Computers & Industrial Engineering 131 (2019) 13–27

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

A game theoretic analysis of knowledge sharing behavior of academics: Bi-level programming application

Mohsen Tabatabaei, Abbas Afrazeh*, Abbas Seifi

Department of Industrial Engineering and Management Systems, Amirkabir University of Technology, Tehran, Iran

ARTICLE INFO

Keywords:
Bi-level programming
Game theory
Knowledge sharing behavior
Academics
Higher education
Motivation-opportunity-ability framework

ABSTRACT

Knowledge sharing amongst academics is a key process for universities to survive in the face of new changes in the education market. Despite the bulk of research on knowledge sharing, there are few studies on knowledge sharing analysis in higher education based on the game theory. Considering this gap, this paper aims to propose a nonlinear Bi-Level Programming (BLP) model to analyze the knowledge sharing behavior of academics. The proposed model considers decisions made by Faculty Head (FH) and Faculty Members (FMs) at two separate but integrated levels. The upper-level problem is related to FH decisions about compensation rates, and the lower-level problem represents FM decisions in the motivation, opportunity and ability (MOA) framework. This modeling approach has several advantages including the consideration of both FHs and FMs decisions, and various factors influencing knowledge sharing using the MOA framework in a single model as well as the analysis of four different activities of FMs, including teaching, learning, sharing tacit knowledge and publishing codified knowledge in a single integrated model. The bi-level programming model was reduced to a single level nonlinear problem using KKT conditions. The resultant problem was solved for a set of randomly generated data. Results indicated that the optimal behavior of an FM varied relative to characteristics of other FMs. Also, the analysis of the solution at different levels of trust showed that its improvement might have a different effect on FMs. Extending the application of the model and developing efficient algorithms for its solution are suggested for future research.

1. Introduction

Globalization, new changes in funding structures, and changing supply and demand conditions in higher education make this business sector highly competitive (Elrehail, Emeagwali, Alsaad, & Alzghoul, 2018). Knowledge sharing is critical for survival of organizations in a competitive environment (Borges, 2013; Kuah, Wong, & Tiwari, 2013), especially in the higher education sector in which generating and disseminating knowledge is of paramount importance (Al-Kurdi, El-Haddadeh, & Eldabi, 2018; Charband & Navimipour, 2018; Kim & Ju, 2008). Academic staffs play a key role in the success of universities. Therefore, it is vital for universities to promote knowledge sharing among academics (Charband & Navimipour, 2018). Despite numerous studies on knowledge sharing, few studies have studied knowledge sharing among academics in the higher education sector (Al-Kurdi et al., 2018).

The Analysis of the linear relationships between knowledge sharing factors and knowledge sharing behaviors through statistical analysis may provide contradictory findings as reported by Akosile and Olatokun (2019) in their study on cultural effects. Therefore, further studies are required to explore these relationships. In this regard, one strategy is to carry out more empirical studies, define more precise variables and explore their interactive relationships (e.g., Oliveira, 2018). A key point in the analysis of knowledge sharing behavior is to consider it as a game in which each player's payoff is contingent on the behavior of others (Chua, 2003; Samieh & Wahba, 2007). Therefore, considering game structure in knowledge sharing behavior analysis allows us to explore relationships between factors more accurately. In other words, analyzing this behavior irrespective of the game structure and the choice of others may lead to biased conclusions. Despite the importance of game structure in the analysis of knowledge sharing behavior (e.g., Sharma & Bhattacharya, 2013; Nasr, Kilgour, & Noori, 2015), there is a lack of research on employing the game theory approach in analyzing the knowledge sharing behavior of academics, based on two recently conducted reviews on knowledge sharing in higher education (Al-Kurdi et al., 2018; Charband & Navimipour, 2018).

Another important point to note is that autonomous behavior of

* Corresponding author.
E-mail addresses: tabatabaie@aut.ac.ir (M. Tabatabaei), afrazeh@aut.ac.ir (A. Afrazeh), aseifi@aut.ac.ir (A. Seifi).

https://doi.org/10.1016/j.cie.2019.03.031
Received 28 August 2018; Received in revised form 16 February 2019; Accepted 14 March 2019
Available online 15 March 2019

academics is an agreed-upon feature of the higher education context (Fullwood, Rowley, & McLean, 2018; Stupnisky, Brckalorenz, Yuhas, & Guay, 2018; Świgoń, 2017). This implies that any decision made by Faculty Head (FH) is not necessarily followed by Faculty Members (FMs). Hence, an FH is not able to impose his decisions on FMs. However, an FH can change the Nash equilibrium of the knowledge sharing among FMs through interventions such as rewarding and providing technological facilities (e.g., Tan, 2015). Some previous studies have developed principal-agent models to offer suggestions about designing a reward system for knowledge sharing behavior (e.g., Wang & Shao, 2012). However, a lack of principal-agent analysis in the area of knowledge sharing among academics is felt.

The bi-level programming considers the above points by integrating a Nash equilibrium and a Stackelberg equilibrium into a single model. The model proposed in this paper, draws on recent progress in the field of knowledge sharing analysis based on the game theory to explain this type of behavior in the context of higher education. Moreover, it has several advantages over previous models in this area.

This paper aims to propose a bi-level programming model for analyzing knowledge sharing behavior of academics based on game theory. One advantage of bi-level programming is that it accounts for the employee-employer contracting (Stackelberg equilibrium) as well as the N-player game of employees (Nash equilibrium) at the same time. In this model, factors affecting the knowledge sharing behavior of academic staff were identified base on a review of the literature. Then, the role of each factor in the game structure was determined based on the previous studies on applying game theory to the knowledge sharing analysis. Although, this study was on organizational knowledge sharing, but here we drew on the results of other studies on inter-organizational knowledge sharing.

Finally, bi-level programming model was developed and examined to draw implications.

The remainder of this paper is organized as follows. Section 2 presents a review of relevant studies on knowledge sharing among academics and knowledge sharing analysis based on game theory. Then, Section 2 discusses the general formulation of bi-level programming. Section 3 proposes a description of the problem and the mathematical formulation of the model, and Section 4 explains the solution approach. A numerical analysis of the proposed model is given in Section 5, and implications derived from discussion are presented in Section 6. Finally, conclusions and directions for future research are proposed in Section 7.

2. Related works

2.1. Knowledge sharing amongst academics in higher education

Knowledge sharing definitions vary in accordance with the nature of knowledge, the channel of sharing, and the level of sharing knowledge (Ho, Hsu, & Oh, 2009). There are two major types of knowledge recognized in the literature: tacit knowledge and explicit knowledge (Hau, Kim, Lee, & Kim, 2013; Maruta, 2014; Razmerita, Kirchner, & Nielsen, 2016). The sharing of tacit knowledge is more complex than the explicit knowledge since it is inherently vague and could not be observed objectively (Nan, 2008). Although sharing tacit academic knowledge such as teaching skills is a time-consuming task, it can support explicit academic knowledge sharing and assist the academics (Charband & Navimipour, 2018).

The knowledge sharing channels could be different in terms of two basic strategies called codification and personalization (Choi, Poon, & Davis, 2008). The codification strategy is more relevant to the purpose of reusing knowledge through its codification and storing in knowledge repositories. Academics share their codified knowledge in form of books, papers, lectures, technical reports and media recorded in the repositories of the faculty via the internet. By contrast, personalization is more pertinent to the purpose of innovation through generating new knowledge from personal interactions (Choi & Lee, 2002; Hislop, 2013: p.57) and daily communications of FMs. Factors affecting face-to-face knowledge sharing could be different from those affecting knowledge sharing in repositories (Witherspoon, Bergner, Cockrell, & Stone, 2013). Each of these two channels provides academics with specific characteristics and benefits.

The knowledge sharing could also be at individual, group and organizational levels. Knowledge sharing among academics is concerned with the individual level. In higher education, knowledge sharing can be between groups (e.g. faculties) and organizations (e.g. universities) or in form of the relationships between universities and industries. This paper focuses on knowledge sharing among academics at the individual level.

In this paper, knowledge sharing is defined as a process of knowledge externalization from a source. This source of knowledge could be a person, group, organization or system. This process may occur as a form of discussion between two sources. This bilateral externalization may lead to the creation of new knowledge as long as it is supplemented by socialization, combination and internalization, as demonstrated in the knowledge creation spiral proposed by Nonaka and Takeuchi (1995). Another form of knowledge sharing is knowledge transference from a source to a repository and then from a repository to the knowledge user. This classification of knowledge sharing process, i.e. direct and intermediate repositories, is comparable to codification – personalization and also tacit knowledge – explicit knowledge typologies.

The time allocation of academics is an interesting area of research in higher education (Bentley & Kyvik, 2013; Stupnisky et al., 2018). Research and teaching are two major activities of academics (Winslow, 2010), which are the focus of this paper. Other activities of academics include administration, service, and self-employment (Inigo & Raufaste, 2018; Rosewell & Ashwin, 2018; Teater & Mendoza, 2018), which are not addressed here.

Understanding the nature of knowledge sharing is followed by a perception of factors influencing knowledge sharing to make decisions about promotion of this process among FMs. Organizational knowledge sharing is a function of Motivation (want), Opportunity (may) and Ability (can) of individuals (Afrazeh, Bartsch, & Hinterhuber, 2003; Argote, McEvily, & Reagans, 2003; Foss, Pedersen, Fosgaard, & Stea, 2015; Minbavea, 2013; Siemsen, Roth, & Balasubramanian, 2008). This framework, Motivation-Opportunity-Ability (MOA), is widely recognized in the realm of behavior studies (Baumhof, Decker, Röder, & Menrad, 2018; Dahlin, Chuang, & Roulet, 2018; Ojo, Arasanmi, Raman, & Tan, 2018; Pak, Kooij, De Lange, & Van Veldhoven, 2018). Other classification of knowledge sharing determinants could be found in works of Ipe (2003), Witherspoon et al. (2013), Wang and Noe (2010), Al-Kurdi et al. (2018) and Charband and Navimipour (2018). Ipe (2003) identified four major factors of knowledge sharing: nature of knowledge, motivation to share, opportunities to share, and the culture of work environment. Witherspoon et al. (2013) divided knowledge sharing antecedents into four categories, including intentions and attitudes, organizational culture, rewards and gender. Wang and Noe (2010) organized knowledge sharing research based on its emphasis, which included organizational context, interpersonal and team characteristics, cultural characteristics, individual characteristics, and motivational factors. In the context of higher education, Al-Kurdi et al. (2018) proposed a classification of knowledge sharing determinants into individual, organizational, technological and cultural areas. Also, Charband and Navimipour (2018) considered three key enablers of KS among academics including people, organization and information technology. Such a categorization can help a designer to develop models by incorporating several factors in a simple structure. Among these classifications, the MOA framework is more relevant to the mathematical modeling, as these factors act as a mediator between organizational initiations and employee performance. However, this framework should be completed by considering other contextual factors as parameters in the model. For example, organizational climate, which covers fairness, innovativeness and affiliation as an antecedent of knowledge sharing behavior (Chen, Chuang, & Chen, 2012) is a great additional parameter.

Al-Kurdi et al. (2018) and Charband and Navimipour (2018) undertook a systematic review of studies on knowledge sharing in higher education institutions and education sector, respectively. Some distinguishing features of the higher education sector are freedom and autonomy of academics, types of leadership and the overall organizational culture (Al-Kurdi et al., 2018). Academics have a tendency to hoard knowledge (Fullwood & Rowley, 2017) and compulsory participation is not an effective means of promoting knowledge sharing among them (Cheng, Ho, & Lau, 2009). Consequently, the bulk of research in this area stresses individual and motivational factors rather than organizational and technological criteria. However, organizational factors such as organizational culture are also important in knowledge sharing behavior of academics (Al-Kurdi et al., 2018). According to Al-Kurdi et al. (2018), trust and the perception of knowledge as a source of power are two key barriers to knowledge sharing among academics. In this context, reward systems, as a solution, can enhance knowledge sharing behavior among academics. Information and communication technologies, reward systems, opportunities for interaction and time for knowledge sharing are some other organizational and technological factors proposed in the literature on higher education (Fullwood & Rowley, 2017; Sandhu, Jain, & Ahmad, 2011).

