SECTION 4. Practitioner's corner

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Leadership capabilities, management selection – game theoretic modelling

Abstract

This paper lays the foundation for constructing a comprehensive analytical tool for selection of managers on the basis of core leadership capabilities.

A game theoretic model, where the key coefficient of the input vector was inferred from the twelve variables of the April² Leadership Enhancement Framework, using a set of structural equations, was adopted to reach the goals of the study. The underlying data for estimation of the coefficient was sampled from the population of graduate management students from a leading South African business school using Likert scale questionnaires.

The paper finds highly significant predictive relationships between the key variables of the April² Leadership Enhancement Framework, confirming the theoretical claim of the model that managers with higher levels of development of these twelve characteristics can be regarded as having greater leadership capability. The structural equations revealed that the key coefficient of the main input vector of the game, despite having highly significant explanatory power over the underlying variables, is not generalizable. Further research should focus on improvement of the fit, by sampling from wider populations in order to make the tool applicable across the board.

An important implication of the constructed model is that the signalling game of incomplete information, combined with key variables of the Leadership Enhancement Framework, serves as a robust foundation for a further development of an analytical tool for a structured selection of managers on the basis of their core leadership capabilities. It is also a first known attempt to combine psychometric techniques with a game theoretic framework in the context of leadership development.

Keywords: leadership enhancement, values, framework, signalling game, HLT coefficient, Bayesian network.
JEL Classification: M51.

Introduction

Over the last decade, there has been a notable shift away from the view that efficient functional management practices (Drucker, 1954) and transactional leadership styles (Burns, 1978) solely create successful organizations. New demands of the contemporary socio-economic global order have led to an increasingly greater emphasis on transformational leadership (Bass, 1990), which although not a new concept in itself (Humphreys and Einstein, 2003), contrasts sharply with functional management and transactional leadership by emphasising mutually empowering co-creation, instead of the optimization of processes and procedures (functional management) and a quid-pro-quo exchange (transactional leadership). The transformational leadership style is ultimately driven by values, instead of by mere attainment of the short-term, numerically measurable objectives (Dolan and Raich, 2009). The logic is that transactional competencies and technical expertise are standard requirements (qualifiers), while transformational leadership capability is what provides distinct competitive advantage and sets the manager apart from the rest.

More recent bodies of literature call for an extension of the concept to a more integrative, holistic model of leadership (Nel, 2007), where congruency of values (Meglino and Ravlin, 1998), mindfulness (Boyatzis and McKee, 2005) and self-awareness (Schön, 1983), emotional (Bradberry and Greaves, 2005) and cultural intelligence (Peterson, 2004), knowledge creation and knowledge management (Gorelick et al., 2004), systems thinking (Gharajedaghi, 2006), diversity and inclusion (April and Shockley, 2007), effective communication (April, 1999), stewardship (Block, 1993), ethics (Kuper, 2008), morality (Jordan, 2009; Rhode, 2006) and authenticity (George et al., 2007; Klenke, 2007) allow for effective creation of a learning organization (Argyris and Schon, 1996) through development of shared vision, in which the objectives of the organization are aligned with the personal aspirations of its individual members (O'Reilly and Chatman, 1996).

We shall broadly describe this concept as 'humanistic leadership', because its underlying philosophy is effective recognition, comprehension and leveraging of interpersonal and intrapersonal dynamics (Gardner, 1999). Thus, individual elements of the humanistic leadership concept can be grouped under three general categories pertaining to these: instrumental and terminal values (Rokeach, 1973) and emotional intelligence (Goleman, 1995).

Individual instrumental and terminal values provide the foundation of the transformational leadership style, as the ultimate guides of behavior within the organization (Ravlin, 1995; Meglino 1996), while the core aspects of emotional intelligence serve as their active enablers by allowing the leader to utilize the value systems to effectively involve, motivate, inspire and ultimately empower the followers (April and April, 2007). An effective humanistic leader acknowledges the complexity of a highly integrated global society, as well as the dynamic nature of organizations, and adopts a systemic view, which appreciates the importance of individuality and allows him/her to harness their unique capabilities through inspiration and intellectual stimulation (Bass and Avolio, 1994).

Few large organizations have committed resources towards developing rigorous systems and practices for discovering and cultivating such leadership capabilities among their managers (Giberson et al., 2005), due to the considerable level of ambiguity on how to assess people in respect of such factors as values, ethics, emotional maturity and authenticity. Therefore, it lends itself towards a general reluctance, on behalf of the majority of organizations, to make significant investments in this area of practice. We attempt to resolve this by combining results of academic studies around the core aspects of humanistic leadership, in a robust mathematical framework, derived through psychometric data around the key determining variables. This, we believe, will provide organizations with the beginnings of a rigorous analytical tool for making strategic decisions in terms of selection of managers on the basis of key aspects of humanistic leadership.

Baysian networks (Ben-Gal, 2007) have been effectively used to model enterprise and individual behavior as sets of complex systems (Potgieter et al., 2005; Potgieter et al., 2009), and game theory has been extensively applied to modelling organizational economic behaviour since its creation (Saloner, 1991). Since humanistic leadership can be adequately regarded as a complex adaptive system (Waldrop, 1994; Schneider and Somers, 2006; Guastello, 2007), and while the decision of selecting managers on the basis of capability is essentially a problem of economic choice (Allingham, 2002; Bicchieri, 2003), it does not appear unreasonable to combine these mathematical instruments in order to create a measurement model, that would provide organizations with a desired analytical tool.

For this purpose, we have used the data gathered over two years from the application of the leadership enhancement method with graduate management students, based on the April² Leadership Enhancement Framework (Table 1), which consists of the twelve seeds of influence which build and grow out of an individual's core values (April and April, 2007). These seeds can be grouped under three main categories: instrumental values, terminal values and those aspects of emotional intelligence which represent cognitive and emotional capacity pertaining to the key factors of the capability to build and sustain effective interpersonal relationships.

