Bi-level Programming Model for Combining Motivation, Opportunity and Ability Factors in Knowledge Sharing

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Abstract

Motivation, Opportunity, and Ability (MOA) are three factors that influence employees' performance and have been accepted widely in the literature, but there is no agreement on the interactions between these three factors in shaping the performance. Therefore, proposing a model for connecting these factors to performance is interesting. All of the previous models are designed based on the regression analysis. This paper aims to apply mathematical programming in this issue for the first time. Knowledge sharing as a proper area and bi-level programming as an extendable framework selected for developing such a model. We implemented our model in General Algebraic Modeling System (GAMS) with randomly generated data for 100 employees. Outputs of optimization model analyzed by SPSS regression analysis. Based on the results obtained in the statistical analysis, predicted performance by the proposed bi-level programming model has a behavior close to the results reported by the previous empirical research. Future research can test the proposed model using empirical data in comparison to currently available regression models.

Keywords:
MOA Framework, Bi-level Programming, Knowledge Sharing, Game Theory

1. Introduction

The combination of motivation, opportunity, and ability (MOA) is an accepted framework for analyzing the employee performance. Based on this framework, employee performance is a function of ability, motivation, and opportunity (Boselie et al., 2005; Boxall & Purcell, 2008). However, the relationship between these factors in shaping the employee performance is under discussion (Collings & Mellahi, 2009; Siemsen et al., 2008; Jiang et al., 2012). This paper aims to propose a new mathematical model based on bi-level programming and game theory to shed lights on the interactions between these three factors.

Bi-level programming allows us to model the autonomous behavior of employee that is common in nowadays organizations where improvement in employees' performance could not be mandatory because of its complex and vague nature. People decide to share knowledge on their own utilities. Therefore, knowledge sharing is an example of duty that cannot be forced by managers (Huysman & Wit, 2004). Some studies have been done on MOA factors affecting the knowledge sharing behavior of employees (Afrazeh et al., 2003; Minbaeva, 2013; Foss et al., 2015). We also developed our model in this context.

Game theory not only is applicable for modeling the interaction of employees in knowledge sharing but also has been used for analyzing the interaction between the organization and its' employees. While the knowledge sharing game between employees usually considered as a simultaneous game and the problem is finding Nash equilibrium, the knowledge sharing game between the organization and its' employees is a sequential game and has a Stackelberg equilibrium. Bi-level Programming can model both of these games simultaneously under well conditions (Dutang, 2013).

In section 2 theoretical foundations and recent progress in the literature of three subjects including MOA framework, Bi-level programming, and contributions of game theory in knowledge sharing have been explored. Then, in section 3, a mathematical representation of MOA framework using bi-level programming and in section 4, numerical results of this model have been proposed. Finally, in section 5, research findings and also directions for future studies have been provided.

2. Background

2.1 Ability-Motivation-Opportunity Framework

Performance can be defined as a set of behaviors related to the organizational purpose (Campbell et al. 1993). In this context, there is a reach literature on factors affecting employee performance (Collings & Mellahi, 2009). Based on Vroom (1964), performance is a function of ability and motivation. These two factors are accepted popularly in management literature (Afrazeh et al., 2003). Effects of the contextual factors on the performance, have been recognized gradually and the opportunity factor together with two previously identified factors resulted in the MOA framework (Blumberg & Pringle, 1982; Campbell et al., 1993).
These three factors shaped the contemporary dominant MOA framework in which the employee performance is the function of ability, motivation, and opportunity (Boselie et al. 2005; Boxall & Purcell 2008). However, the relationship between these factors in shaping the employee performance is under discussion (Collings & Mellahi 2009; Siemsen et al. 2008; Jiang et al. 2012). Siemsen et al. (2008) examined various relations between these three factors and proposed the idea of the constraining-factor.
Want-Can-May framework also is another version of this framework that is applied by Afrazeh et al. (2003) for classification of human resource productivity factors in knowledge sharing. Other applications of MOA framework in knowledge sharing analysis can be seen in works by Minbaeva (2013) and Foss et al. (2015).