2.2. Analysis of knowledge sharing behavior based on game theory

Knowledge sharing behavior could be explained by the game theory (Chua, 2003; Safari & Soufi, 2014; Samieh & Wahba, 2007). In reality, the benefits that an employee derive from knowledge sharing depends on the behavior of others. In this regard, participating in knowledge repositories as a knowledge sharer could be seen as a social dilemma (Cabrera & Cabrera, 2002). Sharma and Bhattacharya (2013) conducted a game theoretic analysis of knowledge sharing behavior under five different scenarios and proposed key insights in formulating knowledge strategies and policies. Other researchers have attempted to model knowledge sharing based on game theory from various aspects as described below. However, scant attention has been paid to powerful models of game theory such as bi-level programming for knowledge sharing behavior analysis.

The majority of studies have considered knowledge sharing behavior as a discrete symmetric strategic game with two strategies of sharing knowledge and hoarding knowledge (e.g. Chua, 2003; Ho et al., 2009). In this line of research, some studies have focused on one shot 2-by-2 game, offering implications about the effects of various parameters on the equilibrium through the analysis of the payoff structure (e.g. Levitt, Wang, Ho, & Javernick-Will, 2013; Zhang et al., 2008). Other studies have analyzed the repetition of this game with incomplete information (e.g. Hao & Yanmei, 2009; Zhu, Wei, Vasilakos, & Wei, 2012) and evolutionary game analysis (Cai & Kock, 2009). Huo (2013) applied evolutionary game theory to the analysis of knowledge sharing behavior of university teachers. Nasr et al. (2015), Wang, Gwebu, Shanker, and Troutt (2009), and Yang and Wu (2008) employed agent-based simulation to examine irrational behaviors. Also, some researchers have extended the game to consider asymmetric payoff functions (e.g. Jolly & Wakeland, 2008; Nasr et al., 2015; Sato & Namatame, 2001).

The analysis of organizational knowledge sharing as a dynamic game with discrete strategies (e.g. Zhang, Chen, Vogel, Yuan, & Guo, 2010), the study of inter-organizational knowledge sharing as a dynamic game with continuous strategies (e.g. Arsenyan, Büyüközkan, & Feyzioğlu, 2015; Bandyopadhyay & Pathak, 2007; Bernstein, Kök, & Meca, 2015; Ding & Huang, 2010; Sakakibara, 2003; Samaddar & Kadiyala, 2006), and the investigation of organizational knowledge sharing as a game with continuous strategies (e.g. Muller, 2007) are three other lines of research in this subject.

2.3. Principal-Agent model

In addition to the analysis of knowledge sharing among individuals and organizations, some studies have applied the principal-agent model to design a reward system for knowledge sharing (e.g. Lee & Ahn, 2007; Nan, 2008; Wang & Shao, 2012). In this regard, an employee may decide about sharing or hoarding his knowledge and the employer can design a rewarding system to tempt employees into sharing knowledge. Principal-agent problem is a distinct instance of the bi-level programming problem with some restrictive assumptions (Cecchini, Ecker, Kupferschmid, & Leitch, 2013). We use the general structure of bi-level programming to develop our model and expand previous rincipal-agent models for the analysis of the knowledge sharing behavior in these five aspects:

(1) Unlike models discussed in the literature (Nan, 2008; Wang & Shao, 2012), our model considers nonlinearity of FMs' payoff and is therefore more practical.
(2) Drawing on the nature of bi-level programming, our model finds both Stackelberg and Nash equilibriums of the game, as explained in the problem statement.
(3) Using the MOA framework our model allows considering various decisions of FH that can impact the knowledge sharing behavior of FMs beyond the reward systems. However, for the sake of simplicity, our analysis is limited to the reward system.
(4) Unlike the previous models that had focused on a single activity as the knowledge sharing behavior, our model considers a set of activities including various types of knowledge sharing and other major knowledge activities to identify the best decision of FH in an integrated and holistic approach. This model also addresses the important issue of time allocation in the context of higher education (Bentley & Kyvik, 2013; Stupnisky et al., 2018).
(5) The possibility of analyzing organizational factors such as trust and reciprocity is another advantage of our model.

2.4. Bi-level programming

Bi-level programming is a hierarchical optimization problem with two levels including leader(s) and follower(s) identical to the Stackelberg game (Dempe, 2003). The relationships between the employer(s) and employees could be modeled in terms of their decisions as a Stackelberg equilibrium (Berr, 2011). Therefore, the bi-level programming is suitable for analyzing these relationships. The general formulation of bi-level programming is as follows (Colson, Marcotte, & Savard, 2005):

$$\begin{aligned}
\min_{x\in X, y\in Y} \quad & F(x,y) \\
s.\,t. \quad & G(x,y) \leqslant 0, \\
& \min_{y\in Y} \quad f(x,y) \\
& s.\,t. \quad g(x,y) \leqslant 0,
\end{aligned} \tag{1}$$

In Eq. (1), $F(x, y)$ and $f(x, y)$ are the objective functions of the leader (upper-level) and followers (lower-level). Similarly, $G(x, y)$ and $g(x, y)$ represent the constraints of leader and followers, respectively. Also, the decision variables of leader and follower are $x \in \Re^{n_1}$ and $y \in \Re^{n_2}$, respectively.

3. Problem statement and mathematical formulation

This section presents a description of the problem and a mathematical formulation of knowledge sharing behavior of academics in bi-level programming structure. FH and FMs are the decision makers for upper and lower-level problems, respectively. In this model, there are one FH and two or more FMs.

As illustrated in Fig. 1, in the upper-level problem, FH as the leader

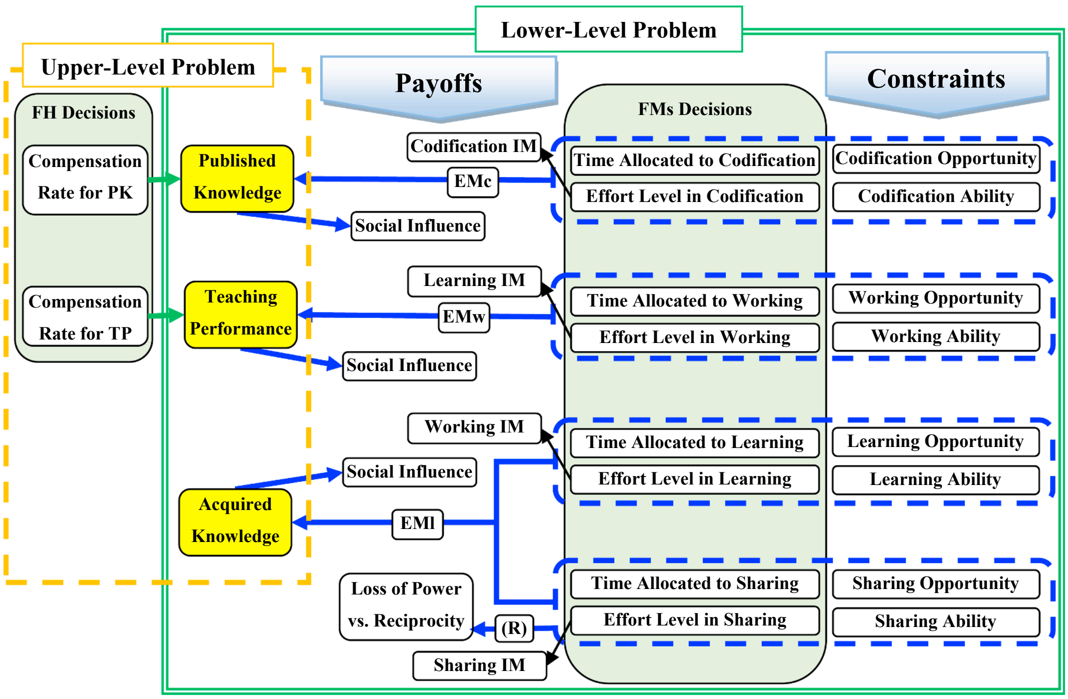

Fig. 1. Bi-level programming model for the problem of knowledge sharing among academics.

decides on the compensation rates for two observable outcomes, including Published Knowledge (PK) and Teaching Performance (TP). Two continuous decision variables in the range of 0 to 10, represent these two compensation rates. After two compensation rates are determined by the FH for the lower-level problems, FMs decide on how to divide their non-work time (as mentioned by Bentley & Kyvik, 2013) among four different activities. Also, they decide on the level of their effort in each activity. These four activities as defined as follows: (1) codification of knowledge with the aim of publishing books and papers (Codification); (2) learning through individual study and practice (Learning); (3) working as educator and advisor with the aim of improving the satisfaction level of students (Teaching); and (4) sharing knowledge in face-to-face communication with other FMs (Sharing).

Therefore, each FM has four continuous decision variables to decide on time allocation. The sum of these four variables should be lower than the maximum time available for that FM. Additionally, each FM has four other continuous decision variables to decide on the level of efforts in each activity so that the decision variable of each effort is a real number between zero and ten.

These four activities of FMs yield three outcomes: Published Knowledge (PK) as the results of knowledge codification, Teaching Performance (TP) as the outcome of teaching and advising students, and Acquired Knowledge (AK) as the result of individual learning and knowledge acquisition through sharing activity. According to these outcomes, FMs are compensated by FH for PK and TP. Although there are no compensation for AK, but it could be helpful to an FM as it can affect his (her) future performance in PK and TP. Therefore, FMs are externally motivated to obtain more AK.

According to the theory of the MOA framework, the performance of academics in each activity is a function of three components including motivation, opportunity, and ability. In this model, motivation has been divided into Internal Motivation (IM) and External Motivation (EM) as two distinct factors. As illustrated in Fig. 1, ability and opportunity are two factors in the constraints of the lower level problems, while IM and EM represent two parameters in the objective function of the lower level problem.

For the sake of simplicity, it is assumed that an FH only could change two compensation rates to improve the Nash equilibrium of FMs. In a more general model, FH will be able to change other MOA factors in an optimized manner to enhance the knowledge sharing behavior of FMs.

In Formulas (2)–(25), the mathematical formulation for the bi-level programming model has been presented. Table 1 and Table 2, show the variables and parameters used in this model, respectively. All variables are positive and bounded in a specified interval. The set of FMs is indexed by $i = 1, \dots, N$ (and j).

The bi-level programming model is formulated as follows. The associated dual variable with each constraint of the lower-level problem is denoted as μ_i^k (k is the index associated with lower-level problem constraints).

Upper-Level Problem

$$\max \quad U_O = \ln\left(\sum_i PK_i/N \times \sum_i AK_i/N \times \sum_i TP_i/N + 1\right) - \varepsilon \times (EMco + EMto) \tag{2}$$

$$\text{subject to:} \quad 0 \leqslant EMco \leqslant 10, \tag{3}$$

$$0 \leqslant EMto \leqslant 10, \tag{4}$$

Lower-Level Problem

$$\begin{aligned}\max \quad U_i = {} & 0.1 \times (EMco \times EMc_i \times PK_i + EMto \times EMt_i \times TP_i + EMl_i \times AK_i) \\ & + Vm_i \times R \times \left(0.01 \times es_i \times \left(\sum_{j \neq i} OAs_j/(N-1)\right) \times ts_i\right) \\ & + Vc_i \times \left(\left(PK_i - \sum_{j \neq i} PK_j/(N-1)\right) + \left(TP_i - \sum_{j \neq i} TP_j/(N-1)\right)\right) \\ & - Ve_i \times ((10 \times ec_i/IMc_i)^2 + (10 \times el_i/IMl_i)^2 + (10 \times et_i/IMt_i)^2 + (10 \times es_i/IMs_i)^2) \\ & + \varepsilon \times (OAc_i + OAl_i + OAt_i + OAs_i)\end{aligned} \tag{5}$$

$$\text{subject to:} \quad PK_i \leqslant 0.217 \times ec_i \times OAc_i \times \ln(tc_i + 1), \quad :\mu_i^1 \tag{6}$$

Table 1
Variables.