Table1. April² Leadership Enhancement Framework (April and April, 2007)

Instrumental values	Terminal values	Emotional intelligence
Mental models	Life balance	Emotional maturity
Social connectedness	Accountability	Locus of control
Ambiguity and uncertainty	Authenticity	Transference
Communication skills	Compassion	
	Ethics	

A signalling game of incomplete information offers a rigorous mathematical framework for selection of candidates on the basis of key competencies, like the level of technical qualification, professional experience and inherent personality type (Spence, 1973). While technical qualifications and professional experience can be relatively easily observed from the official transcripts and professional track record of the candidate, there is no commonly agreed measurement for estimation of the inherent personality type. The variable is simply considered as being 'nature-determined', and no attempt to study the underlying factors behind it has been rigorously made. In our model, we consider this variable as a reflection of the key humanistic leadership capabilities of the candidate, and use the data gathered from the population of graduate management students using the twelve seeds of the April² Framework to infer the underlying causality structure, which can be subsequently used as a measurement tool for selecting future candidates in an applied method of measuring their underlying humanistic leadership type (HLT). This measurement can then be used as an input in the selection process, based on simple backward induction and in combination with the traditional technical qualification and professional experience under the signalling game framework.

1. Measurement model

Since the aim of this paper is to develop the HLT as a measureable proxy for the Type coefficient of the signalling game, a brief overview of the general class of signalling games, with underlying structure and fundamental principles of their mechanics, is required. A signalling game is a dynamic game of incomplete information with the set of players [N, S, R] being Nature, Sender and Receiver respectively. Nature determines a "type" of the sender from the finite set of types $T = \{t_1, \ldots, t_n\}$ according to a probability distribution, and the Sender of each chosen type, s (t_1),..., s (t_n), chooses the message to send to the receiver from the finite set of messages $M = \{m_1, ..., m_j\}$ (Gibbons, 1992). The Receiver observes the message received and chooses an action from the feasible set of actions, $A = \{a_1, ..., a_K\}$. The payoffs to the players are, therefore, the function of the type chosen by Nature, the message sent by the sender and the action taken by the Receiver. The payoff function for Nature is considered indeterminate and irrelevant in the context of this game (Gibbons, 1992), while the payoff functions to the Sender and Receiver can be specified as π_S (t_i, m_j, a_K) and π_R (t_i, m_j, a_K) respectively. These functions take the form of von Neumann-Morgenstern utility functions with their respective properties (von Neumann and Morgenstern, 1944).

In the signalling game so specified, a pure-strategy Perfect Bayesian Equilibrium (PBE) (Fudenberg and Tirole, 1991) is a pair of strategies, respectively for the Sender and Receiver $\{m^*(t_i), a^*(m_j)|\mu(t_i|m_j)\}$ satisfying four conditions, which are necessary and sufficient for existence of PBE in a signalling game of incomplete information (Gibbons, 1992). Kreps and Wilson (1982) show that, in any finite game, there exists a stronger form of PBE – *a sequential equilibrium* – which implies that in any finite game there also exists a PBE. Formally, this means that "an equilibrium no longer consists of just a strategy for each player, but now also includes a belief for each player at each information set at which the player has the move" (Gibbons, 1992, p.179). PBE is therefore a realistic concept that is essentially based on rationality, bounded by the belief of the Receiver about the type of Sender that is conditional on the message from the Sender observed by the Receiver.

Such belief is expressible in different ways, depending on the context of a specific signalling game. Spence (1973) described equilibrium strategies, in job-market signalling games, where the "type" of worker is essentially his or her inherent productive capacity defined by nature. Then the worker invests in education, obtains experience or some other combination of skills, and sends a message to the prospective employer about his or her productive capability. One can view such messages as a set of conventional signalling tools used in the job market around the world, like curriculum vitae, job references, University degree, work experience, etc. The prospective employers base their beliefs about the productive capability of the worker on these kinds of messages, seeking to gather as much qualitative information as possible in order for this belief to be as close to an approximation of reality as possible. This is why companies employ various additional tools, like psychometric evaluations, in-house IQ tests and multiple rounds of interviews (Armstrong, 2006).

In the context of our model, the main weighting in the set that constitutes a message is proposed to be given to the twelve variables representing core value factors of humanistic leadership characteristics, as specified in Table 1, which essentially determine the probability of the "type" being a high quality humanistic leader. In fact, the nature of this game makes the message practically irrelevant, and the outcomes to be solely determined by the accuracy of the estimation of the humanistic leadership capabilities of the Sender. We simply hold the other elements of the message: education, experience, reference letters, etc., constant on assumption, which follows from the foundations of the humanistic leadership view that these factors are standard across the board and do not give the sender significant competitive advantage over other potential candidates (*op cit*). Thus, following from the general characteristics of the signalling game of incomplete information, the problem of determination and selection of a high quality candidate for the leadership position is outlined as follows.

There are three players in the game: Nature, Sender and Receiver. Nature determines "type" of the sender. We shall think of this as being the humanistic leadership quality expressible in the higher combined score of the twelve variables of the April² Framework. It does not matter how these originate, from intrinsic qualities of the person acquired genetically, or from undergoing good coaching and mentoring, or some combination of those. What is important for our purpose, is how the entity that is recruiting a person for a leadership position can use a metric for assessing these qualities, on the basis of interrelationships between the twelve seeds (Table 1) and then, having determined that, make appropriate decisions via a simple mathematical induction via the help of the game theoretic framework.

Under this scenario, we confine ourselves with only two possible types: a high type and low type, which means that nature draws from the following set, $T = \{t_H, t_L\}$. Essentially, the high type corresponds to the high overall score on the twelve variables, while the low type naturally represents the low score on these twelve variables. Understandably, t_H and t_L are mutually exclusive, so that after the draw is made for a specific candidate, T becomes an empty set. Therefore, the probability of one type is the converse of the probability of the other, and the probabilities of each type add up to one. After Nature assigns the type, the Sender of a specific type $S[t_i]$ $i \equiv [H, L]$

chooses to send a message from the set, $M = \{m_1, m_2\}$. The mathematics of this particular game results in the message chosen to have no material bearing on the outcome of the model. The qualitative motivation for this is based on the underlying focus of this research. The model is concerned solely with the leadership qualities of the Sender, which are estimated on the basis of the twelve variables (Table 1). We shall assume, therefore, that relevant signals in a well-ordered message set $m_i = (m_i^a, m_i^b, m_i^c, ..., m_i^k)$, where $a,b,c,...,k$ represent such signals as education, experience and so on, are standardized across particular industries and are common knowledge to all the other competing Receivers. This implies that these signals do not add additional value to the selection process, and can be held constant.

Given such conditions, the full game can be conveniently represented by a graph, illustrated in Figure 1, and its mechanics summarized as follows. Nature assigns a type to the Sender, either a high type t_H or a low type t_L. The Sender of specific type, $S\,[t_H]$ or $S\,[t_L]$, selects a message to send to the Receiver, either m_1 or m_2. The Receiver is not certain about what type sent the message, a high or a low type, and is faced with an identical decision problem – whether to accept the Sender (e.g., hire for a managerial position) or reject the Sender. Given the irrelevance of the message sent in the context of this game, the identical decision problem for the receiver anywhere in the game and the uncertainty about the type that sent the message, the Receiver is essentially faced with four possible payoffs. The two payoffs from accepting or rejecting the candidate, when the candidate turns out to be a high type, and the two payoffs from accepting or rejecting a candidate when the candidate turns out to be a low type, as specified at the terminal nodes of the graph.

