Model 1 which is only a marginal fit model. Therefore, based on this model, the SA of the model was investigated.



Note: Structural equation model, after the investor relationship was removed from the analysis

Figure 2.
The IC

The aim of this SA is to detect the existence of potential outliers, in the data set. The most crucial part on doing the SA using the Lee's approach is the construction of covariance structure Σ. For Model 2 the covariance structure is simply $\Sigma = \Lambda\Phi\Lambda' + \Psi$, where:

$$\Lambda' = \begin{pmatrix} \lambda_{11} & \Lambda & \lambda_{14} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0\ 0 & \Lambda & 0 & \lambda_{21} & \Lambda & \lambda_{26} & 0 & 0 & 0 & 0 \\ 0 & \Lambda & 0 & 0 & \Lambda & 0 & \lambda_{31} & \lambda_{32} & \lambda_{34} & \lambda_{35} \end{pmatrix} \quad \Phi = \begin{pmatrix} 1 & \phi_1 & \phi_3 \\ \phi_1 & 1 & \phi_2 \\ \phi_3 & \phi_2 & 2 \end{pmatrix}$$

and Ψ is treated as free unknown parameters. The Σ was estimated using the result of SEM, where $\lambda_{ij}, i = 1, 2, 3; j = 1, \ldots, 14$ is the loading factors estimate of each IC factor; ϕ_i, $i = 1, 2, 3$ is the correlation among those three capitals, and Ψ is normally random distributed with mean zero and variance equal to residual variance of each factors loading, respectively.

Substitute the estimate covariance structure into equation (6) and compute the equations (7)-(10) we get the $\mathbf{h}_{\max}$, i.e. the eigenvector with respect to the maximum eigenvalue of matrix $\mathbf{A}$ in equation (10). The $\mathbf{h}_{\max}$, will indicate the outlier among the data. The plot of $\mathbf{h}_{\max}$ versus the index of the data are shown in Figure 3-left. Here, we detected that the 55th data point was an influential observation and it can be diagnosed as a potential outlier in the data set. Delete this data point from the data set, and perform the SA once more, we now detect that the 15th data point was the influential observation (Figure 3-middle). After we delete data points from the whole data set twice, the $\mathbf{h}_{\max}$ settle in a certain band (Figure 3-right). The last model, i.e. Model 3 were constructed using this data set (Figure 4), this model is better than Model 2. The RMSEA is decreased from 0.081943 in Model 2 to 0.073678 in Model 3 and Model 3 is a good fit model. Thus, it is the final model of the ICS made in European and made in Germany, which picturing the influential indicators which constructed the ICS-Germany and InCaS. Here, instead of consists of 15 indicators; the ICS model now only consists of 14 indicators.

The strongest correlation occurs between the HC and the SC, and then it follows between the SC and the relationship capital, and the HC and the relationship capital as the weakest. The HC is indicated by the social competence, employee motivation, professional competence, and leadership ability. The order of this composition is based on the factor loading between each factor and the HC. The higher the factor loading, the stronger their relationship is. Similarly, we also can deduce that the SC is indicated by the process optimization and innovation, corporate culture, internal cooperation, leadership instrument, information technology and explicit knowledge, and the