Symbol	Definition	Type
Upper-level problem		
U_o	Utility Function of FH as Leader in the Bi-level Programming	Derived Variable
$EMco$	FH's determined compensation rate for FM's publications	Decision Variable of FH
$EMto$	FH's determined compensation rate for FM's teaching performance	Decision Variable of FH
Lower-level problem		
U_i	Utility Function of FM_i as a Follower in Bi-level Programming	Derived Variable
ec_i	Effort of FM_i in codification of knowledge (0 to 10)	Decision Variable of FM
el_i	Effort of FM_i in learning through study and practice (0 to 10)	Decision Variable of FM
et_i	Effort of FM_i in teaching and advising students (0 to 10)	Decision Variable of FM
es_i	Effort of FM_i in sharing knowledge in face-to-face connection with others (0 to 10)	Decision Variable of FM
tc_i	Time allocated to codification by FM_i (0 to 100)	Decision Variable of FM
tl_i	Time allocated to learning and study by FM_i (0 to 100)	Decision Variable of FM
tt_i	Time allocated to teaching by FM_i (0 to 100)	Decision Variable of FM
ts_i	Time allocated to sharing knowledge with other members by FM_i (0 to 100)	Decision Variable of FM
PK_i	Published Knowledge in form of papers, lectures and books by FM_i (0 to 100)	Derived Variable
AK_i	Acquired Knowledge by FM_i (0 to 100)	Derived Variable
TP_i	Teaching Performance of FM_i (0 to 100)	Derived Variable

Table 2
Parameters.

Symbol	Definition	Type
V_e	Coefficient of the cost of efforts for FM_i (0 to 1)	Parameter
V_c	Importance of compliance with the standards of performance by FM_i (0 to 1)	Parameter
V_m	Benefits and costs coefficient of sharing knowledge to other FMs by FM_i (0 to 1)	Parameter
$T\max(i)$	Maximum time available for FM_i (100 for all FMs)	Parameter
R	The level of trust in the community or a combination of the chance of reciprocity and Negative Reverse Impact in the community (-1 to 1)	Parameter
EMc_i	External Motivation Coefficient for FM_i's publishing works (0 to 10)	Parameter
EMl_i	External Motivation Coefficient for FM_i's acquired knowledge (0 to 10)	Parameter
EMt_i	External Motivation Coefficient for FM_i's teaching performance (0 to 10)	Parameter
IMc_i	Internal motivation Coefficient for FM_i's publishing work (0 to 10)	Parameter
IMl_i	Internal motivation Coefficient for FM_i's learning (0 to 10)	Parameter
IMt_i	Internal motivation Coefficient for FM_i's teaching (0 to 10)	Parameter
IMs_i	Internal motivation Coefficient for FM_i's sharing in communications (0 to 10)	Parameter
Oc_i	Opportunity of publishing for the FM_i (0 to 10)	Parameter
Ol_i	Opportunity of learning for the FM_i (0 to 10)	Parameter
Ot_i	Opportunity of teaching for the FM_i (0 to 10)	Parameter
Os_i	Opportunity of sharing knowledge in communications for FM_i (0 to 10)	Parameter
Ac_i	Ability of publishing for FM_i (0 to 10)	Parameter
Al_i	Ability of learning for FM_i (0 to 10)	Parameter
At_i	Ability of teaching for FM_i (0 to 10)	Parameter
As_i	Ability of sharing knowledge in communications for FM_i (0 to 10)	Parameter
λ	Parameter of adjusting interaction between Ability and Motivation (0 to 0.5)	Parameter
OAc_i	Integrated effect of Ability and Opportunity on publishing for FM_i (0 to 10)	Derived Parameter
OAl_i	Integrated effect of Ability and Opportunity of learning for FM_i (0 to 10)	Derived Parameter
OAt_i	Integrated effect of Ability and Opportunity of teaching for FM_i (0 to 10)	Derived Parameter
OAs_i	Integrated effect of Ability and Opportunity of sharing for FM_i (0 to 10)	Derived Parameter
ε	Small coefficients for modeling purpose	Parameter
N	The number of FMs in the faculty	Parameter

$$AK_i \leqslant 0.217 \times el_i \times OAl_i \times \ln(tl_i + 1) + 0.217 \times es_i \times OAs_i \times \ln(ts_i + 1), \quad :\mu_i^2 \tag{7}$$

$$TP_i \leqslant 0.217 \times et_i \times OAt_i \times \ln(tt_i + 1), \quad :\mu_i^3 \tag{8}$$

$$tc_i + tl_i + tt_i + ts_i \leqslant T\max(i), \quad :\mu_i^4 \tag{9}$$

$$OAc_i \leqslant \lambda \times Oc_i + (1 - \lambda) \times Ac_i, \quad :\mu_i^5 \tag{10}$$

$$OAc_i \leqslant \lambda \times Ac_i + (1 - \lambda) \times Oc_i, \quad :\mu_i^6 \tag{11}$$

$$OAl_i \leqslant \lambda \times Ol_i + (1 - \lambda) \times Al_i, \quad :\mu_i^7 \tag{12}$$

$$OAl_i \leqslant \lambda \times Al_i + (1 - \lambda) \times Ol_i, \quad :\mu_i^8 \tag{13}$$

$$OAt_i \leqslant \lambda \times Ot_i + (1 - \lambda) \times At_i, \quad :\mu_i^9 \tag{14}$$

$$OAt_i \leqslant \lambda \times At_i + (1 - \lambda) \times Ot_i, \quad :\mu_i^{10} \tag{15}$$

$$OAs_i \leqslant \lambda \times Os_i + (1 - \lambda) \times As_i, \quad :\mu_i^{11} \tag{16}$$

$$OAs_i \leqslant \lambda \times As_i + (1 - \lambda) \times Os_i, \quad :\mu_i^{12} \tag{17}$$

$$ec_i \leqslant 10, \quad :\mu_i^{13} \tag{18}$$

$$el_i \leqslant 10, \quad :\mu_i^{14} \tag{19}$$

$$et_i \leqslant 10, \quad :\mu_i^{15} \tag{20}$$

$$es_i \leqslant 10, \quad :\mu_i^{16} \tag{21}$$

$$PK_i \leqslant 100, \quad :\mu_i^{17} \tag{22}$$

$$AK_i \leqslant 100, \quad :\mu_i^{18} \tag{23}$$

$$TP_i \leqslant 100, \quad :\mu_i^{19} \tag{24}$$

$$OAc_i, OAl_i, OAt_i, OAs_i, tc_i, tl_i, tt_i, ts_i, ec_i, el_i, et_i, es_i, PK_i, AK_i, TP_i \geqslant 0 \quad (25)$$

The upper-level problem formulated in (2)–(4) represents decisions about the incentive mechanism made by the FH. Eq. (2) is the objective function of FH, which is a function of three outcomes such as PK, AK and TP. This is continuous and concave function that depends on the behavior of FMs. The argument of this logarithmic function is the multiplication of three outcomes of FMs activities. Accordingly, an FH prefers to nurture these three outcomes in a balanced manner. Constraints (3) and (4) determine the range of two decision variables of FH, including compensation rate of published knowledge and compensation rate of teaching performance, respectively. These two variables only affect the payoff function of FMs. Therefore, the decision space of FMs is variable of FH's decisions.

The lower-level problems represent the knowledge sharing game among N faculty members. Eq. (5) as the payoff function of FMs, consists of multiple components. The first one is a linear term concerned with the external motivation based on three outcomes of FM activities. Of these outcomes, two are observable and could be affected by the FH by adjusting the coefficient of compensation, but the third one, AK, could not be affected by the FH in accordance with the model assumptions.

The second one is a linear term indicating the value of sharing knowledge, which is dependent on trust and reciprocity level in the community. In fact, knowledge sharing in a face-to-face communications could be beneficial or harmful depending on organizational conditions. This may adversely affect the knowledge power (Fullwood & Rowley, 2017; Loebbecke, van Fenema, & Powell, 1999) or reciprocity and seeking help in the future (Mura, Lettieri, Radaelli, & Spiller, 2013; Tamjidyamcholo, Baba, Tamjid, & Gholipour, 2013). When the trust level is low (negative value for R), knowledge sharing would be costly for the FM, but when trust level is high (positive value for R), FMs can benefit from knowledge sharing through reciprocity. Therefore, it is a risky behavior depending on the level of trust in the community.

The third component is a linear term relating to the social influence. It involves the desirability of reaching the performance average in two observable outcomes, which is related to the tendency of FMs to compare themselves with their colleagues. The deviation of FM's performance from the community average is an indicator of social influence.

The fourth component is the cost of efforts dedicated to the above four activities by FM. According to previous research, this function is a quadratic convex (e.g., Lee & Ahn, 2007; Sakakibara, 2003; Arsenyan et al., 2015). By reinforcing the internal motivation of the FM, the cost of efforts will be lessened. Finally, there is another component that includes the sum of *OA* in the objective function for modeling purpose.

Constraints (6) determine the upper bound for the PK value based on a function of time and efforts allocated to knowledge codification activity. In the same vein, Constraints (7) determine the upper bound of TP which is a function of time and efforts dedicated to teaching and advising students. Constraints (8) determine the upper bound of AK, which is a function of both remaining activities, including learning through individual study and practice, and sharing knowledge in face-to-face communications. All of these three functions are concave and differentiable. These characteristics have been explored in many studies (e.g. Lee & Ahn, 2007). According to this function, allocating more time to an activity lessens the effect of time, but the outcome changes linearly with the effort and *OA* factor. In fact, assuming that the time and effort allocated to each activity are constant, a higher level of ability and opportunity is correlate with higher level of relevant outcomes.

Constraints (9) ensure that the aggregation of time allocated to activities for each FM does not exceed from the non-work time of that FM. Constraints (10)–(17) determine the upper bound for *OA* value. According to this formulation, the upper bound of *OA* is a linear combination of the ability and opportunity so that that for $\lambda = 0$, *OA* will be the minimum of *A* and *O* based on the constraining factor theory proposed by Siemsen et al. (2008), and for $\lambda = 0.5$, *OA* will be the average of *A* and *O* based on regular linear regression models. As suggested by Siemsen et al. (2008), it is assumed that the value of zero may provide a better explanation of the knowledge sharing behavior than 0.5, but further empirical research is required to determine the exact suitable value for this parameter. Finally, constraints (18)–(25) define the range of decision variables in the lower-level problem.

4. The solution approach

A feasible solution in both upper and lower problems does not guarantee the feasibility of a bi-level programming problem (Ben-Ayed, 1993). However, we claim that the bilevel program represented by (2)–(25) has a feasible solution. We demonstrated the existence of a Nash equilibrium and its uniqueness in Proposition 1. Then, using Proposition 2, we reduced the problem to a single-level optimization problem by replacing the lower-level problem with its KKT conditions. The KKT conditions are as follows:

Primal Feasibility Constraints: As given by (6)–(25) for each player (i.e. FM) $i = 1, \ldots, N$

Dual Feasibility Constraints and Associated Primal Variables: for each player (i.e. FM) $i = 1, \ldots, N$ we have:

$$PK_i: \quad 0.1 \times EMco \times EMc_i + Vc_i \leqslant \mu_{1i} + \mu_{17i} \quad (26)$$

$$AK_i: \quad 0.1 \times EMl_i \leqslant \mu_{2i} + \mu_{18i} \quad (27)$$

$$TP_i: \quad 0.1 \times EMto \times EMt_i + Vc_i \leqslant \mu_{3i} + \mu_{19i} \quad (28)$$

$$OAc_i: \quad \varepsilon \leqslant -0.217 \times ec_i \times \ln(tc_i + 1) \times \mu_{1i} + \mu_{5i} + \mu_{6i} \quad (29)$$

$$OAl_i: \quad \varepsilon \leqslant -0.217 \times el_i \times \ln(tl_i + 1) \times \mu_{2i} + \mu_{7i} + \mu_{8i} \quad (30)$$

$$OAt_i: \quad \varepsilon \leqslant -0.217 \times et_i \times \ln(tt_i + 1) \times \mu_{3i} + \mu_{9i} + \mu_{10i} \quad (31)$$

$$OAs_i: \quad \varepsilon \leqslant -0.217 \times es_i \times \ln(ts_i + 1) \times \mu_{2i} + \mu_{11i} + \mu_{12i} \quad (32)$$

$$ec_i: \quad -Ve_i \times (200 \times ec_i/IMc_i^2) \leqslant -0.217 \times OAc_i \times \ln(tc_i + 1) \times \mu_{1i} + \mu_{13i} \quad (33)$$

$$el_i: \quad -Ve_i \times (200 \times el_i/IMl_i^2) \leqslant -0.217 \times OAl_i \times \ln(tl_i + 1) \times \mu_{2i} + \mu_{14i} \quad (34)$$

$$et_i: \quad -Ve_i \times (200 \times et_i/IMt_i^2) \leqslant -0.217 \times OAt_i \times \ln(tt_i + 1) \times \mu_{3i} + \mu_{15i} \quad (35)$$

$$es_i: \quad Vm_i \times R \times \left(0.01 \times \left(\sum_{j \neq i} OAs_j/(ni - 1)\right) \times ts_i\right) - Ve_i \times (200 \times es_i/IMs_i^2) \leqslant -0.217 \times OAs_i \times \ln(ts_i + 1) \times \mu_{2i} + \mu_{16i} \quad (36)$$

$$tc_i: \quad 0 \leqslant -0.217 \times ec_i \times OAc_i \times \frac{1}{tc_i + 1} \times \mu_{1i} + \mu_{4i} \quad (37)$$

$$tl_i: \quad 0 \leqslant -0.217 \times el_i \times OAl_i \times \frac{1}{tl_i + 1} \times \mu_{2i} + \mu_{4i} \quad (38)$$

$$tt_i: \quad 0 \leqslant -0.217 \times et_i \times OAt_i \times \frac{1}{tt_i + 1} \times \mu_{3i} + \mu_{4i} \quad (39)$$

$$ts_i: \quad Vm_i \times R \times \left(0.01 \times \left(\sum_{j \neq i} OAs_j/(ni - 1)\right) \times es_i\right) \leqslant -0.217 \times es_i \times OAs_i \times \frac{1}{ts_i + 1} \times \mu_{2i} + \mu_{4i} \quad (40)$$

$$\mu_{1i}, \mu_{2i}, \mu_{3i}, \mu_{4i}, \mu_{5i}, \mu_{6i}, \mu_{7i}, \mu_{8i}, \mu_{9i}, \mu_{10i}, \mu_{11i}, \mu_{12i}, \mu_{13i}, \mu_{14i}, \mu_{15i}, \mu_{16i}, \mu_{17i}, \mu_{18i}, \mu_{19i} \geqslant 0 \quad (41)$$