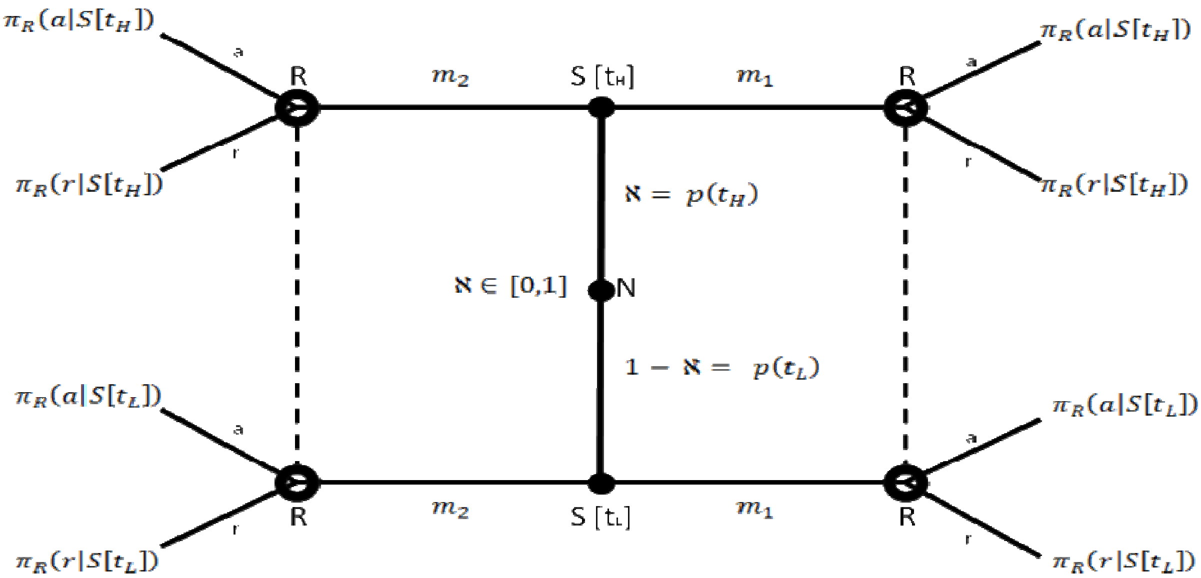

Fig. 1. Incomplete information signalling game with "type" coefficient as the key determinant of the profitable strategy selection

Assuming the Receiver desires to obtain a manager with high humanistic leadership capability (high HLT) and avoid hiring a manager with poor humanistic leadership capability (low HLT), where this capability is estimated by the relevant scores on the twelve variables listed in Table 1, the Receiver has the following preference ordering:

$$\pi_R(a|S[t_H])\rangle\pi_R(r|S[t_H]) \geq \pi_R(a|S[t_i])\rangle\pi_R(r|S[t_i]).$$

If these payoffs take the form of the von Neumann-Morgenstern utility functions, with their relevant properties (Dutta, 1999), then the Receiver makes a decision of whether to accept or reject the candidate by solving

$$E(a) = p(t_H)\pi_R(a|S[t_H]) - (1 - p(t_H))\pi_R(a|S[t_L])$$

and comparing it to

$$E(r) = p(t_H)\pi_R(r|S[t_H]) - (1 - p(t_H))\pi_R(r|S[t_L]).$$

The higher absolute value will result in the choice of one action over the other. Given the monotonicity condition of these functions and this preference ordering of the receiver, the choice of action will be determined by the likelihood of the sender being a high type, or a high quality humanistic leader, in the context of the twelve variables of the April² Framework. This likelihood is the probability coefficient, which we estimate through the instrumentality of the Bayesian Networks (Ben-Gal, 2007), using the twelve variables of the April² Framework (Table 1) as the key underlying explanatory variables of the multiple causality construct.

2. Methodology

To infer the HLT coefficient as a dependent variable from the multiple causality structure around the twelve variables of the April² Framework, data had to be collected in a way which would satisfy the following conditions: (1) consistency with the underlying theory behind each of the variables; and (2) sufficient measurability for constructing a Bayesian Network. In order to fulfil these conditions, we have developed a Likert scale questionnaire, illustrated in Table 2. The questionnaire was tested for reliability, with a Cronbach alpha coefficient of 0.837 reported, leading us to accept the questionnaire as an adequate measurement tool for the purpose considered.

Table 2. Likert scale questionnaire

	Question	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1	I am well aware of my emotions and feel that I can control them.					
2	I am able to convey my thoughts, views, perspectives and feelings in a way that is easily understood by others.					
3	I seek sufficient factual evidence to my assumptions before acting them.					
4	I have a good life balance and feel in harmony with my physical, mental and spiritual self.					
5	I know that I believe in and act according to my beliefs.					
6	I note that I often behave towards others in ways similar to those that certain significant people from my past used to behave towards me.					
7	I feel sincere empathy for other people experiencing pain or emotional distress and try to act to relieve some or all of that pain or distress.					
8	I have a strong sense of responsibility for my actions, not because I fear retribution, but because I feel it is the right (moral) thing to do.					
9	I feel like I am generally in control of my life and can achieve many things if I set my mind to it.					
10	I am fairly comfortable living in uncertain world and don't always need a clear cut instruction to make sound decisions.					
11	In most situations I tend to act on what I feel is the right thing to do.					
12	I feel strong sense of connection to society and live in harmony with my circle of friends, family, colleagues.					

The questionnaire was distributed via Intranet to current graduate management students of the UCT Graduate School of Business. The responses were then combined with data from previous research (April and April, 2007), gathered using the same questionnaire from the students of the school in the preceding year, in order to construct probability distributions around each of the twelve variables as nodes in the Bayesian Network, and subsequently determine causal interdependencies amongst them. The range of scores was consistent with the sample from previous research (April and April, 2007).