2.2 Bi-level Programming

Bi-level programming is a general representation of Stackelberg game between a leader and a follower. This model can be used to explain the relationship between organization as leader and employees as followers (Berr, 2011). The general formulation of this problem is as follow (Colson et al., 2005):

$$\begin{aligned} \min_{x \in X, y \in Y} \quad & F(x, y) \\ s.t. \quad & G(x, y) \leq 0, \\ & \min_{y \in Y} \quad f(x, y) \\ & \quad s.t. \quad g(x, y) \leq 0, \end{aligned}$$

So that $F(x, y)$ and $f(x, y)$ are the objective functions of the leader (upper-level) and the follower (lower-level). Similarly, $G(x, y)$ and $g(x, y)$ are the leader constraints and the follower constraints, respectively. Also, decision variables of the leader and the follower are $x \in \Re^{n_1}$ and $y \in \Re^{n_2}$, respectively.
One way to solve bi-level programming is to reduce two levels into one level by writing Karush–Kuhn–Tucker (KKT) conditions for follower problem (Dempe, 2003). If there were more than one follower, then the followers may engage in the simultaneous game and tend to the Nash Equilibrium. In this situation, and under conditions of convexity in followers' model, Dutang (2013) proved that KKT conditions for followers' problem lead to the Nash Equilibrium of the game.

2.3 Knowledge Sharing and Game Theory

Knowledge sharing is an important process enabling other knowledge management processes and preventing knowledge loss (Borges 2013; Kuah, Wong, & Tiwari 2013). Also, several empirical studies confirmed knowledge sharing effects on Innovation capacity (Sáenz, Aramburu, & Blanco, 2012) and organizational performance (Choi, Lee & Yoo, 2010; Du, Ai, & Ren, 2007). The importance of the subject drives researchers to conduct several literature reviews on knowledge sharing (e.g., Witherspoon et al., 2013; Ipe, 2003; Wang & Noe 2010; Sharma & Bhattacharya 2013).

There are two classes of knowledge sharing based on the two well-known types of knowledge: explicit knowledge and tacit knowledge (Hau et al., 2013; Razmerita et al., 2016). One is related to information systems, knowledge repositories, and codification strategy and the other is related to individuals and personalization strategy. Codification and personalization are two familiar types of strategies in knowledge management practice (Choi, Poon, and Davis, 2008). Codification is more related to technology and explicit knowledge and referred to the system strategy. Whereas, personalization is about human aspect and tacit knowledge and referred to the human strategy (Choi and Lee, 2002). People share knowledge differently in these two situations (Witherspoon et al., 2013).

This classification is important so that some researchers develop two scales for knowledge sharing based on tacit and explicit knowledge (Oliveria & Nodari 2015). Also, some researchers restrict their study on one of these two types of knowledge (Lee & Ahn, 2007). Sharing explicit knowledge is more observable than sharing tacit knowledge (Nan, 2008). This paper focused on explicit knowledge sharing. Therefore, knowledge sharing in this paper means the process of sharing explicit knowledge in knowledge repositories.

Organizational knowledge has the characteristics of public good and knowledge sharing among employees is an especial type of social dilemma. The case in which people tend to show free-riding behavior and dominant strategy is not-contributing or hoarding knowledge (Cabrera & Cabrera 2002). In this situation, individual rationality make collective irrationality. The social dilemma can be represented as an n-person prisoner's dilemma. Prisoner's dilemma is one of the most discussed models in the game theory explaining how two prisoners decide to defect each other while cooperation is more beneficial for both of them. However, repetition of the play could change the equilibrium of the prisoner's dilemma to cooperation (Zhao, Xu and Liu 2009; Hao and Yanmei 2009).

Restructuring the payoff function, increasing the efficacy of contributions, increasing group identity and personal responsibility are three types of solutions for the social dilemma and consequently for knowledge sharing dilemma (Cabrera & Cabrera, 2002). Most of the literature on knowledge sharing dilemma focused on reward systems, especially on the principal-agent model (Nan, 2008; Lee & Ahn, 2007; Wang & Shao, 2012) that is a type of simplified bi-level programming. Some researchers tried to explore components of payoff function for knowledge workers in knowledge sharing game (Zhao, Xu, and Liu 2009; Hao and Yanmei, 2009; Sato and Namatme, 2001; Levitt et al., 2012; Levitt et al., 2013). Knowledge sharing game in the literature mostly considered as a simple 2-by-2 symmetric structure for this game (Chua, 2003; Samieh and Wahba, 2007; Ho, Hsu, and Oh, 2009). Some of them extend it to a repetitive game (Zhao, Xu, and Liu, 2009; Hao and Yanmei, 2009). However, the assumption of symmetric payoff function for employees is far from reality in very actual cases. Different needs and different knowledge states of employees may change their preferences and therefore their payoff functions. Analyzing asymmetric game and respecting individual differences are limited in the literature (Jully and Wakeland, 2008; Sato and Namatme, 2001; Nasr et al., 2015). Knowledge sharing game with continuous strategies also examined in some studies (Lee & Ahn, 2007; Bandyopadhyay & Pathak, 2007).