Complementary Slackness: for each player (i.e. FM) $i = 1, \ldots, N$ we have:

Table 3
Generated sample problems.

p	i	Ac_i	Al_i	At_i	As_i	Oc_i	Ol_i	Ot_i	Os_i	IMc_i	IMl_i	IMt_i	IMs_i	EMc_i	EMl_i	EMt_i	V_c	V_e	V_m
1	1	3	7	4	5	9	9	9	6	5	7	8	5	5	8	10	0.5	0.5	0.6
	2	8	3	8	7	8	3	4	10	7	4	8	8	8	4	6	0.5	0.3	1
2	3	7	5	3	3	7	3	5	9	9	9	10	8	8	6	10	0.9	0.7	0.8
	4	10	6	4	5	3	9	10	7	10	5	10	7	4	5	7	0.4	0.3	0.8
3	5	5	5	7	5	6	3	8	10	4	7	8	9	8	5	10	0.8	0.7	0.5
	6	3	3	7	5	5	7	8	5	5	4	7	6	7	10	8	0.3	0.6	1
4	7	3	10	3	10	10	8	5	5	9	10	3	6	8	3	8	0.9	1	1
	8	4	5	7	5	7	8	3	7	3	10	8	4	6	7	10	0.9	0.6	0.7
5	9	3	7	4	7	8	8	3	8	5	7	7	8	6	3	9	0.9	0.7	1
	10	8	7	5	9	7	3	8	6	4	3	6	5	8	9	10	0.4	0.8	0.3

Table 4
Comparing the results for five sample problems after fixing FH decisions and increasing O and A factors.

		Sample Problem 1			Sample Problem 2			Sample Problem 3			Sample Problem 4			Sample Problem 5		
		1–1	1–2	1–3	2–1	2–2	2–3	3–1	3–2	3–3	4–1	4–2	4–3	5–1	5–2	5–3
FH Decisions	EMco	1.61	10	1.15	2.47	10	0.78	10	10	7.56	9.15	10	1.95	10	10	9.36
	EMto	4.87	10	1.37	5.50	10	0.44	2.73	10	6.25	1.30	10	0.42	9.39	10	5.84
FH Payoff	Uo	8.652	8.565	10.534	7.810	7.765	10.709	6.874	6.299	10.340	5.519	3.965	10.009	7.098	7.076	9.506
	PKo	34.31	37.33	51.74	30.04	31.92	42.25	8.38	4.33	42.94	15.02	0.74	50	12.49	12.15	42.96
	AKo	9.89	9.89	17.22	6.50	6.50	25.10	3.77	3.77	17.25	3.57	4.81	14.27	4.34	4.34	7.50
	TPo	16.97	14.49	42.25	12.72	11.58	42.25	30.96	33.92	42.37	4.68	14.82	31.23	22.71	22.85	42.35
First FM Behaviors	ec	0	0	2.16	10	10	0	4.11	2.95	0	10	0	9.99	0	0	10
	el	2.67	2.67	3.24	0	0	3.07	0	0	1.34	0	1.20	0	0.60	0.60	0
	et	0	0	0	10	10	0	10	10	0	0	0	0	0	0	10
	es	0.56	0.56	1.24	0	0	2.24	0	0	2.65	0	0	0	0.85	0.85	0
	tc	0	0	39.56	51.22	65.89	0	42.06	13.95	0	100	0	100	0	0	51.44
	tl	87.67	87.67	44.21	0	0	58	0	0	33.34	0	100	0	40.95	40.95	0
	tt	0	0	0	48.78	34.11	0	57.94	86.05	0	0	0	0	0	0	48.56
	ts	12.33	12.33	16.23	0	0	42	0	0	66.66	0	0	0	59.05	59.05	0
Second FM Behaviors	ec	10	10	10	0	0	10	0	0	10	0	0.88	0	4.58	4.52	0
	el	0	0	0	1.01	1.01	0	0.16	0.16	0	2.04	0	4.08	0	0	0.33
	et	10	10	10	0	0	10	0	0	10	3.31	10	6.63	10	10	0
	es	0	0	0	1.82	1.82	1.39	1.49	1.49	0	0	0	0	0	0	1.34
	tc	51.07	72.79	51.9	0	0	48.09	0	0	51.35	0	6.02	0	35.21	33.49	0
	tl	0	0	0	39.58	39.58	0	5.06	5.06	0	24.13	0	24.12	0	0	19.08
	tt	48.93	27.21	48.1	0	0	48.09	0	0	48.65	75.87	93.98	75.88	64.79	66.51	0
	ts	0	0	0	60.42	60.42	3.82	94.94	94.94	0	0	0	0	0	0	80.92

Table 5
Changes of FM 1 behavior in playing the knowledge sharing game with other FMs.

Sample Problems		1–2	1–3	1–4	1–5	1–6	1–7	1–8	1–9	1–10
FH Decisions	EMco	1.61	2.47	4.86	10	10	9.15	10	7.95	10
	EMto	4.87	5.50	1.94	2.73	3.83	1.35	3.38	9.72	9.39
FH Payoffs	Uo	8.652	8.229	7.671	7.838	6.886	6.376	5.961	5.742	7.920
	PKo	34.31	30.04	12.80	8.38	3.35	15.02	3.03	5.48	12.49
	AKo	9.89	9.89	9.89	9.89	9.89	4.70	7.33	3.89	9.89
	TPo	16.97	12.72	17.06	30.96	29.88	8.39	17.65	14.81	22.71
FM 1 Behaviors	ec	0	0	0	0	0	0	2.89	3.22	0
	el	2.67	2.67	2.67	2.67	2.67	1.92	0	1.75	2.67
	et	0	0	0	0	0	4.45	9.37	0	0
	es	0.56	0.56	0.56	0.56	0.56	0	0	0	0.56
	tc	0	0	0	0	0	0	24.17	82.19	0
	tl	87.67	87.67	87.67	87.67	87.67	24.13	0	17.81	87.67
	tt	0	0	0	0	0	75.87	75.83	0	0
	ts	12.33	12.33	12.33	12.33	12.33	0	0	0	12.33
Second FM Behaviors	ec	10	10	10	4.11	3.19	10	0	1.31	4.58
	el	0	0	0	0	0	0	2.89	0	0
	et	10	10	10	10	9.06	0	0	10	10
	es	0	0	0	0	0	0	0.18	0	0
	tc	51.07	51.22	50	42.06	24.17	100	0	6.3	35.21
	tl	0	0	0	0	0	0	94.94	0	0
	tt	48.93	48.78	50	57.94	75.83	0	0	93.7	64.79
	ts	0	0	0	0	0	0	5.06	0	0

$$PK_i \quad PK_i \times [-0.1 \times EMco \times EMc_i - Vc_i + \mu_{1i} + \mu_{17i}] = 0 \tag{42}$$

$$AK_i \quad AK_i \times [-0.1 \times EMl_i + \mu_{2i} + \mu_{18i}] = 0 \tag{43}$$

$$TP_i \quad TP_i \times [-0.1 \times EMto \times EMt_i - Vc_i + \mu_{3i} + \mu_{19i}] = 0 \tag{44}$$

$$OAc_i \quad OAc_i \times [-\varepsilon - 0.217 \times ec_i \times \ln(tc_i + 1) \times \mu_{1i} + \mu_{5i} + \mu_{6i}] = 0 \tag{45}$$

$$OAl_i \quad OAl_i \times [-\varepsilon - 0.217 \times el_i \times \ln(tl_i + 1) \times \mu_{2i} + \mu_{7i} + \mu_{8i}] = 0 \tag{46}$$

$$OAt_i \quad OAt_i \times [-\varepsilon - 0.217 \times et_i \times \ln(tt_i + 1) \times \mu_{3i} + \mu_{9i} + \mu_{10i}] = 0 \tag{47}$$

$$OAs_i \quad OAs_i \times [-\varepsilon - 0.217 \times es_i \times \ln(ts_i + 1) \times \mu_{2i} + \mu_{11i} + \mu_{12i}] = 0 \tag{48}$$

$$ec_i \quad ec_i \times [Ve_i \times (200 \times ec_i/IMc_i^2) - 0.217 \times OAc_i \times \ln(tc_i + 1) \times \mu_{1i} + \mu_{13i}] = 0 \tag{49}$$

$$el_i \quad el_i \times [Ve_i \times (200 \times el_i/IMl_i^2) - 0.217 \times OAl_i \times \ln(tl_i + 1) \times \mu_{2i} + \mu_{14i}] = 0 \tag{50}$$

$$et_i \quad et_i \times [Ve_i \times (200 \times et_i/IMt_i^2) - 0.217 \times OAt_i \times \ln(tt_i + 1) \times \mu_{3i} + \mu_{15i}] = 0 \tag{51}$$

$$es_i \quad es_i \times \left[Ve_i \times (200 \times es_i/IMs_i^2) - Vm_i \times R \times \left(0.01 \times \left(\sum_{j\neq i} OAs_j/(ni-1)\right) \times ts_i\right) - 0.217 \times OAs_i \times \ln(ts_i + 1) \times \mu_{2i} + \mu_{16i}\right] = 0 \tag{52}$$

$$tc_i \quad tc_i \times \left[-0.217 \times ec_i \times OAc_i \times \frac{1}{tc_i + 1} \times \mu_{1i} + \mu_{4i}\right] = 0 \tag{53}$$

$$tl_i \quad tl_i \times \left[-0.217 \times el_i \times OAl_i \times \frac{1}{tl_i + 1} \times \mu_{2i} + \mu_{4i}\right] = 0 \tag{54}$$

$$tt_i \quad tt_i \times \left[-0.217 \times et_i \times OAt_i \times \frac{1}{tt_i + 1} \times \mu_{3i} + \mu_{4i}\right] = 0 \tag{55}$$

$$ts_i \quad ts_i \times \left[-Vm_i \times R \times \left(0.01 \times \left(\sum_{j\neq i} OAs_j/(ni-1)\right) \times es_i\right) - 0.217 \times es_i \times OAs_i \times \frac{1}{ts_i + 1} \times \mu_{2i} + \mu_{4i}\right] = 0 \tag{56}$$

$$\mu_i^1 \times [0.217 \times ec_i \times OAc_i \times \ln(tc_i + 1) - PK_i] = 0 \tag{57}$$

$$\mu_i^2 \times [0.217 \times el_i \times OAl_i \times \ln(tl_i + 1) + 0.217 \times es_i \times OAs_i \times \ln(ts_i + 1) - AK_i] = 0 \tag{58}$$

$$\mu_i^3 \times [0.217 \times et_i \times OAt_i \times \ln(tt_i + 1) - TP_i] = 0 \tag{59}$$