Further, given that the model suggested is an empirical-based inference about the causal structure of the April² Framework, a key question had to be answered, which can broken down into two parts: (1) is there a significant multiple relationship between the twelve seeds of influence on individual core values, as specified by the April² Framework; and (2) if there is one, what does it look like? The question addresses the mathematical structure of the model with respect to the key variables, by asking if a meaningful Bayesian Network can be constructed out of these variables so that there is a clear set of conditional interdependencies among them, and what direction these interdependencies will take? In other words, which variables will constitute parent nodes, which will be child nodes, and which subsets of variables may collapse onto one or few lead variables. Essentially, given the way these variables have been defined by academia and measured by the selected instruments, is there a significant structure of multiple relationships amongst them? These questions, which essentially allow or disallow one to construct the required predictive inference model, can be stated as the following hypotheses.

H1: X_i has no significant predictive power over Y_j.

In the hypothesis Y_j is a non-empty set of different seeds of core influence of the April² Framework, from the total of twelve seeds taken one at a time, as a dependent variable; and X_i is a non-empty set of all the possible combinations of all the seeds of core influence other than *j*, taken as a vector of explanatory variable(s), with the degree and direction of predictive influence derived from the fitted equations. Stated this way, the hypothesis claims that for every *i* and *j*, there is a functional relationship of the form $y_j = f(x_i, \varepsilon)$, where $y_j \in Yj, x_i \in Xi$ and ε is a stochastic error term of the fitted equation.

H2: The latent HLT coefficient is not significant in explaining the variability in the model so constructed.

H3: The constructed model does not follow a distribution significantly different from the true population distribution.

Rejection of the hypothesis 1 means that there is indeed a highly significant set of multiple relationships between the twelve variables of the April² Framework, with clearly identifiable predictive influences on each other. Rejection of the hypothesis 2 means that a HLT coefficient can indeed be inferred from this set of predictive influences. Rejection of hypothesis 3 means that the constructed prediction model is generalizable across the board. Hence, rejecting all three hypotheses implies that the twelve variables of the April² Framework, as measured by the statistically reliable questionnaire we constructed, provide a robust foundation for inferring the HLT coefficient, and serve as a measuring tool for the level of development of the candidates under the signalling game selection framework, and that such tool is applicable to a general population of management candidates.

We constructed discrete frequency distributions from the scores produced by the questionnaire, and used ordinary least squares regressions to determine the predictive influence of the twelve variables onto each other. We then fitted the structural equation model to infer the directions of causality, and hence formulate the relevant child-parent set of nodes with appropriate directional edges (Ben-Gal, 2007). The resultant functional relationships between the variables and the inferred leadership type coefficient were then used as the basis for the measurement model.

Out of the data sample, 81% was collected from the full-time and modular MBA students of the UCT Graduate School of Business, using the averages from the 1 (strongly disagree) to 5 (strongly agree) Likert scale scores produced by these students as a part of their Communication, Learning and Leadership course (April and April, 2007), where they were asked to gather scores from their peers on the basis of those peers' perception about the level of development of the students on each one of the twelve seeds of core influence. 19% of the data was sampled from the non-MBA students of the UCT Graduate School of Business, using the questionnaire on-line via the Intranet of the school. Once the data was collected and sorted, the basic descriptive statistics and the correlation matrix were then analysed to get the preliminary feel for the general fit of the data and the overall strength of associative tendencies between the twelve variables. The distribution of the data was analysed using the Q-Q plots in order to determine how robust the constructed measurement model would be, based on how close to normal the distribution of the gathered data was.

Factor analysis was performed in order to analyse the explanatory power of the twelve variables when looked at in conjunction with each other. A principal component extraction method was used to account for the multivariate nature of the data, and reported results were clustered under three main component groups based on the individual explanatory power of each individual variable under each respective component. The groups with eigenvalues above one were included in the model and the cumulative explanatory power of the included groups was determined, with the groups with higher eigenvalues ranked above the groups with lower eigenvalues in explanatory power. Groups with eigenvalues below one were discarded as having, individually, no statistically significant explanatory power of the variability in the data.

Following the derivation of the main cluster groups and noting their cumulative explanatory power, we conducted a pairwise multiple regression analysis, modelling each one of the twelve variables of April² Framework as a dependent variable with the other eleven variables as explanatory variables. This was done in order to determine the strength and direction of the predictive power of the twelve variables onto each other, in order to establish whether the multiple causality network could be built out of them. Each of the resulting twelve functional relationships was analysed, with the focus on the significance and direction of the coefficients of each of the explanatory variables on the respective dependent variable.

Finally, we fitted the direct causality model, where the latent HLT variable was inferred from the multiple causality between the twelve seeds of core influence, based on the multiple regression models described. We analysed the goodness of fit statistics to determine the generalizability and refitted the model several times to improve it. We then constructed a structural equations model, to infer the HLT coefficient from the three main cluster groups produced by the principal component analysis. It was inferred as the latent variable in the model on the basis of the explanatory power of the individual variables forming each of the three main component cluster groups. We then used the resultant functional relationships to construct the Bayesian network as a measurement model, based on the multiple causality relationship produced by these structural equations.

3. Findings

We have obtained a sample of 151 observations with twelve scores (one for each variable) per respondent, giving a total of 1812 data points. All the respondents were graduate management students at UCT Graduate School of Business. Basic descriptive statistics (Table 3) revealed fairly densely distributed data, and a Q-Q plots test for normality confirmed this observation, leading us to conclude that the twelve variables are approximately normally distributed.

Table 3. Descriptive statistics

Variable	Mean	Std. dev	N
EM	3.73	0.69	151
CL	3.75	0.65	151
MM	3.52	0.59	151
LB	3.31	0.92	151
AUT	4.11	0.62	151
TRF	3.13	0.83	151
COM	3.86	0.74	151
ACC	4.13	0.63	151
LOC	3.91	0.63	151
AU	3.58	0.67	151
ETH	4.16	0.55	151
SCN	3.84	0.77	151

We proceeded to examine the closeness of association. Strong pairwise correlations were found among most of the variables (Table 4). Out of the total of 66 pairings, 53 have significant correlation at the 1% level of significance, and 10 have significant correlation at the 5% level. Thus, in general, an individual who scores higher on some combination of the twelve variables can be expected to score higher on the others as well. This is in line with theoretical expectation, as the twelve variables are defined in a way that presupposes that in conjunction they reflect the level of humanistic leadership capabilities of an individual.