3. Model Development and Mathematical Formulation

This paper employed bi-level programming for examining MOA framework in the organization. Applying bilevel programming in modeling the behavior of employees could be interesting because it allows analyzing the interaction between managerial decisions and employee decisions. In this modeling, the managerial decisions could be examined in the upper-level problem and employees' decisions could be simulated in the lower-level problem.

These two problems could be considered as two mathematical programming models, separately. Each one has three main components: the objective function, a set of decision variables, and a set of constraint. These three components should be defined based on the reality and in accordance with modeling limits. This paper benefits from some findings of previous studies on the knowledge sharing analysis based on the game theory that tried to model some aspect of the behavior of employees through mathematics.

For simplicity, this paper supposed that there are not any decision for the organization as the leader in the upper-level problem. Therefore, the leader problem has not any constraint and just include an objective function that is equal to the aggregated performance of employees. Performance of each employee is defined as the percent of codified knowledge (PCK) by that employee.

The decision variable is the core element of the mathematical programming model. Objective function and constraints are dependent on decision variables. In the optimal solution, values for decision variables determined, so that decision maker reaches the best value for objective function without violating the constraints. Decision variables can be discrete such as the employee decide to share knowledge or to hoard knowledge or continuous as the amount of knowledge that employee decides to share or amount of time and efforts that employee spends in knowledge sharing process. In this paper, time and effort allocated to knowledge sharing activity for each employee have been defined as two continuous decision variables. Time and effort for each employee are limited to some extent. Therefore, two constraints used to set upper bound for these two variables, as formulated below:

$$t_i \le T\max(i),$$
$$e_i \le 10,$$

Upper bound for effort supposed to be 10 and upper bound for Tmax(i) supposed to be 100, to scale the problem.

PCK is the performance indicator of employee and also based on MOA framework, is a function of motivation, opportunity, and ability. Decision variables used to connect these three factors in the form of mathematical programming. In the proposed formulation, employee performance is the function of opportunity, ability and time and efforts of the employee. employee decide on time and effort based on external motivation, internal motivation, cost of time, cost of effort, and cost of losing knowledge formulated in the objective function. In addition, there are three constraints designed for determining the percent of codified knowledge (PCK) by each employee as a function of his (her) effort and time allocated to knowledge sharing activity and also his (her) opportunity and ability in this activity. This function is concave based on suggestions in the literature (e.g., Lee & Ahn, 2007) as formulated below:

$$PCK_i \le 0.217 \times e_i \times OA_i \times \ln(t_i + 1),$$
$$OA_i \le \lambda \times O_i + (1-\lambda) \times A_i,$$
$$OA_i \le \lambda \times A_i + (1-\lambda) \times O_i,$$

In which, 0.217 is a parameter for scaling PCK between 0 and 100. According to two constraints defined on OA_i, for $\lambda = 0.5$, OA_i is the average of ability and motivation of the employee and for $\lambda = 0$, OA_i is the minimum of two values indicating the ability and the motivation of the employee. The latter is consistent with the idea of constraining factor proposed by Siemsen et al. (2008).
The external motivation for an employee supposed to be linear in his (her) performance in sharing knowledge (PCK). There are three other components in the objective function, including the cost of time, the cost of effort, and the cost of losing the knowledge that is a convex quadratic function in PCK. The cost of time and the cost of effort are convex quadratic functions. The internal motivation reduces the cost of effort. For scaling objective function elements in a similar span, some correcting coefficients used in the formulation such as 0.1 in the cost of time and the cost of losing knowledge and 10 in the cost of effort.
The employee's problem formulated based on MOA framework and defining time and effort as main decisions of the employee. Integrated with the upper-level problem, resulted bi-level formulation is as follow:

$$\max \quad U_O = \sum_i PCK_i$$

$$\max \quad U_i = EM_i \times PCK_i - V_t \times \left(0.1 \times t_i\right)^2 - V_e \times \left(\frac{10 \times e_i}{IM_i}\right)^2 - V_m \times \left(0.1 \times PCK_i\right)^2$$

$$s.t.$$
$$t_i \le T\max(i),$$
$$e_i \le 10,$$
$$PCK_i \le 0.217 \times e_i \times OA_i \times \ln(t_i + 1),$$
$$OA_i \le \lambda \times O_i + (1-\lambda) \times A_i,$$
$$OA_i \le \lambda \times A_i + (1-\lambda) \times O_i,$$

Variables and parameters of this model have been described in table 1.