$$\mu_i^4 \times [T\max(i) - tc_i - tl_i - tt_i - ts_i] = 0 \tag{60}$$

$$\mu_i^5 \times [\lambda \times Oc_i + (1 - \lambda) \times Ac_i - OAc_i] = 0 \tag{61}$$

$$\mu_i^6 \times [\lambda \times Ac_i + (1 - \lambda) \times Oc_i - OAc_i] = 0 \tag{62}$$

$$\mu_i^7 \times [\lambda \times Ol_i + (1 - \lambda) \times Al_i - OAl_i] = 0 \tag{63}$$

$$\mu_i^8 \times [\lambda \times Al_i + (1 - \lambda) \times Ol_i - OAl_i] = 0 \tag{64}$$

$$\mu_i^9 \times [\lambda \times Ot_i + (1 - \lambda) \times At_i - OAt_i] = 0 \tag{65}$$

$$\mu_i^{10} \times [\lambda \times At_i + (1 - \lambda) \times Ot_i - OAt_i] = 0 \tag{66}$$

$$\mu_i^{11} \times [\lambda \times Os_i + (1 - \lambda) \times As_i - OAs_i] = 0 \tag{67}$$

$$\mu_i^{12} \times [\lambda \times As_i + (1 - \lambda) \times Os_i - OAs_i] = 0 \tag{68}$$

$$\mu_i^{13} \times [10 - ec_i] = 0 \tag{69}$$

$$\mu_i^{14} \times [10 - el_i] = 0 \tag{70}$$

$$\mu_i^{15} \times [10 - et_i] = 0 \tag{71}$$

$$\mu_i^{16} \times [10 - es_i] = 0 \tag{72}$$

$$\mu_i^{17} \times [100 - PK_i] = 0 \tag{73}$$

$$\mu_i^{18} \times [100 - AK_i] = 0 \tag{74}$$

$$\mu_i^{19} \times [100 - TP_i] = 0 \tag{75}$$

Proposition 1. *The knowledge sharing game with N FMs as defined by an objective function (5) and constraint functions (6)–(25), admits a unique Nash equilibrium.*

Proof. Each FM has 15 continuous decision variables limited by Constraints (6)–(25). These constraints make a convex set because in (6)–(8) logarithmic functions are concave and other equations are linear. Therefore, the strategy set of each FM is nonempty, convex, closed and bounded. The payoff function of each FM consists of some linear terms and some negative quadratic functions with second-degree terms. Therefore, payoff functions are continuous and (strictly) concave. Also, according to the strategy set of each FM, this function is bounded. Based on the Theorem 1 proposed by Rosen (1965), the knowledge sharing game admits a Nash equilibrium. Based on Theorem 2 of Rosen (1965), the uniqueness of Nash equilibrium is also verified by the following inequality (76) which is correct for $r = (1, \ldots, 1)$ as shown in (77) and (78).

$$\sum_{k=1}^{15} r_k (x_{ik}^0 - x_{ik}^1).\ \nabla U_i(x_{ik}^1) + \sum_{k=1}^{15} r_k (x_{ik}^1 - x_{ik}^0).\ \nabla U_i(x_{ik}^0) > 0 \tag{76}$$

$$x_i = \begin{bmatrix} PK_i \\ AK_i \\ TP_i \\ OAc_i \\ OAl_i \\ OAt_i \\ OAs_i \\ ec_i \\ el_i \\ et_i \\ es_i \\ tc_i \\ tl_i \\ tt_i \\ ts_i \end{bmatrix} \quad \nabla U_i = \begin{bmatrix} 0.1 \times EMco \times EMc_i + Vc_i \\ 0.1 \times EMl_i \\ 0.1 \times EMto \times EMt_i + Vc_i \\ \varepsilon \\ \varepsilon \\ \varepsilon \\ \varepsilon \\ -Ve_i \times (200 \times ec_i/IMc_i^2) \\ -Ve_i \times (200 \times el_i/IMl_i^2) \\ -Ve_i \times (200 \times et_i/IMt_i^2) \\ -Ve_i \times (200 \times es_i/IMs_i^2) \\ \varepsilon \\ \varepsilon \\ \varepsilon \\ \varepsilon \end{bmatrix} \tag{77}$$

$$\sum_{k=1}^{15} r_k (x_{ik}^0 - x_{ik}^1).\ \nabla U_i(x_{ik}^1) + \sum_{k=1}^{15} r_k (x_{ik}^1 - x_{ik}^0).\ \nabla U_i(x_{ik}^0) = 200 \times Ve_i \times [(ec_i^1 - ec_i^0)^2/IMc_i^2 + (el_i^1 - el_i^0)^2/IMl_i^2 + (et_i^1 - et_i^0)^2/IMt_i^2 + (es_i^1 - es_i^0)^2/IMs_i^2] > 0 \tag{78}$$

In Proposition 2, it is shown that the solution of KKT conditions for the lower-level problem is equivalent to the Nash equilibrium of the knowledge sharing game with N players (i.e., FMs). □

Proposition 2. *The Nash equilibrium of the knowledge sharing game as defined by an objective function (5) and constraint set (6)–(25) for each*

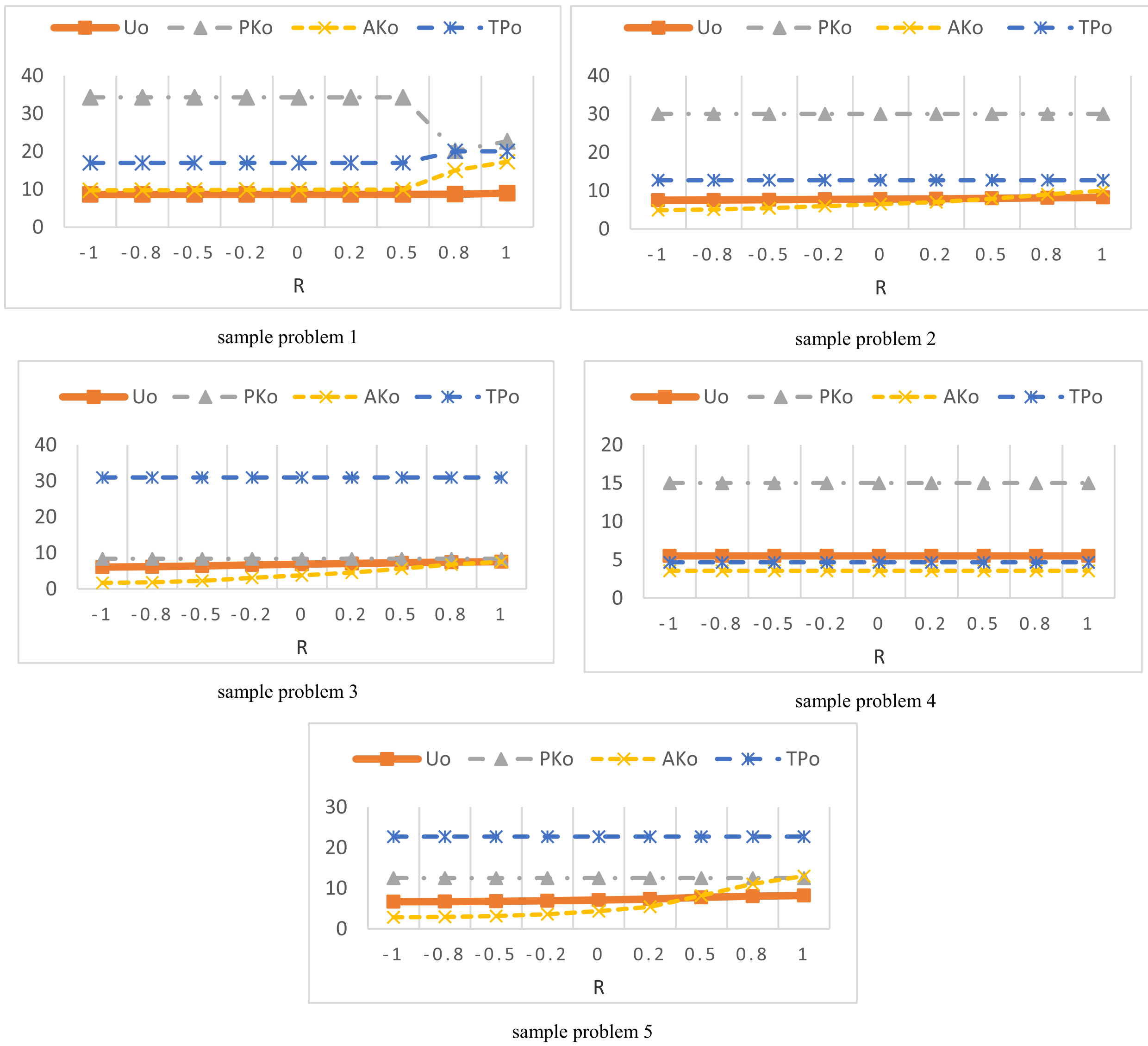

Fig. 2. FH payoffs at different levels of trust in five sample problems.

player, is equivalent to the solution of Karush-Kuhn-Tucker (KKT) conditions of N simultaneous lower level optimization problems as defined by functions (6)–(75).

Proof. Both constraints and objective functions of lower level problems are twice continuously differentiable and based on Proposition 1, there is a unique Nash equilibrium for the subgame of our model. Thus, according to Theorem 1 proposed by Dutang (2013) and considering that the objective function of the lower-level problem is concave and lower level constraints are closed convex sets, the solution of the KKT system will be equivalent to the Generalized Nash Equilibrium (GNE) of N optimization problems. □

Based on Proposition 2, the lower level problem can be replaced by its KKT conditions. This reformulation reduces the bi-level programming to a single-level nonlinear non-convex problem, commonly known as Mathematical Program with Equilibrium Constraints (MPEC) (Dempe, 2003). The Branch-And-Reduce Optimization Navigator (BARON) (Sahinidis, 1996) is a solver used for nonconvex optimization problems. It has a number of features that make it suitable for solving MPECs (Sahinidis, 2018; Ferris, 2002). Sahinidis (2018) claimed that "BARON implements deterministic global optimization algorithms of the branch-and-bound type that are guaranteed to provide global optima under fairly general assumptions. These assumptions include the existence of finite lower and upper bounds on nonlinear expressions in the NLP to be solved." These assumptions are held in our resulting MPEC model. Accordingly, the resultant MPEC model was implemented in GAMS and solved using BARON solver.

5. Numerical results

We generated five sample problems for the numerical analysis, each with one FH and two FMs. The time available to FMs was assumed to be 100 units. Also, in all sample problems, ε is equal to 0.001 and λ is equal to zero. Other parameters were generated randomly based on the uniform distribution. They constitute 15 parameters including EMc_i, EMl_i, EMt_i, IMc_i, IMl_i, IMt_i, IMs_i, Oc_i, Ol_i, Ot_i, Os_i, Ac_i, Al_i, At_i, and As_i with values in the range of 3 and 10, and three parameters including V_e, V_c, V_m with values in the range of 0.3 and 1. Table 3 shows the generated data for five sample problems indexed by p and 10 FMs indexed by i.

Sample problems were solved using BARON solver version 17.8.7 developed by Tawarmalani and Sahinidis (2005) in GAMS. The locally optimal solution was obtained for each sample with a relative gap of 0.01 between the solution and the upper bound of the problem.