Table 4. Correlation matrix

Variable	EM	CL	MM	LB	AUT	TRF	COM	ACC	LOC	AU	ETH
CL	.491**										
MM	.255**	.438**									
LB	0.06	.161*	.296**								
AUT	.167*	.423**	.536**	.404**							
TRF	0.16	.244**	.482**	.377**	.284**						
COM	.328**	.474**	.391**	.187*	.446**	.186*					
ACC	.279**	.407**	.479**	.299**	.588**	.184*	.550**				
LOC	0.051	.249**	.234**	.223**	.323**	.241**	.179*	.378**			
AU	.196*	.161*	.400**	.275**	.337**	.208*	.360**	.313**	.297**		
ETH	.280**	.252**	.321**	.322**	.419**	.263**	.329**	.512**	.210**	.278**	
SCN	.234**	.285**	.250**	.471**	.325**	0.143	.502**	.382**	.227**	.338**	.304**
**Correlation is significant at the 0.01 level (2-tailed).											
* Correlation is significant at the 0.05 level (2-tailed).											

We then clustered correlated variables under the main uncorrelated groups, in order to explain the overall variability. Three main components were extracted using the principle component analysis method (Table 5). In addition, the cluster of the twelve variables has been constructed in three-dimensional rotated spaces (Figure 3), to further test the evidence in favor of these three components. Both methods confirm that the variables are tightly clustered under the three components, which adds additional confidence to the conclusion that the constructed components represent major latent groups and should serve well as the key input-output vectors for generation of the HLT coefficient.

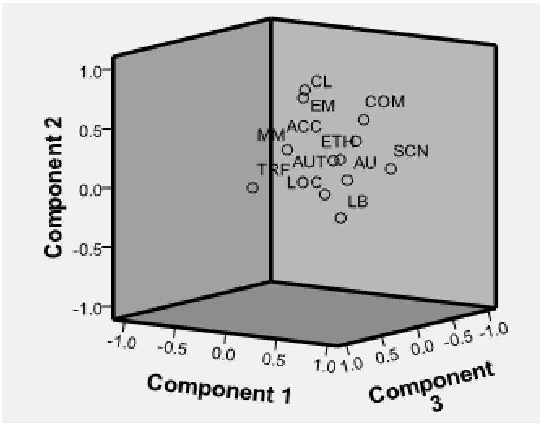

Fig. 2. Principal component extraction 3D plot

Table 5. Principal component analysis

Variable	Comp 1	Comp 2	Comp 3
EM	0.456	-0.628	0.162
CL	0.63	-0.473	0.239
MM	0.708	0.055	0.404
LB	0.543	0.528	-0.115
AUT	0.744	0.113	0.021
TRF	0.489	0.343	0.624
COM	0.695	-0.322	-0.257
ACC	0.761	-0.086	-0.166
LOC	0.472	0.302	-0.004
AU	0.559	0.185	-0.166
ETH	0.617	0.035	-0.083
SCN	0.608	0.049	-0.522

Having established the robustness of the components, we analysed the division of the explanatory power over the total variability among them (Table 6). The second and third components explained 10.6% and 8.7% of the variability respectively. Combined, the three components explained 57% of the overall variability, while the remaining 43% are explained by nine other components marked 4 to 12, but since their eigenvalues are below 1 they can not be considered as significant predictors of the output coefficient and have, therefore, been excluded from the final model.

Table 6. Total variance explained

Comp.	Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of var.	Cum %	Total	% of var.	Cum %	Total	% of var.	Cum %
1	4.542	37.85	37.85	4.542	37.85	37.85	2.921	24.34	24.34
2	1.271	10.59	48.45	1.271	10.59	48.45	2.147	17.89	42.24
3	1.05	8.749	57.19	1.05	8.749	57.19	1.795	14.96	57.19
4	0.917	7.639	64.83						
5	0.817	6.809	71.64						
6	0.765	6.375	78.02						
7	0.736	6.132	84.15						
8	0.542	4.52	88.67						
9	0.401	3.34	92.01						
10	0.376	3.135	95.15						
11	0.33	2.754	97.9						
12	0.252	2.101	100						

To add an extra layer of confidence in the explanatory power of the extracted cluster groups we performed the analysis of the statistical significance of each individual variable and found all of the twelve variables to be highly statistically significant (Table 7). According to the reported result (Table 7), we can be 95% confident to find the mean values for each of the twelve variables falling within these narrow intervals.

Table 7. One-sample test for parameter significance

Variable	t	Df	p-value	Mean diff.	95% CI	
					Lower	Upper
EM	66.68	150	0.00000	3.7346342	3.623967	3.845301
CL	70.372	150	0.00000	3.7457416	3.640568	3.850915
MM	72.854	150	0.00000	3.5217207	3.426207	3.617235
LB	44.473	150	0.00000	3.3127244	3.165543	3.459906
AUT	81.894	150	0.00000	4.1142042	4.014938	4.21347
TRF	46.137	150	0.00000	3.1321624	2.998022	3.266303
COM	64.055	150	0.00000	3.8556659	3.73673	3.974602
ACC	81.096	150	0.00000	4.1286939	4.028098	4.22929
LOC	76.269	150	0.00000	3.9072719	3.806046	4.008498
AU	65.557	150	0.00000	3.5799614	3.472061	3.687862
ETH	92.996	150	0.00000	4.1631365	4.074682	4.251591
SCN	61.148	150	0.00000	3.841238	3.717114	3.965362

Based on these results, we concluded that the sample data on the twelve variables has a highly significant explanatory power, and individual variables so constructed have significant predictive influence over the humanistic leadership characteristics of individual candidates. Component analysis has identified three major categories under which the twelve variables form a dense cluster. These three components serve as the key latent variables, through which the twelve core factors of individual humanistic leadership produce the final output parameter, the HLT coefficient. These conclusions are also in line with the robustness of the measurement tool reported earlier, and give us confidence in employing the twelve variables for the construction of the multiple causality networks for estimating the HLT coefficient through the three cluster groups.

Having established that the data is well distributed, we tested hypothesis 1 by fitting multiple regression equations and examining the functional pairings to determine the relative predictive influence of the variables onto each other. All twelve models are highly statistically significant (Table 8), and the hypothesis is rejected at below 0.1% level of significance. We conclude that there is a high degree of causal interdependency among the twelve variables. This result is important, as it provides a high degree of confidence in the multiple causality network model, based on the twelve variables as key drivers of the final output. In addition, individual predictive influences of the variables onto each other presents a whole body of new findings by itself, which should be thoroughly explored in separate research.

