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Yong Liu
Jiangnan University

Kevin Li
University of Windsor

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A two-sided matching decision method for supply and demand of technological knowledge

Yong Liu

School of Business, Jiangnan University

Wuxi, Jiangsu 214122, China

Kevin W. Li*

College of Economics and Management, Fuzhou University

Fuzhou, Fujian 350116, China

and

Odette School of Business, University of Windsor

401 Sunset Ave., Windsor, Ontario, N9B 3P4, Canada

Email: *kwli@uwindsor.ca*

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* Corresponding author. Telephone: 1 (519) 253-3000 ext 3456. Email: kwli@uwindsor.ca

A two-sided matching decision method for supply and demand of technological knowledge

Abstract:
Purpose – The purpose is to propose a novel prospect-based two-sided matching decision model for matching supply and demand of technological knowledge assisted by a broker. This model enables the analyst to account for the stakeholders' psychological behaviours and their impact on the matching decision in an open innovation setting.
Design/methodology/approach – The prospect theory and grey relational analysis are employed to develop the proposed two-sided matching decision framework.
Findings – By properly calibrating model parameters, the case study demonstrates that the proposed approach can be applied to real-world technological knowledge trading in a market for technology (MFT) and yields matching results that are more consistent with the reality.
Research limitation/implications – The proposed model does not differentiate the types of knowledge exchanged (established vs. novel, tacit vs. codified, general vs specialized) [Ardito et al. 2016, Nielsen and Nielsen 2009]. Moreover, the model focuses on incorporating psychological behaviour of the MFT participants and does not consider their other characteristics.
Practical implications – The proposed model can be applied to achieve a better matching between technological knowledge suppliers and users in a broker-assisted MFT.
Social implications – A better matching between technological knowledge suppliers and users can enhance the success of open innovation, thereby contributing to the betterment of the society.
Originality/value – This paper furnishes a novel theoretical model for matching supply and demand in a broker-assisted MFT. Methodologically, the proposed model can effectively capture market participants' psychological considerations.
Keywords – Open innovation, Market for technology, Two-sided matching, Grey relational analysis, Prospect theory
Paper type – Research paper

1 Introduction

In the current competitive environment, enterprises face increasing pressure to produce innovative products and respond to customer needs and market demand expeditiously [Ivascu, Cirjaliu, Draghici, 2016]. Nowadays, it becomes increasingly difficult for a firm to purely rely on in-house talents for product innovation. Instead, a more efficient and convenient way is to meet the challenge by open innovation, trading in or out technological knowledge in the market. It is observed that open innovation and effective and expeditious transfer of technological knowledge often result in significant economic benefit [Petruzzelli et al., 2015]. As such, more and more enterprises count on open innovation for enhancing profitability and securing competitive advantages [Chesbrough, 2003; Cheng & Huizingh, 2014].

A common form of open innovation is to trade technological knowledge such as patents from markets for technology (MFTs) [Petruzzelli et al., 2015; Hansen et al., 1999]. In MFTs, universities and research institutes are key creators or suppliers of technological knowledge, and enterprises are potential users and adopters [Arora et al. 2014; Arora et al. 2001a, b; Arora and Gambardella 2010]. In this market, suppliers select appropriate users as per expected benefits as a result of knowledge transfer, while users often acquire technological knowledge based on their specific needs [Gielen et al., 2003], prior ties with suppliers as well as technological knowledge characteristics [Petruzzelli, 2011; Capaldo et al., 2016]. Success of open innovation depends on how well enterprises collaborate with suppliers [Enkel et al. 2009; Ivascu, Cirjaliu, Draghici, 2016]. To expedite knowledge transfer and promote open innovation, governments can create polices and regulations to reduce barriers between suppliers and users of technological knowledge [Maas et al., 2016; Dulipovici et al., 2016; Girard, 2015]. To implement these policies, public or private brokers are often formed to facilitate technological knowledge exchange between suppliers and users in the MFT [Hoppe and Ozdenoren, 2005]. By providing value-added service, brokers can also obtain some benefit. Given that finding appropriate suppliers and users in the MFT can be conveniently structured as a typical two-sided matching problem [Gale and Shapley, 1962; Roth, 1985], this article proposes a novel decision model for matching supply and demand of technological knowledge in a broker-assisted MFT.