Table 1. Parameters and Variables

Symbol	Definition	Type
U_o	Utility function of organization as the leader in Bi-level Programming	Derived Variable
U_i	Utility function of employee i as the follower in Bi-level Programming	Derived Variable
e_i	Effort of employee i in codification of his(her) knowledge (Between 0 and 10)	Decision Variable
t_i	Time allocated to codification for employee i (Between 0 and Tmax(i))	Decision Variable
PCK_i	Percent of knowledge that is codified by employee i (Between 0 and 100)	Derived Variable
V_{ei}	Cost of effort coefficient for employee i (Between 0 and 1)	Parameter
V_{ti}	Cost of time coefficient for employee i (Between 0 and 1)	Parameter
V_{mi}	Cost of losing knowledge for employee i (Between 0 and 1)	Parameter
$T\max(i)$	Maximum time available for employee i (Between 0 and 100)	Parameter
EM_i	External Motivation coefficient for employee i (Between 0 and 10)	Parameter
IM_i	Internal Motivation coefficient for employee i (Between 0 and 10)	Parameter
O_i	Opportunity of employee i in codification (Between 0 and 10)	Parameter
A_i	Ability of employee i in codification (Between 0 and 10)	Parameter
λ	Parameter for adjusting the interaction of Ability and Motivation (Between 0 and 0.5)	Parameter
OA_i	Interacting effect of Ability and Opportunity for employee i (Between 0 and 10)	Derived Parameter

4. Experiment Design and Numerical Results

Simulated data have been used to test the proposed model compared with other models in the literature. Firstly, random data have been generated for 100 employees. Then, the performance of each employee has been predicted by solving the proposed bi-level model optimally in five groups of 20 employees. Finally, the fitness of data has been analyzed for three regression models including linear model, multiplicative model, and constraining factor model.

100 employees' data have been generated using random function in Microsoft Excel. Random data generated between 3 and 10 for parameters including A, O, IM, and EM and between 0.3 and 1 for parameters including V_e, V_t, and V_m. The maximum time available ($T\max(i)$) supposed to be fix and equal to 100 for all employees. The following equation calculates the value of motivation (M) factor.

$$M_i = \left(IM_i + EM_i + 10 \times \left(\frac{3 - V_{ei} - V_{ti} - V_{mi}}{3} \right) \right) \Big/ 3$$

Bi-level model has been implemented in GAMS application and runs using Extended Mathematical Programming (EMP) syntax for bi-level programs developed by Kim and Ferris (2017) and BARON algorithm developed by Tawarmalani and Sahinidis (2005).

After solving the model for $\lambda = 0$ and $\lambda = 0.5$, we applied regression analysis using IBM SPSS software to compare the fitness of these two results in accordance with three popular regression model in MOA framework literature. These models include linear model, multiplicative model and constraining factor model that are showed in the following formulas, respectively:

$$PCK_i = \alpha_C + \alpha_M \times M_i + \alpha_O \times O_i + \alpha_A \times A_i + \varepsilon \qquad \text{(Linear Model)}$$

$$\begin{aligned} PCK_i = {} & \alpha_C + \alpha_M \times M_i + \alpha_O \times O_i + \alpha_A \times A_i + \alpha_{MO} \times M_i \times O_i + \\ & \alpha_{MA} \times M_i \times A_i + \alpha_{OA} \times O_i \times A_i + \alpha_{MOA} \times M_i \times O_i \times A_i + \varepsilon \end{aligned} \qquad \text{(Multiplicative Model)}$$

$$\begin{aligned} PCK_i = {} & \alpha_{CM} + \alpha_{MM} \times M_i + \alpha_{OM} \times O_i + \alpha_{AM} \times A_i + \\ & \theta_O \left(\alpha_{CO} + \alpha_{MO} \times M_i + \alpha_{OO} \times O_i + \alpha_{AO} \times A_i \right) + \\ & \theta_A \left(\alpha_{CA} + \alpha_{MA} \times M_i + \alpha_{OA} \times O_i + \alpha_{AA} \times A_i \right) + \varepsilon \end{aligned} \qquad \text{(Constraining Factor Model)}$$

In which, parameters indicated by α are regression multiples and θ_O and θ_A are two dummy variables so that defined to be 1 if the opportunity (or ability, respectively) is the constraining factor and 0 otherwise.
Table 2 and 3 shows standardized coefficients of regression for three models and two datasets including $\lambda = 0$ and $\lambda = 0.5$, respectively. Results of regression analysis are close to the results of the previous empirical research. Similar to findings of Siemsen et al. (2008), there are some improvements in R-squares after adding multiplications to the linear model, and also constraining factor model shows better fit compare to other models.