Table 8. Summary of multiple regression models

Depend. var.	R-squared	df	F-stat.	P-value
EM	0.318	150	5.89	0.00000
CL	0.458	150	10.68	0.00000
MM	0.504	150	12.84	0.00000
LB	0.405	150	8.58	0.00000
AUT	0.507	150	12.97	0.00000
TRF	0.348	150	6.73	0.00000
COM	0.505	150	12.87	0.00000
ACC	0.564	150	16.32	0.00000
AUT	0.304	150	5.53	0.00000
ETH	0.342	150	6.56	0.00000
SCN	0.431	150	9.56	0.00000
LOC	0.253	150	4.28	0.00000

Proceeding, we first fitted a direct causal relationship between the twelve explanatory variables and the HLT coefficient using Maximum Likelihood (ML). Thirteen iterations were performed with the adjusted goodness of fit index reported at 0.79, and the p-values of the Chi-Squared statistics insignificant with p-values less than 0.000. The test statistic for the close fit was also insignificant, with the p-values well below 0.05 (0.000). These results suggested that the model so specified does not provide the best fit for estimating HLT, as some of the direct interactions between the fitted variables should not be in the model. Highly insignificant p-values for the Chi-Square statistics indicated that some of the parameters in the data-based model differ significantly across populations.

A modification indices diagnostic was performed to determine which casual paths should be included, in order to improve the fit. Chi-Squared statistics could be significantly reduced by fitting the causal paths in between the listed pairs of variables (Table 9). A structural equation model was warranted for inferring the HLT via the group of latent variables derived from additional paths of causality between the suggested pairings and, consequently, improvement of the fit. In addition, latent variables usually eliminate the measurement error, and allows for derivation of coefficients with greater predictive validity (Dion, 2008).

Table 9. Modification indices suggestion

Between	And	Decrease in Chi-Square	New estimate
CL	EM	20.4	0.13
TRF	MM	16.4	0.12
TRF	LB	8.2	0.15
ACC	TRF	8.9	-0.09
SCN	LB	13.7	0.17
SCN	COM	11.3	0.11

In order to ensure preservation of the theoretical assumptions, we inferred the key latent variables and predicted the HLT coefficient via the Maximum Likelihood method, using the key coefficients under the three major factor groups derived via the principal component analysis. Components with eigenvalues greater than one were selected to represent the main factors for inferring the HLT coefficient. The resulting system produced a model with significantly lower Chi-Square, and increased the adjusted goodness of fit from 0.79 to 0.82. However, the p-values remained insignificant and there was, thus, strong evidence to suggest that the data set does not follow the theoretical distribution.

Therefore, hypothesis 3 could not be rejected and we concluded that that the distribution of the data, upon which the model is built, does not approximate the population distribution. However, given the purpose of building a measurement model designed to show the relationship between the HLT coefficient and its root drivers, it is not sufficient to focus on the goodness of fit alone. Reliability of individual factors must be considered. Factor coefficients above 0.7 are adequate, while coefficients above 0.8 are very good, and excellent if they are above 0.9. The three factors generated by the model have coefficients of 0.96 (factor 1), 0.82 (factor 2) and 0.72 (factor 3), together explaining 57% of the variability, while the structure of the model is congruent with the component analysis reported above. Therefore, the factors are highly reliable and the fitted model provides robust representation of the theoretical construct, at least in its predictive influence over the HLT coefficient on the basis of the responses to the constructed questionnaire.

This was also confirmed by the covariance matrix of latent variables (Table 10), where the strong associative tendency of the latent variables further supports the evidence of strong predictive power of the fitted model in respect of the HLT coefficient. Thus, hypothesis 2 was rejected and we conclude that the latent HLT coefficient has significant explanatory power over the underlying variables of the constructed model.

Table 10. Covariance matrix of latent variables

	Factor 1	Factor 2	Factor 3	HLT
Factor 1	1.00			
Factor 2	0.78	1.00		
Factor 3	0.70	0.60	1.00	
HLT	0.96	0.82	0.73	1.00

The structural equations model (Figure 3) represents the functional relationships indicated by the coefficients in the individual variables. The HLT explains 96%, 82% and 73% of factor 1, 2, and 3 respectively. The factor values are, in turn, attributable to the distributions of the various scores of the twelve seeds of influence on individual core values, measured by the Likert scale type questionnaire. Together, the three factors explain 57% of the variability in the underlying variables, while the remaining variability is explained by the excluded factors (Table 6).