2 Technological knowledge exchange under the open innovation paradigm

Technological knowledge such as patents is often a crucial asset for a firm [Petruzzelli et al., 2015; Hansen et al., 1999]. Rapid pace of technology advancement makes it difficult for any firm to achieve self-sufficiency in R&D, technological knowledge exchange has become a much more effective and efficient way for suppliers and users to collaborate in R&D and implement open innovation.

In order to handle technological knowledge exchange problems, Arora et al. [2001a, b] proposed the concept of MFTs. Subsequently, more and more research has been carried out on this topic and some useful results have been obtained. For example, by surveying recent research on MFTs, Arora and Gambardella [2010] analyzed the supply and demand of technology, examined what factors affect MFT formation and growth, and explored the dynamic interactions between industry structure and MFTs [Arora et al. 2014]. In contrast to the traditional focus on either external technology acquisition or exploitation, Lichtenthaler and Ernst [2007] and Lichtenthaler [2008] took an integrative view to investigate a firm’s inward and outward technology transfers and treated them as the key dimensions of the firm’s strategic approaches to open innovation. Natalicchio et al. [2014] reviewed recent literature on markets for ideas (MFIs) arising from the open innovation paradigm and furnished an overview of MFIs from three aspects: ideas, knowledge owners, and knowledge seekers. Messeni Petruzzelli et al. [2015] investigated what affected biotechnological firms’ patent acquisition by examining four main characteristics of the patent.

From a matching point of view, some scholars utilized game theory and decision models to deal with technological knowledge exchange. For instance, in the context of demand-driven production chains in the Dutch agricultural sector, Klerkx and Leeuwis [2008] discussed the contributions of innovation intermediaries to matching supply and demand of agricultural knowledge and challenges that they face in their functioning. Hoppe and Ozdenoren [2005] presented a game theoretic framework to analyze the function of a single intermediary and competing intermediaries in matching supply and demand of new inventions. Chen et al. [2010] put forward a two-stage decision analysis method for handling two-sided matching of technological knowledge supply and demand. While the aforesaid methods are important tools to handle technological knowledge exchange under the open innovation paradigm, they ignored the impact of the stakeholders' psychological behaviours on the matching of technological knowledge supply and demand. This omission often leads to matching results that are inconsistent with what happens in reality. This inconsistency is due to the fact that stakeholders (suppliers, users, and brokers) typically have bounded rationality and the success of a matching pair is often affected by perceptions and considerations that are psychological rather than economic in MFTs [Erel, 2004]. This article attempts to introduce a novel two-sided matching decision model for unbalanced numbers of suppliers and users assisted by a single intermediary or broker. The prospect theory proposed in [Kahneman and Tversky, 1979; Tversky and Kahneman, 1992] is employed to characterize stakeholders' psychological considerations and their impact on the matching decision. The grey relational analysis [Liu and Lin, 2011] is then applied to derive positive and negative correlation coefficients, thereby obtaining final prospect values for different stakeholders. Optimization models are subsequently constructed to find optimal matching of suppliers and users in terms of prospect values.

The remainder of this paper is organized as follows: The basic model is presented for two-sided matching of technological knowledge supply and demand in Section 3. Section 4 proposes a novel framework for two-sided matching of suppliers and users in a broker-assisted MFT by considering stakeholders' psychological behaviours. A real-world open innovation case study is furnished in Section 5 to illustrate how the proposed method can be applied. The paper is concluded with some remarks in Section 6.

3 A framework for two-sided matching of technological knowledge exchange

In a MFT, three parties are often involved: suppliers, users, and an independent intermediary or broker. Suppliers of technological knowledge are usually universities or research institutions who own patents and other technological knowledge. Users stand for entrepreneurs, investors, or firms who are interested in commercializing technological knowledge for perceived benefits. An intermediary or broker is a service organization that assists in matching supply with demand of technological knowledge based on the information provided by the two parties and charges commissions for successful matching. In the matching process, suppliers and users first submit to the broker relevant information on their needs and requirements, the broker then conducts necessary decision analysis to choose potential matching pairs in the pools. The broker aims for best matching results by maximizing its own expected profit as well as meeting the needs and requirements of the suppliers and users to the greatest possible extent. In order to characterize their interactions, a two-sided matching method is proposed below.

Assume that the supplier and user sets in the matching problem are denoted by $S=\left\{S_1,...,S_i,...,S_n\right\}$ and $D=\left\{D_1,...,D_j,...,D_m\right\}$, $S_i(i=1,2,...,n)$ and $D_j(j=1,2,\ \ ...,m)$, respectively, stands for the i^{th} supplier and the j^{th} user of technological knowledge. Suppliers and users often assess their potential matching partners against multiple criteria.