As described in the model, the payoff function value for FH is Uo, which consists of three outcomes of PKo, AKo, and TPo. The FH determines two compensation rates including EMto and EMco to find the

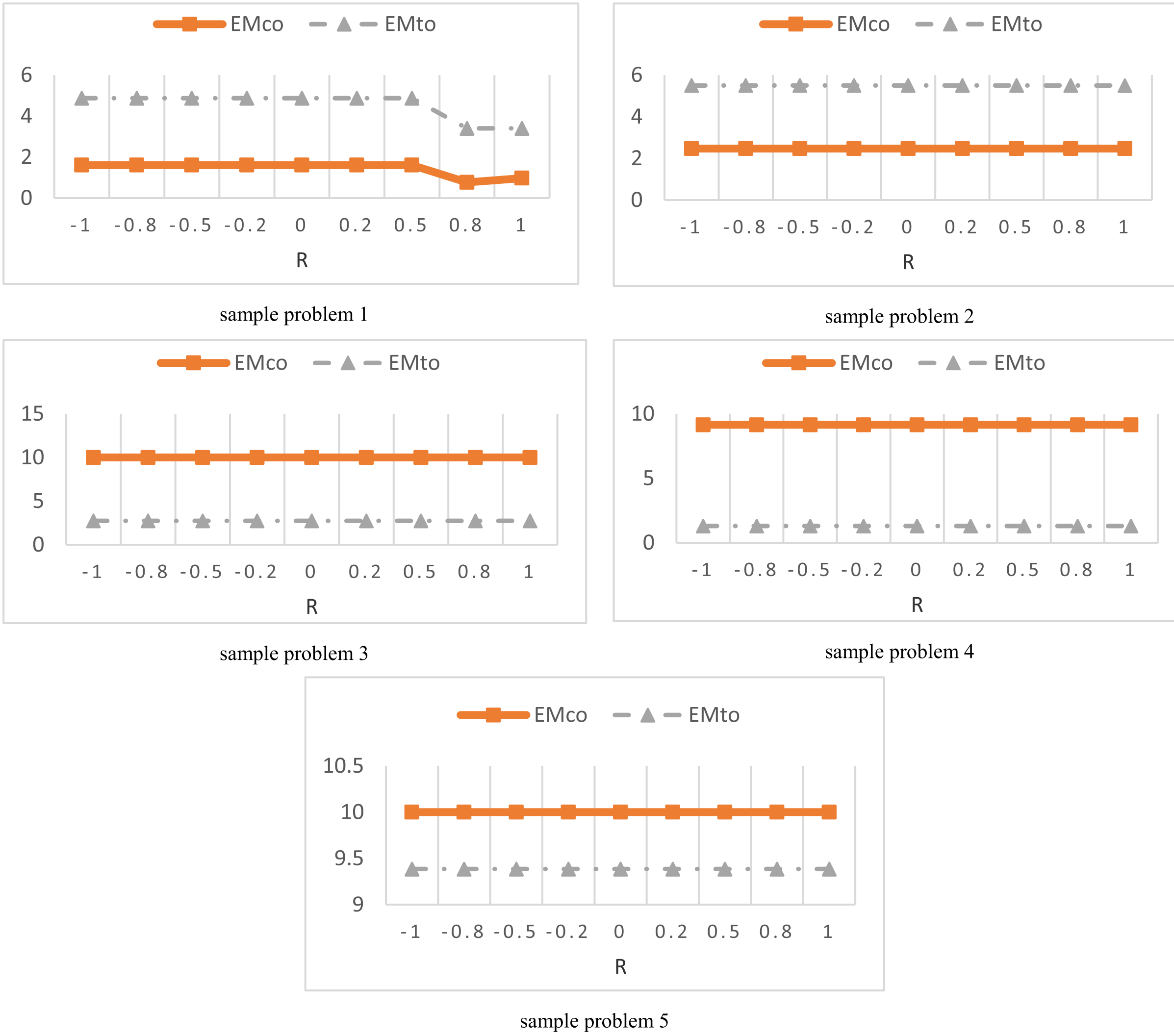

Fig. 3. FH decisions at different levels of trust in five sample problems.

best value for Uo. Based on the decisions of FH, FMs' behaviors are shaped in the Nash equilibrium. The payoff function of FH (the performance of faculty), the FH's decisions about two compensation rates, and FMs' decisions about time and effort allocated to activities were analyzed based on the numerical analysis of sample problems.

5.1. Compensation rates (Motivation), opportunity and ability factors

The value of R is set to zero for five sample problems as reference samples indexed by 1–1 to 5–1. Then, FH decisions (i.e., EMco and EMto) were fixed to their upper bound (10) in reference samples and the new sample problems were indexed by 1–2 to 5–2. Then, opportunity and ability factors were replaced with their upper bound (10) in reference samples and new ones were indexed by 1–3 to 5–3. Table 5 demonstrates the solutions of these three series of sample problems.

As illustrated in Table 4, by increasing opportunity and ability factors, FH payoff rises in all of its three components (PKo, AKo, and TPo) and in most of the cases, both compensation rates, EMco and EMto, decrease except for the sample problem 3. In contrast, by increasing compensation rates up to their upper bound, the FH payoff drops as expected. Accordingly, increased compensation rates does not seem to be beneficial in some cases.

Behaviors of FMs change by altering compensation rates and adjusting opportunity and ability factors. These changes depend on the characteristics of FMs and trade-offs made between benefits and costs of time and efforts allocating to the four activities.

5.2. Effects of R

In this paper, five sample problems (Table 3) were solved for different values of R to investigate the effect of trust on the performance of the faculty. Figs. 2–5 show the results of solving these five sample problems. Fig. 2 displays results of the payoff function of FH (Uo) and its three components including the average of published knowledge in the organization (PKo), the average of acquired knowledge in the organization (AKo), and the average of teaching performance in the organization (TPo). Fig. 3 demonstrates the FH's decisions about two compensation rates including EMco and EMto. Figs. 4 and 5 show FMs behaviors in terms of the time and effort allocated to activities, respectively.

As illustrated in Fig. 2, in all sample problems except for sample problem 1, PKo and TPo values are similar for different values of R, with AKo values and subsequently Uo increasing with a rise in R values. However, none of variables and outcomes in sample problem 4 exhibits any difference for different values of R. As depicted in Fig. 3 in all sample problems except for the sample problem 1, the FH's decisions are identical for different values of R. However, for the sample problem 1 and when R is equal to 0.8 and 1, the FH's decisions vary in both compensation rates. These differences cause radical changes in FMs behaviors and subsequently induce irregular changes in the FH payoff

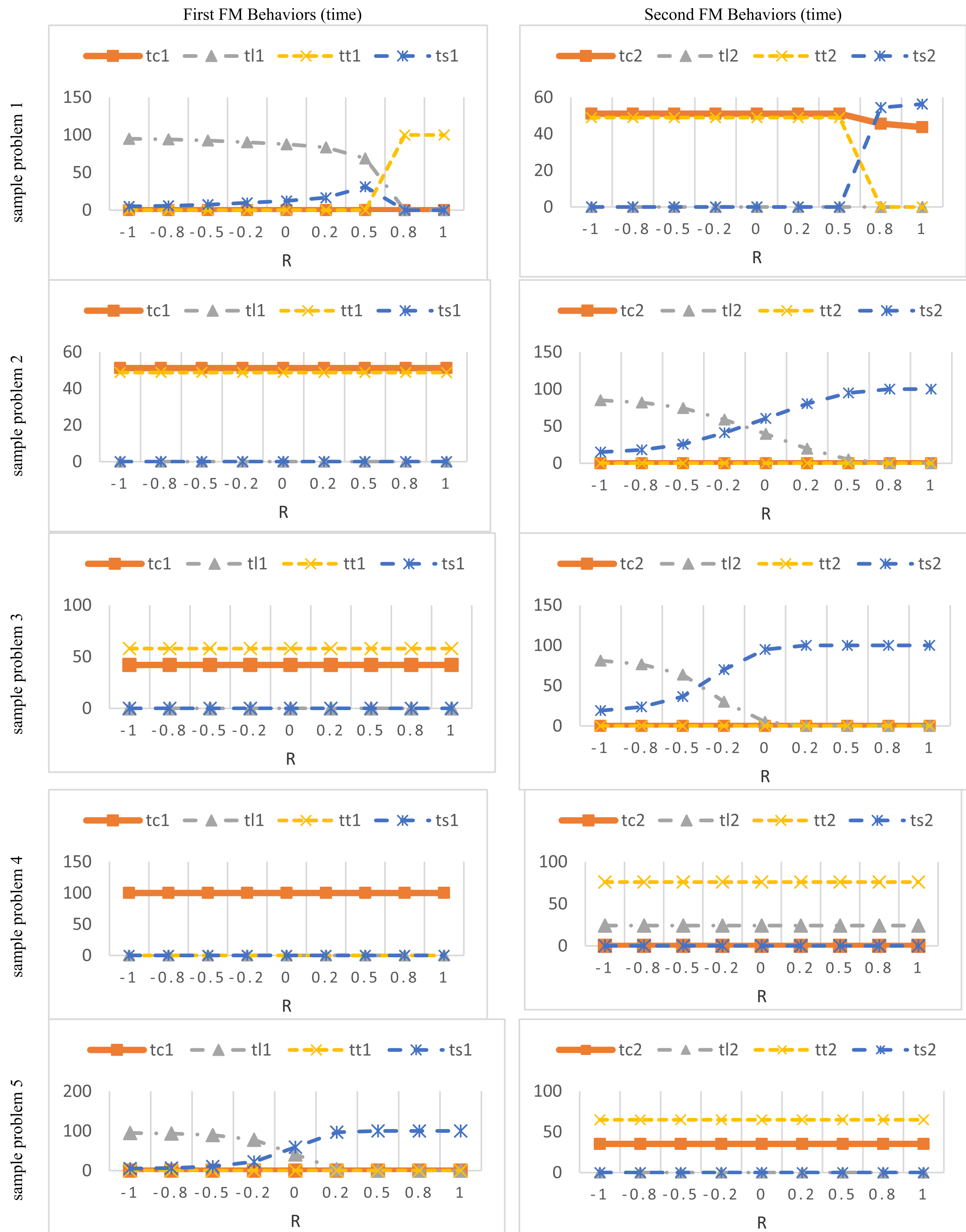

Fig. 4. FMs behaviors (time) at different levels of trust in five sample problem.

components.

FMs behaviors consist of eight variables indicating time and effort allocated to each of four defined activities. Figs. 4 and 5 illustrate behaviors of FMs in sample problems. For FMs 4, 6, and 9, who are motivated to reach higher AK, with an increases in the value of R, they prefer to increase the time and effort allocated to sharing knowledge activity and to decrease the time and effort allocated to individual learning. On the contrary, behaviors of FMs 3, 5, 7, 8, and 10, who are motivated to reach higher PK and TP, are identical for different values of R.

However, the FH could change the preferences of FMs by modifying compensation rates. The sample problem 1 shows that the manner of adjusting compensation rates can alter preferences of FMs. In this sample, FMs' behaviors changed dramatically in response to modifying

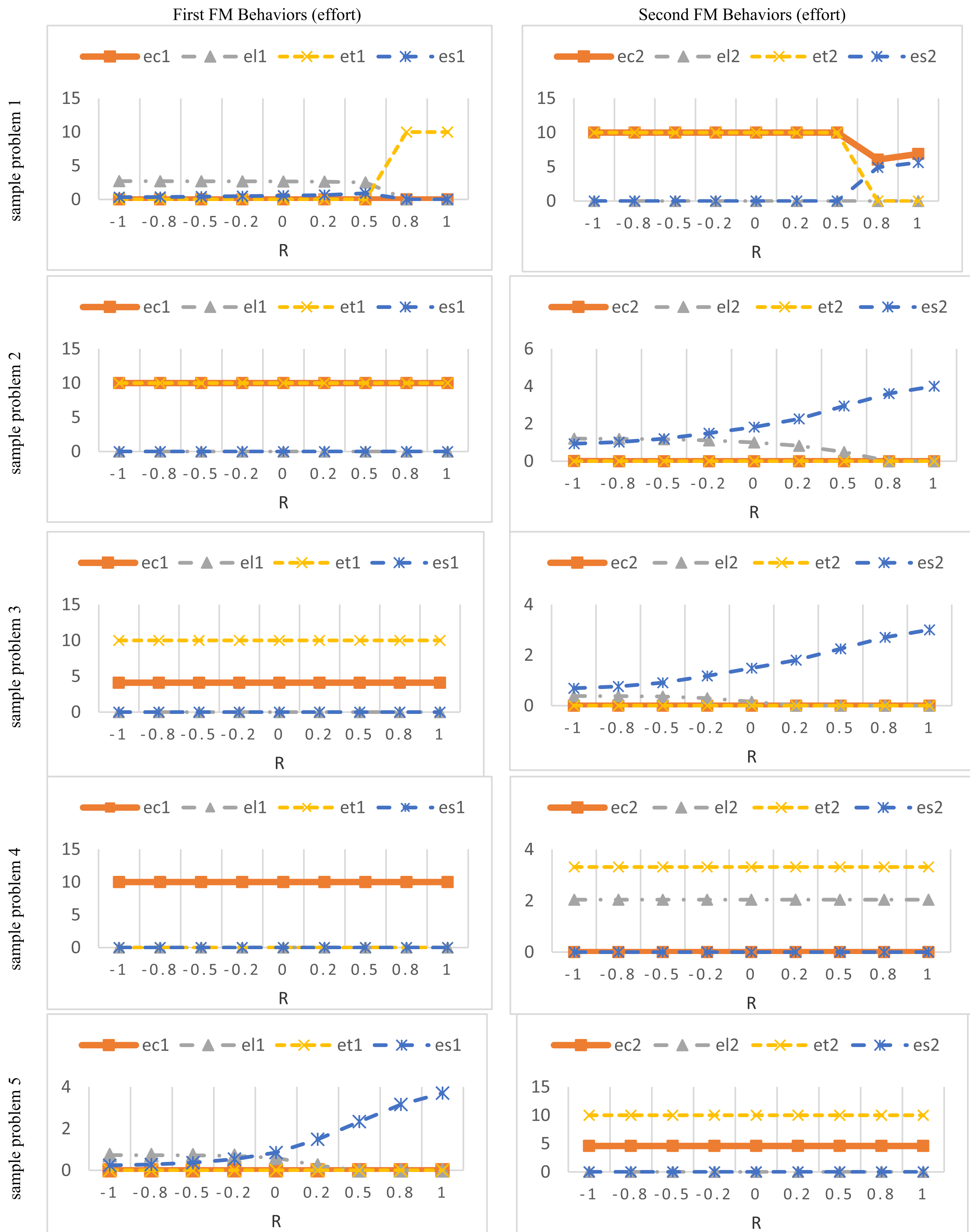

Fig. 5. FMs behaviors (effort) at different levels of trust in five sample problems.