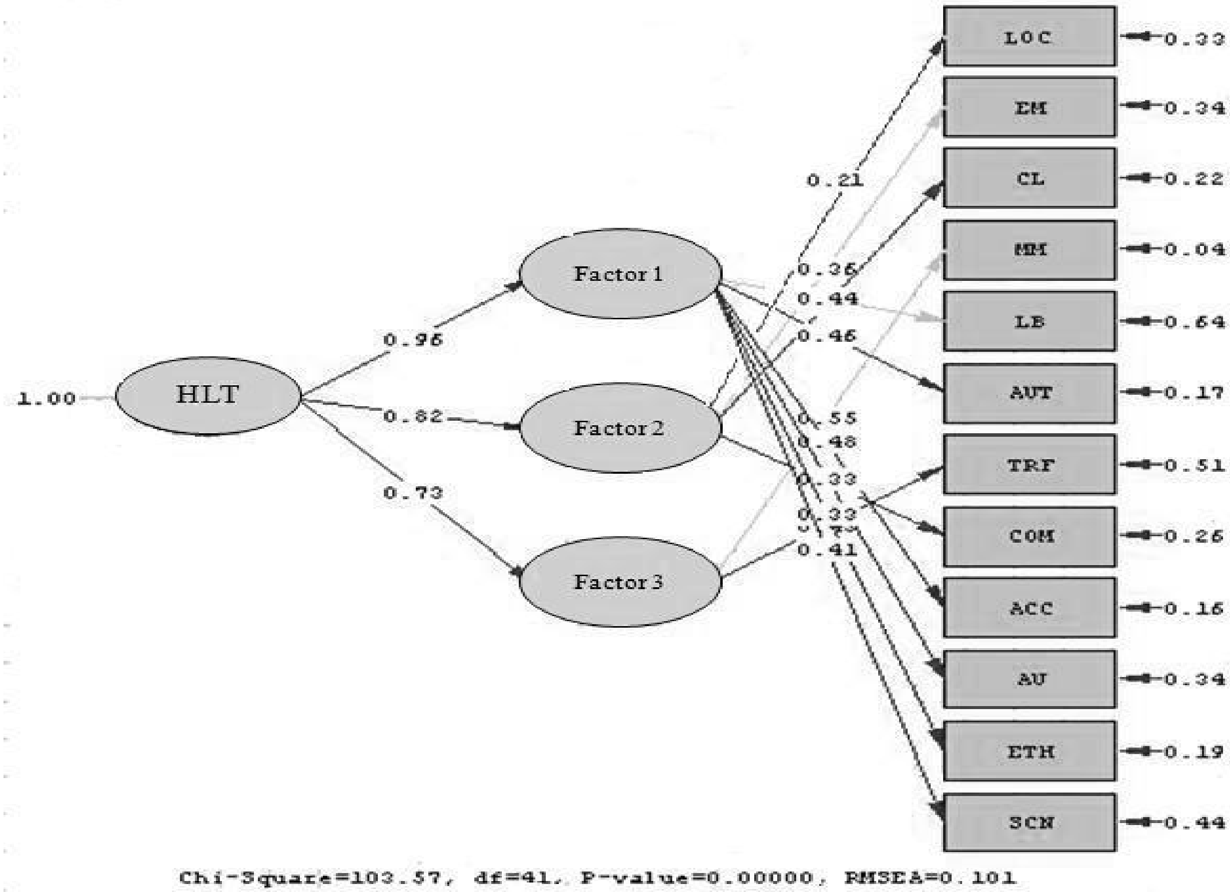

Fig. 3. Structural equations model of multiple causality network

The measurement model reported in the previous Section has been used to construct a Bayesian network (BN). The BN is a type of graph structure, in which the nodes represent random variables and connectors represent conditional probabilistic dependencies amongst these variables (Ben-Gal, 2007). The functional forms produced by the measurement model provide the basis for constructing these conditional probabilities.

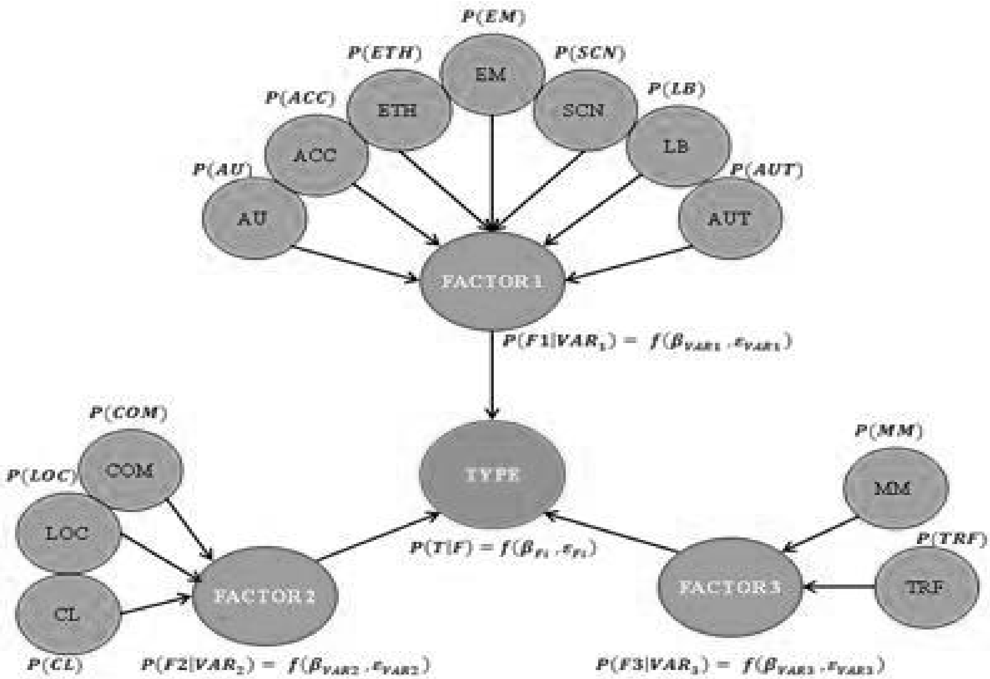

Fig. 4. Bayesian network model for measurement of the HLT score

We interpret this model as follows. The underlying variables (seeds) serve as the conditions for the posterior probabilities of the three main factors, which in turn serve as the conditions for the posterior probability of the HLT coefficient. Since the HLT coefficient is in essence the probability of a high HLT, the resulting posterior probability is effectively the measure of the probability of the respondent possessing strong humanistic leadership qualities. The values closer to 1 give the Receiver (see the measurement model) an indication of the probability of a particular candidate having high humanistic leadership capabilities and thus, more confidence in selecting that candidate for a position, where those are required.

Conclusion

We have presented an analytical model for selection of managers on the basis of humanistic leadership capabilities, utilising a game theoretic framework with HLT, based on the twelve underlying variables as the key input coefficient. We discovered strong predictive influence of the key underlying variables on each other, thus confirming the theoretical foundation of the April² Framework. This allowed us to make a robust inference of the HLT coefficient and propose a probability measurement model that could be used to estimate the likelihood of a particular candidate having high humanistic leadership capabilities, subject to the same metric (questionnaire) being employed for assessing these capabilities.

We have also found that our measurement model to be non-generalized. However, given a very highly significant set of mutual predictive influences of the underlying variables and high explanatory power of the resultant inference model for the HLT coefficient, we are lead to conclude, that this problem is most likely a result of a poor sample, rather than of some flaw in the theoretical conjecture of the proposed model. In light of that, we strongly suggest that the strategy for future research should be to refit the model with data based on a much larger sample, drawn from a wider population and combine it with a thorough examination of the individual functional forms between the twelve underlying variables to uncover the nature of the predictive relationships between them and thus rearrange the structure in order to provide a better fit and, consequently, make the model more generalizable across various populations of managers.