Assume that $A=\left\{A_1,....,A_k,...,A_p\right\}$ is the suppliers' criterion set to evaluate potential users. a_{ijk} $(i=1,2,...,n,\ j=1,2,...,m,k=1,2,...,p)$ denotes S_i's evaluation value for user D_j as per criterion A_k and $w_k (k = 1, 2, ..., p,\ w_k \geq 0, \sum_{k=1}^{p} w_k = 1)$ represents the weight of criterion A_k.

Then S_i's overall assessment value of D_j is obtained as

$$a_{ij} = \sum_{k=1}^{p} a_{ijk} w_k \tag{1}$$

Let $B = \{B_1, ..., B_s, ..., B_q\}$ be the users' criterion set to assess suppliers, b_{ijs} (i = 1, 2, …, n; j = 1, 2, …, m, and s = 1, 2, …, q) be D_j's evaluation value of supplier S_i with respect to the index B_s, and $\lambda_s (s = 1, 2, ..., q, \lambda_s \geq 0, \sum_{s=1}^{q} \lambda_s = 1)$ be the weight of criterion B_s. Then D_j's overall evaluation value of S_i is derived as

$$b_{ij} = \sum_{s=1}^{q} b_{ijs} \lambda_s \tag{2}$$

Brokers commonly exist in the knowledge service industry. A broker often has better access to the pools on both supply and demand sides and is thus able to achieve more efficient matching between technological knowledge suppliers and users. By providing this service, a broker typically collects a commission based on the realized satisfaction for the traders in a successful matching pair. For a single broker in our model, let r_{ij} stand for the broker's commission for the matching pair S_i and D_j.

In the context of technological knowledge exchange, a particular patent can often be licensed to at most one user. In this case, a proper constraint should be imposed on the suppliers of technological knowledge. On the other hand, due to high cost of licensing and limited resources, a user typically has an upper limit on the number of technology transfers that it can accept. Based on these considerations, a generic framework can be set up below for matching supply and demand of technological knowledge.

Definition 1 Assume that $\mu : S \to D$ is a matching rule. For $\forall S_i \in S, \forall D_j \in D$, if $\mu(S_i) = D_j$, then μ and (S_i, D_j) are, respectively, called two-sided matching and a matching pair of supply and demand of technological knowledge.

$\mu(S_i) = D_j$ represents two-sided matching of S_i and D_j under μ. Presumably, this matching rule reflects the evaluation values of S_i on D_j, D_j on S_i, the commission of the broker as well as any practical constraints on the number of technology transfers that a user can accept and the number of users to which a supplier can sell its technological knowledge. If $\mu(S_i) = S_i$ and

$\mu(D_j) = D_j$, no matching is achieved for S_i or D_j under μ. It is apparent that if (S_i, D_j) is a matching pair under μ, then (D_j, S_i) is also a matching pair under μ.

4 A two-sided matching decision model for technological knowledge exchange with psychological considerations

The aforesaid generic framework takes stakeholders' original evaluation values as basic decision input in identifying appropriate matching pairs. This treatment implicitly assumes that the decision-makers (DMs) are perfectly rational and the matching is conducted based on the best aggregate evaluation score. However, stakeholders often consider other factors such as prior ties and geographical distance [Petrizzelli, 2011]. In addition, stakeholders typically possess bounded rationality and their matching decision behaviour is often affected by psychological other than economic considerations. As such, when a matching decision is considered, raw evaluation values certainly matter, but psychological assessments of the differences between a stakeholder's raw evaluation and expectation often play a critical role in the decision process. Depending on a DM's risk attitude, decision results under psychological influence can be quite different from what are obtained from the expected utility theory under complete rationality.

Kahneman and Tversky [1979] and Tversky and Kahneman [1992] conceived decision making as a two-stage process. The first stage establishes a reference point for evaluating potential decision outcomes. When a decision outcome is better than the reference point, it would be regarded as a "gain"; when a decision outcome is worse than the reference point, it would be referred to as a "loss". After recoding the decision outcomes as gains or losses, prospects can be extracted by performing segregation, cancellation, and other operations. The second stage assesses the prospects based on a value function that measures changes in welfare relative to the reference point rather than the absolute magnitude of the final states [Kahneman and Tversky, 1979; Tversky and Kahneman, 1992]. By employing the prospect theory to account for psychological influences and expected values (prospect values) of suppliers, users, and the broker on technological knowledge matching decision, this section proposes a novel framework for two-sided matching of suppliers and users in a broker-assisted MFT. This method starts with constructing prospect value matrices for the stakeholders.