FH decisions for R values of 0.8 and 1. In the context of the new compensation rates, the desired outcome changed from AK to TP for FM 1 and from PK and TP to PK and AK for FM 2.

5.3. *The game structure*

Considering that the game among FMs is necessary to make the best decisions and policies for FH, in this paper nine sample problems were analyzed to verify this argument. We shows that in the case of two FMs, the optimal behavior of each FM depended on the other FM. In each sample problem, FM 1 together with another FM (including FM 2 to FM 10) were considered as two FMs following an FH. We set R to zero for these sample problems. Table 5 demonstrates the results of solving these nine sample problems. The behavior of FM 1 did not change when he played the knowledge sharing game with FM 2–6 and FM 10, but his behavior was affected when playing with FM 7, 8 and 9. By changing one player in the game, FH decisions are adjusted and subsequently the behaviors of FMs are modified. As illustrated in Table 5, FM 1 shows four different behaviors in game playing with nine different FMs.

6. Discussions

It is obvious that increasing compensation rates beyond the best solution would not improve the FH payoff. However, by augmenting the opportunity and ability of FMs to the upper bound (i.e., 10), FH can gain more payoff with fewer compensation rates. Therefore, considering the costs of improving opportunity and ability, it seems more reasonable to invest in improving the opportunity and ability level of FMs rather than in fueling their motivation by offering compensations. Lambda variations could also be discussed as a change in opportunity and ability factors, so that by increasing lambda from 0 to 0.5, the OA factor rises.

The enhanced trust level can improve the performance of the faculty, especially in terms of the average of acquired knowledge. By increasing the trust level, FMs who are motivated to reach higher AK prefer to participate in face-to-face knowledge sharing rather than individual learning. In contrast, for FMs that are motivated to reach higher PK and TP, the trust level does not have any significant effect on their behaviors. However, the FH can change the desired outcomes of FMs by modifying compensation rates.

A comparison of nine sample problems that involve FM 1 as the follower demonstrates that behaviors of FM 1 can change in partnership with different FMs. Also, FH decisions, as the optimal solution, vary in these nine sample problems. Therefore, determining compensation rates based on the individual analysis of FMs may result in suboptimal solutions. The proposed model lays the ground for considering the Nash equilibrium of the knowledge sharing game among FMs as well as Stackelberg equilibrium of the game among FH and FMs.

7. Conclusion

Knowledge sharing is a key process in higher education. There are many studies on the knowledge sharing behavior, but few researchers have analyzed knowledge sharing among academics based on game theory. Most of research on knowledge sharing behavior of academics were based on empirical research that relied on statistical analysis of the linear relationships between knowledge sharing factors. Game theory provides a basis for analyzing the interactions of knowledge sharing factors. This paper proposes a novel model to analyze the behavior of FMs under the influence of FH. A bi-level programming model was developed for the analysis of knowledge sharing among academics based on the game theory.

Based on the two provided propositions, by replacing lower-level problems with equivalent KKT conditions, the bi-level model was reduced to a single-level nonlinear problem. The resultant problem was implemented in GAMS and solved using BARON solver for a set of randomly generated samples.

According to the results, deciding on compensation rates without consideration of other important factors such as opportunity and ability would be tantamount to wasting resources. The proposed model integrates decisions on motivation with two other important factors of opportunity and ability.

The results partially indicated that trust could improve the performance of the faculty, especially in terms of AK, which is consistent with the findings of Kim and Ju (2008), and Goh and Sandhu (2013), but in some cases, trust did not have any effect on FMs behaviors. In fact, without the power of bi-level programming, it is difficult to predict the behavior of FMs.

Studies have shown that the optimal decisions of FH and the optimal behavior of an FM are a variable of the behavior of other FMs. The proposed model provides a basis for considering the game among FMs, though it needs to be further developed and improved for real-life analysis.

The proposed model assumed that the FMs were rational and familiar with the states and behaviors of their colleagues. However, under many circumstances, knowledge sharing is a game characterized with incomplete information. In such cases, an equilibrium is achieved progressively when the FMs become familiar with each other. Moreover, the irrational behavior of some FMs could change the equilibrium of the game. Therefore, researchers need to work on developing a mathematical model of knowledge sharing behavior using simulation and optimization tools to account for the irrationality of some FMs. Modeling the evolution of the game through time and coalition formation can be a possible extension of this paper.

Another line of research is to consider other FH decisions beyond the reward systems, including motivation systems, training systems, formal and informal governance mechanisms and socio-technical support, which were of interest to this study. Integrating the MOA framework in our model provides a helpful structure for examining a wide range of leadership decisions. In this paper, motivation, opportunity and the ability of FMs were presumed as parameters. However, they could be modified by FH by taking some initiatives. Therefore, formulating each of these three factors as a function of FH's decisions rather than a parameter could extend the applications of the model.

One limitation of this paper was the size of analyzed problems. The problems discussed in this paper consisted of only two FMs in the game. Increasing the number of FMs in the model can provide deeper insights into the problem. However, solving larger problems require further improvement in the modeling or algorithm. Therefore, researchers are recommended to develop an efficient algorithm for such a bi-level programming model and to improve the model formulation for effective solution. Simulation-based optimization methods and metaheuristics such as genetic algorithm (Hu, Ma, Gao, Lv, & Yao, 2017) are other options for developing an algorithm for this problem.

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

8. Declaration of interest

None

References

Afrazeh, A., Bartsch, H. and Hinterhuber, H. (2003), Effective factors in human activities and knowledge sharing. In G. Zülch (ed.), Current Trends in Production Management, Proceedings of the International Working Conference IFIP WG 5.7, Human Aspects in Production Management (Vol. 2), European Series in Industrial Management – Esim (Vol. 6). Germany: Shaker Verlag.

Akosile, A., & Olatokun, W. (2019). Factors influencing knowledge sharing among academics in Bowen University, Nigeria. *Journal of Librarianship and Information Science*. https://doi.org/10.1177/0961000618820926.

Al-Kurdi, O., El-Haddadeh, R., & Eldabi, T. (2018). Knowledge sharing in higher education institutions: A systematic review. *Journal of Enterprise Information Management, 31*(2), 226–246.

Argote, L., McEvily, B., & Reagans, R. (2003). Managing knowledge in organizations: An integrative framework and review of emerging themes. *Management Science, 49*(4), 571–582. https://doi.org/10.1287/mnsc.49.4.571.14424.

Arsenyan, J., Büyüközkan, G., & Feyzioğlu, O. (2015). Modeling collaboration formation with a game theory approach. *Expert Systems with Applications, 42*(4), 2073–2085.

Bandyopadhyay, S., & Pathak, P. (2007). Knowledge sharing and cooperation in outsourcing projects — a game theoretic analysis. *Decision Support Systems, 43*, 349–358.

Baumhof, R., Decker, T., Röder, H., & Menrad, K. (2018). Which factors determine the extent of house owners' energy-related refurbishment projects? A Motivation-Opportunity-Ability Approach. *Sustainable Cities and Society, 36*, 33–41. https://doi.org/10.1016/j.scs.2017.09.025.

Ben-Ayed, O. (1993). Bilevel linear programming. *Computers & Operations Research, 20*, 485–501.

Bentley, P. J., & Kyvik, S. (2013). Individual differences in faculty research time allocations across 13 countries. *Research in Higher Education, 54*(3), 329–348. https://doi.org/10.1007/s11162-012-9273-4.

Bernstein, F., Kök, A. G., & Meca, A. (2015). Cooperation in assembly systems: The role of knowledge sharing networks. *European Journal of Operational Research, 240*(1), 160–171.

Berr, F. (2011). Stackelberg equilibria in managerial delegation games. *European Journal of Operational Research, 212*, 251–262.

Borges, R. (2013). Tacit knowledge sharing between IT workers: The role of organizational culture, personality, and social environment. *Management Research Review, 36*(1), 89–108.

Cabrera, A., & Cabrera, E. F. (2002). Knowledge sharing dilemmas. *Organization Studies, 23*(5), 687–710.

Cai, G., & Kock, N. (2009). An evolutionary game theoretic perspective on e-collaboration: The collaboration effort and media relativeness. *European Journal of Operational Research, 194*, 821–833.

Cecchini, M., Ecker, J., Kupferschmid, M., & Leitch, R. A. (2013). Solving nonlinear principal-agent problems using bilevel programming. *European Journal of Operational Research, 230*(2), 364–373. https://doi.org/10.1016/j.ejor.2013.04.014.

Charband, Y., & Navimipour, N. J. (2018). Knowledge sharing mechanisms in the education: A systematic review of the state of the art literature and recommendations for future research. *Kybernetes*. https://doi.org/10.1108/K-06-2017-0227.

Chen, S.-S., Chuang, Y.-W., & Chen, P.-Y. (2012). Behavioral intention formation in knowledge sharing: Examining the roles of KMS quality, KMS self-efficacy, and organizational climate. *Knowledge-Based Systems, 31*, 106–118.

Cheng, M. Y., Ho, J. S. Y., & Lau, P. M. (2009). Knowledge sharing in academic institutions: A study of multimedia University Malaysia. *Electronic Journal of Knowledge Management, 7*(3), 313–324.

Choi, B., & Lee, H. (2002). Knowledge management strategy and its link to knowledge creation process. *Expert Systems with Applications, 23*(3), 173–187.

Choi, B., Poon, S., & Davis, J. (2008). Effects of knowledge management strategy on organizational performance: A complementarity theory-based approach. *Omega, 36*(2), 235–251.

Chua, A. (2003). Knowledge sharing: A game people play. *Aslib Proceedings, 55*(3), 117–129.

Colson, B., Marcotte, P., & Savard, G. (2005). Bilevel programming: A survey. *4OR, 3*, 87–107.

Dahlin, K. B., Chuang, Y.-T., & Roulet, T. J. (2018). Opportunity, motivation, and ability to learn from failures and errors: Review, synthesis, and ways to move forward. *Academy of Management Annals, 12*(1), 252–277. https://doi.org/10.5465/annals.2016.0049.

Dempe, S. (2003). Annotated bibliography on bilevel programming and mathematical programs with equilibrium constraints. *Optimization, 52*, 333–359.

Ding, X.-H., & Huang, R.-H. (2010). Effects of knowledge spillover on inter-organizational resource sharing decision in collaborative knowledge creation. *European Journal of Operational Research, 201*(3), 949–959.

Dutang, C. (2013), A survey of GNE computation methods: theory and algorithms, working paper, hal-00813531, Available at: < https://hal.archives-ouvertes.fr/hal-00813531/document > .

Elrehail, H., Emeagwali, O. L., Alsaad, A., & Alzghoul, A. (2018). the impact of Transformational and Authentic leadership on innovation in higher education: The contingent role of knowledge sharing. *Telematics and Informatics, 35*, 55–67.

Foss, N. J., Pedersen, T., Fosgaard, M. R., & Stea, D. (2015). Why complementary HRM practices impact performance: The case of rewards, job design, and work climate in a knowledge sharing context. *Human Resource Management, 54*(6), 955–976.