References

1. Allingham, M. (2002). Choice Theory: A Very Short Introduction, Oxford University Press, Oxford.
2. April, K.A. (1999). Leading through communication and dialogue, *Leadership and Organization Development Journal*, Vol. 20, No. 5, 231-241.
3. April, K.A. and April, A.R. (2007). Growing leaders in emergent markets: leadership enhancement in the New South Africa, *Journal of Management Education*, Vol. 31, No. 2, 214-244.
4. April, K.A. & Shockley, M. (2007). Diversity in Africa: the Coming of Age of a Continent, Palgrave Macmillan, Basingstoke.
5. Argyris, C. & Schon, D.A. (1996). Organizational Learning II: Theory, Method and Practice, Addison-Wesley, Boston, MA.
6. Armstrong, M. (2006). *Recruitment* and Selection: a Handbook of Human Resource Management Practices, 10th ed, Kogan Page, Philadelphia, PA.
7. Bass, B.M. (1990). From transactional to transformational leadership: learning to share the vision, *Organizational Dynamics*, Vol. 18, No. 3, 19-31.
8. Bass, B. and Avolio, B. (1994). *Improving Organisational Effectiveness through Transformational Leadership*, Sage Publications, Thousand Oaks, CA.
9. Ben-Gal, I. (2007). Bayesian Networks, In F. Ruggeri, F. Faltin & R. Kenett (Eds.), *Encyclopedia of Statistics in Quality and Reliability*, Wiley and Sons, New York, NY.
10. Bicchieri, C. (2003). Rationality and Game Theory, The Handbook of Rationality, Oxford University Press, Oxford.
11. Block, P. (1993). Stewardship: Choosing Service Over Self-Interest, Berret-Koehler, San Francisco.
12. Boyatzis, R. and McKee, A. (2005). Resonant Leadership, Harvard Business School Press, Boston, MA.
13. Bradberry, T. and Greaves, J. (2005). Emotional Intelligence Quick Book, Fireside, New York, NY.
14. Burns, J.M. (1978), *Leadership*, Harper, New York, NY.
15. Dolan, S.L. and Raich, M. (2009). The great transformation in business and society, *Cross Cultural Management: an International Journal*, Vol. 16, No. 2, 121-130.
16. Dion, P. (2008). Interpreting structural equation modeling results: a reply to Martin and Cullen, *Journal of Business Ethics*, Vol. 83, No. 3, 365-368.
17. Drucker, P.F. (1954). The Practice of Management, Harper and Row, New York, NY.
18. Dutta, P. (1999). Strategies and Games, MIT Press, Boston, MA.
19. Fudenberg, D. and Tirole, J. (1991). Perfect bayesian equilibrium and sequential equilibrium, *Journal of Economic Theory*, Vol. 53, 236-260.
20. Gardner, H. (1999). Intelligence Reframed: Multiple Intelligences for the 21st Century, Basic Books, New York.
21. George, B., Sims, P., McLean, A.N. and Mayer, D. (2007). Discovering your authentic leadership, *Harvard Business Review*, Vol. 85, No. 2, 129-138.

22. Gharajedaghi, J. (2006). Systems Thinking: Managing Complexity – a Platform for Designing Business Architecture, Butterworth-Heinemann, Burlington, MA.
23. Gibbons, R. (1992). A Primer in Game Theory, Pearson Education Limited, Essex.
24. Giberson, T.R., Resick, C.J. and Dickson, M.W. (2005). Embedding leader characteristics: an examination of personality and values in organizations, *Journal of Applied Psychology*, Vol. 90, No. 5, 1002-1010.
25. Goleman, D. (1995). Emotional Intelligence, Bantam Dell, New York, NY.
26. Gorelick, C., Milton, N. and April, K. (2004). Performance Through Learning: Knowledge Management in Practice, Elsevier Butterworth-Heinemann, Burlington, MA.
27. Guastello, S.J. (2007). Non-linear dynamics and leadership emergence, *The Leadership Quarterly*, Vol. 18, No. 4, 357-369.
28. Humphreys, J.H. and Walter, O.E. (2003). Nothing new under the sun: transformational leadership from historical perspective, *Management Decision*, Vol. 41, No. 1, 85-95.
29. Jordan, J. (2009). A social cognition framework for examining moral awareness in managers and academics, *Journal of Business Ethics*, Vol. 84, No. 3, 237-258.
30. Kreps, D. and Wilson, R. (1982). Sequential equilibrium, *Econometrica*, Vol. 50 , No. 4, 863-894.
31. Klenke, K. (2007). Authentic leadership: a self, leader, and spiritual identity perspective, *International Journal of Leadership Studies*, Vol. 3, No. 1, 68-97.
32. Kuper, L. (2008). Ethics – the Leadership Edge, Zebra Press, Cape Town.
33. Meglino, B. (1996). Work Values, In L. Peters, S. Youngblood and C. Greer (Eds.), *The Blackwell Encyclopedic Dictionary of Human Resource Management*, Blackwell, Oxford.
34. Meglino, B.M. and Ravlin, E.C. (1998). Values in organisations, *Journal of Management*, Vol. 24, No. 3, 351-389.
35. Nel, C. (2007). Leadership: the primary driver in high performance organisations, *Management Today*, October 2007, 24-26.
36. O'Reilly, C. and Chatman, J.A. (1996). Culture as social control: corporations, cults and commitment, In B.M. Staw and L.L. Cummings (Eds.). *Research in Organisational Behaviour*, Vol. 18, pp. 157-200, JAI Press, Stamford, CT.
37. Peterson, B. (2004). Cultural Intelligence: a Guide to Working with People from Other Cultures, Intercultural Press, Yarmouth.
38. Potgieter, A., April, K. & Bishop, J. (2005). Complex Adaptive Enterprises, in M. Khosrow-Pour (Ed.), *Encyclopaedia of Information Science and Technology*, Vol. 1, Hershey, PA: Idea Group Reference, pp. 475-480.
39. Potgieter, A., April, K.A., Cooke, R.J.E. and Osunmakinde, I.O. (2009). Temporality in Link Prediction: Understanding Social Complexity, *Emergence: Complexity & Organization (E: CO)*, Vol. 11, No. 1, pp. 69-83.
40. Ravlin, E. (1995). Values, In N.I. Nicholson (Ed.), *The Blackwell Ecnyclopedic Dictionary of Organisational Behaviour*, Blackwell Publishing, Oxford, pp. 598-599.
41. Rokeach, M. (1973). The Nature of Human Values, Free Press, New York, NY.
42. Rhode, D.L. (Ed.) (2006). Moral Leadership: The Theory and Practice of Power, Judgment and Policy, Jossey-Bass, San Francisco, CA.
43. Saloner, G. (1991). Modelling, game theory and strategic management, *Stragtegic Management Journal*, Vol. 12, No. 2, 119-136.
44. Schön, D. (1983). The Reflective Practitioner, Basic Books, New York.
45. Schneider, M. and Somers, M. (2006). Organizations as complex adaptive systems: implications of complexity theory for leadership research, *The Leadership Quarterly*, Vol. 17, No. 4, 351-365.
46. Spence, M. (1973). Job market signalling, *The Quarterly Journal of Economics*, Vol. 87, No. 3, 355-374.
47. Von Neumann, J. and Morgenstern, O. (1944). Theory of Games of Economic Behaviour, Princeton University Press, Chicago, IL.
48. Waldrop, M.M. (1994). Complexity: the Emerging Science at the Edge of Order and Chaos, Simon and Schuster, New York, NY.