4.1 Construction of prospect value matrices

Many statistical methods, such as regression analysis and principal-component analysis, are commonly used in analyzing system behaviour. These methods typically require a large amount of data following certain probability distributions. But in reality, many applications have limited historical data, making it difficult to apply these methods. For instance, in the two-sided matching decision considered here, due to the unique feature of technology innovation, it is often the case that limited data are available for the stakeholders to make the final choice. To properly handle this type of small sample data problems, the grey relational analysis can be a handy tool as it is applicable to cases of various sample sizes and different distributions. The fundamental idea of grey relational analysis is that the closeness of a relationship is judged by the similarity level of the geometric patterns of sequence curves. The more similar the curves, the higher the degree of incidence between sequences, and vice versa [Liu and Lin, 2011]. Given that suppliers, users, and the broker typically have limited historical data, the grey relational analysis is employed here to obtain their prospect values for making the matching decision.

First, we consider the suppliers.

4.1.1 The prospect value matrix for the suppliers

After identifying positive and negative ideal users, we will employ the grey relational analysis to obtain suppliers' positive and negative prospect values for users.

Definition 2 Assume that $A=\begin{bmatrix} a_{11},....,a_{1j},...,a_{1m} \\ \vdots \;\; \vdots \;\; \vdots \;\; \vdots \;\; \vdots \\ a_{i1},....,a_{ij},...,a_{im} \\ \vdots \;\; \vdots \;\; \vdots \;\; \vdots \;\; \vdots \\ a_{n1},....,a_{nj},...,a_{nm} \end{bmatrix}$ is the evaluation matrix of suppliers on users, if

$$(a_j^+) = \max_i(a_{ij}) = \max(a_{1j},...,a_{ij},...,a_{nj}) \tag{3}$$

$$(a_j^-) = \min_i(a_{ij}) = \min(a_{1j},...,a_{ij},...,a_{nj}) \tag{4}$$

Then $D_0^+ = \left(a_1^+,...,a_j^+,...,a_m^+\right)$ and $D_0^- = \left(a_1^-,...,a_j^-,...,a_m^-\right)$ are, respectively, called the positive and negative ideal users for the suppliers. Let $a_{ij}^+ = a_j^+$, $a_{ij}^- = a_j^-$, $i = 1,2,...,n; j = 1,2,...,m,$ one has $D^+ = \left(a_{ij}^+\right)_{n\times m}$ and $D^- = \left(a_{ij}^-\right)_{n\times m}$.

Let $d_{ij}^+ = \left|a_{ij} - a_{ij}^+\right|$ and $d_{ij}^- = \left|a_{ij} - a_{ij}^-\right|$, based on the grey relational analysis [Liu and Lin, 2011], the positive and negative correlation coefficients ε_{ij}^+ and ε_{ij}^- of supplier S_i 's evaluations from the positive and negative ideal users D_0^+ and D_0^- are obtained as

$$\varepsilon_{ij}^+ = \frac{\min_i \min_j d_{ij}^+ + \rho \max_i \max_j d_{ij}^+}{d_{ij}^+ + \rho \max_i \max_j d_{ij}^+} \tag{5}$$

$$\varepsilon_{ij}^- = \frac{\min_i \min_j d_{ij}^- + \rho \max_i \max_j d_{ij}^-}{d_{ij}^- + \rho \max_i \max_j d_{ij}^-} \tag{6}$$

where ρ is a distinguishing coefficient and is usually set at 0.5 [Liu and Lin, 2011].