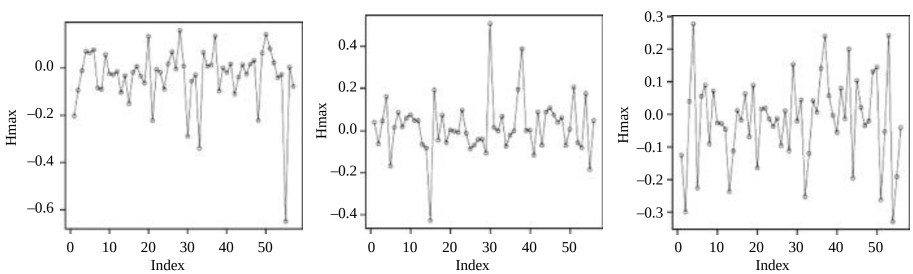
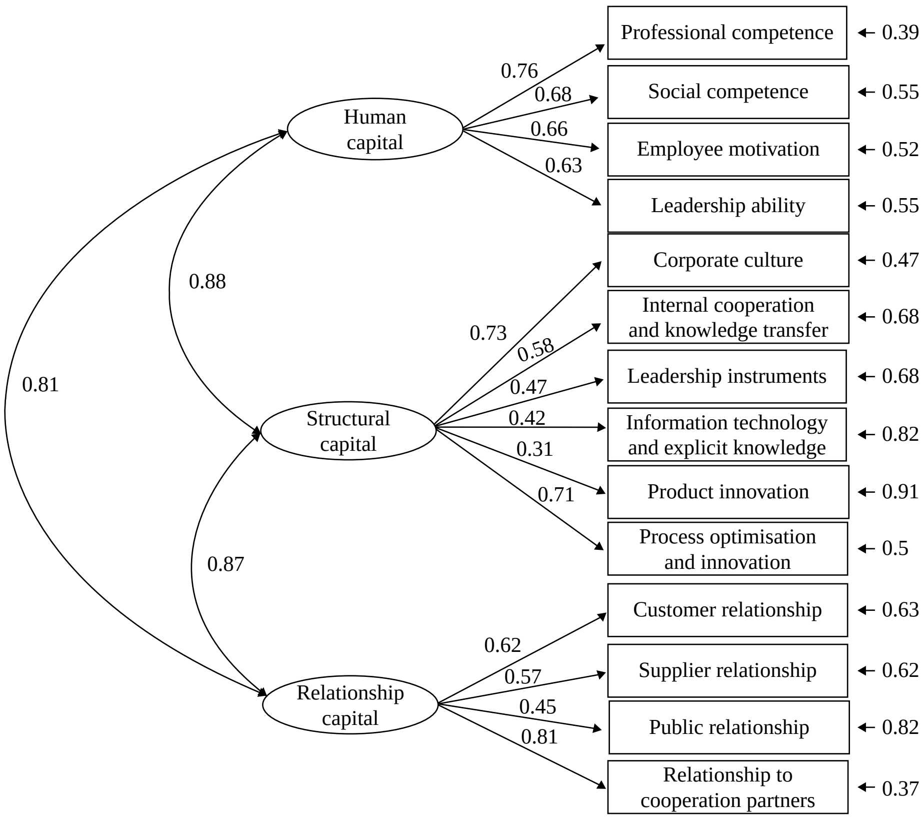


Figure 3.
The sensitivity analysis of Model 2 with the whole data set (left), after the 55th observation is deleted (middle), after the 15th data were deleted (right)



Note: Structural equation model

Figure 4.
The final IC

product innovation. Finally, the relationship capital is indicated by the relationship to the other partners, customer, supplier, and public relationships.

In practice, we have two results from the data analysis. First, this data analysis shows that there is a weak correlation between investor relationship and the RC. It implies that the investor relationship cannot be an indicator for measuring the RC in the ICS-Germany and InCaS models. Second, in this data set, we found two outliers. The outliers in the 15th and 55th SMEs indicate that a small perturbation on those two assessments may lead to significant changes. The outliers show that the two SMEs assessed the QQS very differently from the others. This might be because of cultural differences among the European countries.

5. Conclusion

We investigated the correlation of each indicator with its respective capital which builds the IC using the QQS assessment data using the recorded data and statistical tools. The result exposes that among those 15 factors for measuring the human, structural and relationship capitals, only the investor relationship has no significant correlation to the relationship capital. We also can conclude that strong correlations present among those three capitals a similar weight that is 0.8.

On the statistical point of view, the SA that we used in this work depends on the covariance structure. Once the covariance structure is changed then all derivatives of this covariance function has to be recalculated.

For further research, at least two things can be investigated. First, adapting the global sensitivity for SEM. Global sensitivity will help us to identify the robustness of model to the variation of data input. Second, improving the local SA to be more adaptable, if the model is changed. Combining these two sensitivities, we are going to have a clean data set and a statistically robust model.

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