Fullwood, R., & Rowley, J. (2017). An investigation of factors affecting knowledge sharing amongst UK academics. *Journal of Knowledge Management, 21*(5), 1254–1271.

Fullwood, R., Rowley, J., & McLean, J. (2018). Exploring the factors that influence knowledge sharing between academics. *Journal of Further and Higher Education*. https://doi.org/10.1080/0309877X.2018.1448928.

Goh, S., & Sandhu, M. (2013). Knowledge sharing among Malaysian academics: Influence of affective commitment and trust. *The Electronic Journal of Knowledge Management, 11*(1), 38–48.

Hao, Z. and Yanmei, F. (2009), Game analysis of knowledge sharing in the organization. In IITA International Conference on Services Science, Management and Engineering, IEEE, 2009, doi: https://doi.org/ 10.1109/ICMSS.2009.5305577.

Hau, Y. S., Kim, B., Lee, H., & Kim, Y.-G. (2013). The effects of individual motivations and social capital on employees' tacit and explicit knowledge sharing intentions. *International Journal of Information Management, 33*(2), 356–366.

Hislop, D. (2013). *Knowledge management in organizations: A critical introduction* (third ed.). Oxford: Oxford University Press.

Ho, C. T. B., Hsu, S.-F., & Oh, K. B. (2009). Knowledge sharing: Game and reasoned action perspectives. *Industrial Management and Data Systems, 109*(9), 1211–1230.

Hu, Z., Ma, N., Gao, W., Lv, C., & Yao, L. (2017). Modelling diffusion for multi-generational product planning strategies using bi-level optimization. *Knowledge-Based Systems, 123*, 254–266.

Huo, M. (2013). Analysis of knowledge-sharing evolutionary game in university teacher team. *International Journal of Higher Education, 2*(1), 60–66.

Inigo, M., & Raufaste, E. (2018). Academics' motivations explain time-allocation and well-being at work. *Revue Européenne De Psychologie Appliquée/European Review of Applied Psychology*. https://doi.org/10.1016/j.erap.2018.11.002.

Ipe, M. (2003). Knowledge sharing in organizations: A conceptual framework. *Human resource development review, 2*(4), 337–359.

Jolly, R. and Wakeland, W. (2008), Using agent based simulation and game theory analysis to study information sharing in organizations. In Proceedings of the 41st Hawaii International Conference on System Sciences, IEEE, doi: https://doi.org/10.1109/HICSS.2008.483.

Kim, S., & Ju, B. (2008). An analysis of faculty perceptions: Attitudes toward knowledge sharing and collaboration in an academic institution. *Library & Information Science Research, 30*(4), 282–290.

Kuah, C. T., Wong, K. Y., & Tiwari, M. K. (2013). Knowledge sharing assessment: An Ant Colony System based Data Envelopment Analysis approach. *Expert Systems with Applications, 40*, 3137–3144.

Lee, D.-J., & Ahn, J.-H. (2007). Reward systems for intra-organizational knowledge sharing. *European Journal of Operational Research, 180*, 938–956.

Levitt, R. E., Wang, C.-M. A., Ho, S. P., & Javernick-Will, A. (2013). Encouraging knowledge sharing in engineering firms—part II: Game theory analysis and firm strategies. *Engineering Project Organization Journal, 3*(1), 22–31.

Loebbecke, C., van Fenema, P., & Powell, P. (1999). Co-opetition and knowledge transfer. *The Data Base for Advances in Information Systems, 30*(2), 14–25.

Maruta, R. (2014). The creation and management of organizational knowledge. *Knowledge-Based Systems, 67*, 26–34.

Minbavea, D. B. (2013). Strategic HRM in building micro-foundations of organizational knowledge-based performance. *Human Resource Management Review, 23*, 378–390.

Muller, R. M. (2007), Knowonomics - The Economics of Knowledge Sharing, ECIS 2007 Proceedings, Paper 91. < http://aisel.aisnet.org/ecis2007/91 > .

Mura, M., Lettieri, E., Radaelli, G., & Spiller, N. (2013). Promoting professionals' innovative behavior through knowledge sharing: The moderating role of social capital. *Journal of Knowledge Management, 17*(4), 527–544.

Nan, N. (2008). A principal-agent model for incentive design in knowledge sharing. *Journal of Knowledge Management, 12*(3), 101–113.

Nasr, E. S., Kilgour, M. D., & Noori, H. (2015). Strategizing niceness in co-opetition: The case of knowledge exchange in supply chain innovation projects. *European Journal of Operational Research, 244*, 845–854.

Nonaka, I., & Takeuchi, H. (1995). *The Knowledge-Creating Company.* Oxford, UK: Oxford University Press.

Ojo, A. O., Arasanmi, C. N., Raman, M., & Tan, C. N.-L. (2018). Ability, motivation, opportunity and sociodemographic determinants of Internet usage in Malaysia. *Information Development*. https://doi.org/10.1177/0266666918804859.

Pak, K., Kooij, D. T. A. M., De Lange, A. H., & Van Veldhoven, M. J. P. M. (2018). Human Resource Management and the ability, motivation and opportunity to continue working: A review of quantitative studies. *Human Resource Management Review*. https://doi.org/10.1016/j.hrmr.2018.07.002.

Razmerita, L., Kirchner, K., & Nielsen, P. (2016). What factors influence knowledge sharing in organizations? A social dilemma perspective of social media communication. *Journal of Knowledge Management, 20*(6), 1225–1246.

Rosen, J. B. (1965). Existence and uniqueness of equilibrium points for concave N-person games. *Econometrica, 33*(3), 520–534.

Rosewell, K., & Ashwin, P. (2018). Academics perceptions of what it means to be an academic. *Studies in Higher Education, 1–11*. https://doi.org/10.1080/03075079.2018.1499717.

Safari, H., & Soufi, M. (2014). A game theory approach for solving the knowledge sharing problem in supply chain. *International Journal of Applied Operational Research. 4*(3), 13–24.

Sahinidis, N. V. (1996). BARON: A general purpose global optimization software package. *Journal of Global Optimization, 8*, 201–205.

Sahinidis, N. V. (2018), BARON user manual v. 2018.12.26, The Optimization Firm, LLC, < http://www.minlp.com > , Available from < https://minlp.com/downloads/docs/baron manual.pdf > .

Sakakibara, M. (2003). Knowledge sharing in cooperative research and development. *Managerial and Decision Economics, 24*, 117–132.

Samaddar, S., & Kadiyala, S. (2006). An analysis of inter-organizational resource sharing decisions in collaborative knowledge creation. *European Journal of Operational Research, 170*(1), 192–210.

Samieh, M. H. and Wahba, K. (2007), "Knowledge Sharing Behavior From Game Theory And Socio-Psychology Perspectives", In Proceedings of the 40th Hawaii International Conference on System Sciences, IEEE, 2007.

Sandhu, M., Jain, K., & Ahmad, I. (2011). Knowledge sharing among public sector employees: Evidence from Malaysia. *International Journal of Public Sector Management, 24*(3), 206–226.

Sato, K. and Namatame, A. (2001), Social interaction as knowledge trading games. In: T. Terano, Y. Ohsawa, T. Nishida, A. Namatame, S. Tsumoto, T. Washio (eds.), New Frontiers in Artificial Intelligence. JSAI 2001. Lecture Notes in Computer Science (vol. 2253.). Berlin, Heidelberg: Springer.

Sharma, R. S., & Bhattacharya, S. (2013). knowledge dilemmas whitin organizations: Resolutions from game theory. *Knowledge-Based Systems, 45*, 100–113.

Siemsen, E., Roth, A. V., & Balasubramanian, S. (2008). How Motivation, opportunity and ability drive knowledge sharing: The constraining-factor model. *Journal of Operations Management, 26*, 426–445.

Stupnisky, R. H., Brckalorenz, A., Yuhas, B., & Guay, F. (2018). Faculty members' motivation for teaching and best practices: Testing a model based on self-determination theory across institution types. *Contemporary Educational Psychology, 53*, 15–26. https://doi.org/10.1016/j.cedpsych.2018.01.004.

Świgoń, M. (2017). Knowledge sharing practices in informal scholarly communication amongst academics in Poland. *Malaysian Journal of Library & Information Science, 22*(2), 101–115. https://doi.org/10.22452/mjlis.vol22no2.7.

Tamjidyamcholo, A., Baba, M. S. B., Tamjid, H., & Gholipour, R. (2013). Information security – Professional perceptions of knowledge-sharing intention under self-efficacy, trust, reciprocity, and shared-language. *Computers & Education, 68*, 223–232.

Tan, C. N. (2015). Enhancing knowledge sharing and research collaboration among academics: The role of knowledge management. *Higher Education, 71*(4), 525–556. https://doi.org/10.1007/s10734-015-9922-6.

Tawarmalani, M., & Sahinidis, N. V. (2005). A polyhedral branch-and-cut approach to global optimization. *Mathematical Programming, 103*(2), 225–249.

Teater, B., & Mendoza, N. (2018). Workload of social work academics and factors that contribute to time spent on research. *Journal of Social Work Education, 54*(2), 250–260. https://doi.org/10.1080/10437797.2017.1404520.

Wang, J., Gwebu, K., Shanker, M., & Troutt, M. D. (2009). An application of agent-based simulation to knowledge sharing. *Decision Support Systems, 46*(2), 532–541.

Wang, S., & Noe, R. A. (2010). Knowledge sharing: A review and directions for future

research. *Human Resource Management Review, 20*, 115–131.
Wang, M., & Shao, C. (2012). Special knowledge sharing incentive mechanism for two clients with complementary knowledge: A principal-agent perspective. *Expert Systems with Applications, 39*, 3153–3161.
Winslow, S. (2010). Gender inequality and time allocations among academic faculty. *Gender & Society, 24*(6), 769–793. https://doi.org/10.1177/0891243210386728.
Witherspoon, C. L., Bergner, J., Cockrell, C., & Stone, D. N. (2013). Antecedents of organizational knowledge sharing: A meta-analysis and critique. *Journal of Knowledge Management, 17*(2), 250–277.
Yang, H.-L., & Wu, T. C. T. (2008). Knowledge sharing in an organization. *Technological Forecasting and Social Change, 75*, 1128–1156.
Zhang, X., Chen, Z., Vogel, D., Yuan, M., & Guo, C. (2010). Knowledge-sharing reward dynamics in knowledge management systems: Game theory-based empirical validation. *Human Factors and Ergonomics in Manufacturing and Service Industries, 20*(2), 103–122.
Zhang, L., Zheng, X., Li, J., Nie, G., Huo, G., & Shi, Y. (2008). A way to improve knowledge sharing: From the perspective of knowledge potential. *Journal of Service Science and Management, 1*, 226–232.
Zhu, P., Wei, G., Vasilakos, A. V., & Wei, H. Y. (2012). Knowledge Sharing in Social Network Using Game Theory. In J. Suzuki, & T. Nakano (Vol. Eds.), *Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering: . 87. Bio-Inspired Models of Network, Information, and Computing Systems, BIONETICS 2010* (pp. 542–553). Berlin, Heidelberg: Springer.

Mohsen Tabatabaei is PhD Candidate in Department of Industrial Engineering and Management Systems of Amirkabir University of Technology, Tehran, Iran. His major areas of research and teaching are as follows: Knowledge Management, Human Resource Management, Mathematical Programming, Decision Science and Game Theory. He has published about 40 papers in different Iranian and international journals and conferences.

Abbas Afrazeh is Associate Professor in Department of Industrial Engineering and Management Systems of Amirkabir University of Technology, Tehran, Iran. His major areas of research and teaching are as follows: Knowledge Management, Human Resource Management, Human Computer Interaction, Motivation and Productivity at Work. He has written a book on knowledge management. He has published more than 150 scientific in different Iranian and international journals and conferences. He is Member of the 5 Scientific Societies.

Abbas Seifi is Professor in Department of Industrial Engineering and Management Systems of Amirkabir University of Technology, Tehran, Iran. His major areas of research and teaching are as follows: Design Engineering, Applied and Computational Mathematics, Operations Research, Optimization Methods, Production Engineering, Logistics and Supply Chain Management. He has written a book titled "Advanced Linear Programming (Interior Point Methods)". He has published more than 100 scientific in different Iranian and international journals and conferences. He is Member of Operations Research Society.