Based on the prospect theory [Kahneman and Tversky, 1979], when a DM faces definite losses, he/she tends to be risk-seeking. Conversely, if a DM faces sure gains, he/she tends to be risk-averse. In the matching decision process, for the suppliers of technological knowledge, if the positive ideal users D_0^+ are taken as reference points, definite losses will encourage them to seek risk; if the negative ideal users D_0^- are set as reference points, certain gains will induce them to avoid risk. This analysis indicates that the positive and negative correlation coefficients can be, respectively, taken as the basic input to determine S_i's negative and positive prospect values as shown below:

$$\begin{cases} v_{ij}^+ = (\varepsilon_{ij}^-)^\alpha \\ v_{ij}^- = -\theta(\varepsilon_{ij}^+)^\beta \end{cases} \quad (7)$$

where α and β stand for the concave and convex degrees of the power function in gain and loss areas, respectively; θ is a risk-averse parameter of the value function; If $\theta > 1$, a DM tends to be more sensitive to losses, and the bigger the θ, the higher the degree of loss aversion.

Experimental data from different countries and regions indicate that, if $\alpha > 1, \beta > 1$, DMs tend to be conservative, while if $\alpha \le 1, \beta \le 1$, DMs are more aggressive. Therefore, when the prospect values are determined, the DMs' risk profiles should be properly considered.

The overall prospect value v_{ij} for S_i matching with D_j is thus obtained by taking into account both the positive and negative prospect values v_{ij}^+ and v_{ij}^- as follows:

$$v_{ij} = v_{ij}^+ + v_{ij}^- \quad (8)$$

This results in the prospect value matrix $P = \left[v_{ij} \right]_{n\times m}$ for the suppliers.

4.1.2 The prospect value matrix for the users

In a similar fashion, one can determine the prospect values of the users on the suppliers.

Definition 3 Assume that $B = \begin{bmatrix} b_{11}, \ldots, b_{i1}, \ldots, b_{n1} \\ \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \\ b_{1j}, \ldots, b_{ij}, \ldots, b_{nj} \\ \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \\ b_{1m}, \ldots, b_{im}, \ldots, b_{nm} \end{bmatrix}$ is the evaluation matrix of users on suppliers, if

$$(b_i^+) = \max_j (b_{ij}) = \max(b_{i1}, \ldots, b_{ij}, \ldots, b_{im}) \quad (9)$$

$$(b_i^-) = \min_j (b_{ij}) = \min(b_{i1}, \ldots, b_{ij}, \ldots, b_{im}) \quad (10)$$

Then $S_0^+ = \left(b_1^+, \ldots, b_i^+, \ldots, b_n^+\right)^T$ and $S_0^- = \left(b_1^-, \ldots, b_i^-, \ldots, b_n^-\right)^T$ are, respectively, called the positive and negative ideal suppliers for the users of technological knowledge. Let $b_{ij}^+ = b_i^+$,

$b_{ij}^{-} = b_i^{-}$, $i = 1,2,...,n; j = 1,2,...,m$, one has $S^{+} = \left(b_{ij}^{+}\right)_{n\times m}$ and $S^{-} = \left(b_{ij}^{-}\right)_{n\times m}$.

Similarly, let $\bar{d}_{ij}^{+} = \left|b_{ij} - b_{ij}^{+}\right|$ and $\bar{d}_{ij}^{-} = \left|b_{ij} - b_{ij}^{-}\right|$. By using the grey relational analysis method [Liu and Lin, 2011], the positive and negative correlation coefficients between D_j's evaluations and S_0^{+} and S_0^{-} are determined as follows:

$$\bar{\varepsilon}_{ij}^{+} = \frac{\min_i \min_j \bar{d}_{ij}^{+} + \rho \max_i \max_j \bar{d}_{ij}^{+}}{\bar{d}_{ij}^{+} + \rho \max_i \max_j \bar{d}_{ij}^{+}} \tag{11}$$

$$\bar{\varepsilon}_{ij}^{-} = \frac{\min_i \min_j \bar{d}_{ij}^{-} + \rho \max_i \max_j \bar{d}_{ij}^{-}}{\bar{d}_{ij}^{-} + \rho \max_i \max_j \bar{d}_{ij}^{-}} \tag{12}$$

where ρ is a distinguishing coefficient and is generally set at 0.5 [Liu and Lin, 2011].

Based on the prospect theory, D_j's positive prospect value $\bar{v}_{ij}^{+}$ and negative prospect value v_{ij}^{-} are computed as

$$\begin{cases} \bar{v}_{ij}^{+} = (\bar{\varepsilon}_{ij}^{-})^{\alpha} \\ v_{ij}^{-} = -\theta(\bar{\varepsilon}_{ij}^{+})^{\beta} \end{cases} \tag{13}$$

Accordingly, the overall prospect value $\bar{v}_{ij}$ for user D_j is obtained as

$$\bar{v}_{ij} = \bar{v}_{ij}^{+} + \bar{v}_{ij}^{-} \tag{14}$$

which can be represented as a prospect value matrix $Q = \left[\bar{v}_{ij}\right]_{m\times n}$ for the users.