Table 2. Regression Analysis ($\lambda = 0$) – p values are reported in parentheses

Model	Linear Model	Multiplicative Model	Constraining Factor Model
Constant	**-93.58 (0.000)**	-6.032 (0.922)	**-11.274 (0.000)**
M	**0.472 (0.000)**	0.259 (0.583)	**0.604 (0.000)**
O	**0.523 (0.000)**	-0.387 (0.615)	**0.425 (0.000)**
A	**0.534 (0.000)**	-0.418 (0.614)	**0.358 (0.000)**
M×A		0.116 (0.901)	
O×A		0.924 (0.383)	
M×O		0.075 (0.932)	
M×O×A		0.284 (0.803)	
C_O×M			-0.348 (0.095)
C_O×O			**0.496 (0.010)**
C_O×A			**-0.408 (0.015)**
C_A×M			**-0.537 (0.007)**
C_A×O			**-0.345 (0.042)**
C_A×A			**0.590 (0.001)**
N	100	100	100
F	**101.979 (0.000)**	**71.864 (0.000)**	**57.932 (0.000)**
R-square	0.761	0.845	0.853
Adjusted R- square	0.754	0.834	0.838

Table 2 indicates that all of three models are significant. However, coefficients in the linear model, and also in the constraining factor model, are significant for resulted data based on the proposed model, but coefficients in the multiplicative model are not significant. Negative coefficients in the constraining factor model indicate that if one factor was a constraining factor then the coefficient of that factor will increase and the coefficients of two other factors will decrease.
Table 3 shows results of regression analysis when λ sets to be equal with 0.5 in the model. Comparing the value of R-square in three models indicate that the constraining factor model has more fitness with outputs of our model. However, some coefficients of this model are not significant. Therefore, as we expect, $\lambda = 0$ is more compatible with the constraining factor model.

Table 3. Regression Analysis ($\lambda = 0.5$) – p values are reported in parentheses

Model	Linear Model	Multiplicative Model	Constraining Factor Model
Constant	**-85.529 (0.000)**	-71.926 (0.276)	**-85.277 (0.000)**
M	**0.529 (0.000)**	0.326 (0.525)	**0.609 (0.000)**
O	**0.511 (0.000)**	0.374 (0.653)	**0.369 (0.000)**
A	**0.539 (0.000)**	0.386 (0.667)	**0.550 (0.000)**
M×A		0.368 (0.714)	
O×A		0.123 (0.915)	
M×O		0.349 (0.710)	
M×O×A		-0.390 (0.751)	
C_O×M			-0.220 (0.324)
C_O×O			0.091 (0.658)
C_O×A			0.035 (0.844)
C_A×M			-0.388 (0.067)
C_A×O			**0.372 (0.041)**
C_A×A			0.048 (0.787)
N	100	100	100
F	**140.887 (0.000)**	**59.361 (0.000)**	**48.620 (0.000)**
R-square	0.815	0.819	0.829
Adjusted R- square	0.809	0.805	0.812

6. Conclusion

MOA framework is an accepted but challenging model for explaining the performance of employees. Several competing models exist in the literature for defining the inter-relationships between three popular drivers of performance. All of these models are designed based on regression. This research proposes a novel mathematical model based on the bi-level programming for predicting the performance of employee's based on MOA framework in the context of knowledge sharing.

After developing the bi-level programming model, random data used to compare the predicted performance by the proposed model in three various regression models. Results showed that the generated data by the proposed model has a behavior close to those reported in the empirical research by Siemsen et al. (2008). Therefore, this model could explain the reality with more precision according to its flexibility in parameters.

However, it should be tested by empirical research before proposing arguments. So, one direction of future research is testing the proposed model with empirical data for various setting parameters.

Another limitation of this research is some assumptions regarding the formulation and parameters that should be examined and compared in different situations. So, analyzing various structures in the model both analytically and numerically could be interesting.

By approving the benefits of bi-level programming in predicting the behavior of employees, future research can focus on extending the model to multiple behaviors such as including tacit knowledge sharing decision in addition to explicit knowledge sharing decision, and also, on including managerial decisions in the upper-level problem to develop a decision support system.

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