4.1.3 The prospect value matrix for the broker

In facilitating matching supply with demand of technological knowledge, as an independent economic agent, the broker typically has its own preferences on different matching pairs. As a profit-driven organization, after considering the prospect values of suppliers and users, it is understandable that the broker is more willing to promote a matching pair with a higher commission than the one with a lower commission.

Definition 4 For a matching pair (S_i, D_j), let r_{ij} be the broker's commission for the matching pair and f_0 be the broker's common expected profit for any matching pair, then

$$h_{ij} = \frac{\left|f_0 - r_{ij}\right|}{\max\left\{r_{ij}\right\}} \tag{15}$$

is called the normalized distance between r_{ij} and f_0.

Generally speaking, the expected profit value f_0 reflects the broker's historical profit and its psychological considerations.

If $r_{ij} < f_0$, then h_{ij} represents a loss for the broker relative to its expected value f_0; if $r_{ij} > f_0$, then h_{ij} stands for a gain for the broker with respect to its expected value f_0. According to different risk attitudes towards gains and losses, the prospect value $\overline{\overline{v}}_{ij}$ of matching pair (S_i, D_j) for the broker can be defined as

$$\overline{\overline{v}}_{ij} = \begin{cases} (h_{ij})^{\alpha}, \quad r_{ij} > f_0 \\ 0, \quad r_{ij} = f_0 \\ -\theta(h_{ij})^{\beta}, r_{ij} < f_0, i = 1,2,...,m; j = 1,2,....,n \end{cases} \tag{16}$$

leading to the prospect value matrix $R = \left[\overline{\overline{v}}_{ij}\right]_{m \times n}$ for the broker.

4.2 A framework of a two-sided matching decision model based on prospect value matrices

The prospect value matrices for the suppliers, users, and broker given in Section 4.1 reflect the stakeholders' psychological considerations under uncertainty. This information can now serve as the decision input for two-sided matching of technological knowledge supply and demand.

$$\max\ Z_S = \sum_{i=1}^{n}\sum_{j=1}^{m} v_{ij}x_{ij} \tag{17a}$$

$$\max\ Z_D = \sum_{i=1}^{n}\sum_{j=1}^{m} \overline{v}_{ij}x_{ij} \tag{17b}$$

$$\max\ Z_I = \sum_{i=1}^{n}\sum_{j=1}^{m} \overline{\overline{v}}_{ij}x_{ij} \tag{17c}$$

$$s.t. \sum_{j=1}^{m} x_{ij} \le 1, i = 1,2,...,n \tag{17d}$$

$$\sum_{i=1}^{n} x_{ij} \le c_j, j = 1,2,...,m \tag{17e}$$

$$c_j \ge 1 \tag{17f}$$

$$x_{ij} \in \{0,1\}, i = 1,2,...,n; j = 1,2,...,m \tag{17g}$$

where x_{ij} is a binary decision variable, indicating if the matching pair (S_i, D_j) is a success or not. $(17a-c)$ are the objective functions for the stakeholders: $(17a)$ maximizes the aggregate prospect value for all suppliers; $(17b)$ refers to the users' maximization of their total prospect value, and $(17c)$ represents the broker's maximization of its prospect value for all matching pairs; $(17d)$ restricts each supplier S_i to match with at most one user to reflect the practical constraints on technology transfer. $(17e)$ establishes the upper limit on the number of technology transfers that user D_j may possibly accept.

The optimization model (17) has three objectives from the three parties, which can be conveniently converted to a single objective optimization model by using the weighted average approach as follows:

$$\max\ Z = \eta_S \sum_{i=1}^{n}\sum_{j=1}^{m} v_{ij}x_{ij} + \eta_D \sum_{i=1}^{n}\sum_{j=1}^{m} \bar{v}_{ij}x_{ij} + \eta_B \sum_{i=1}^{n}\sum_{j=1}^{m} \bar{\bar{v}}_{ij}x_{ij} = \sum_{i=1}^{n}\sum_{j=1}^{m} c_{ij}x_{ij} \qquad (18a)$$

$$s.t.\ \sum_{j=1}^{m} x_{ij} \le 1, i = 1,2,...,n \qquad (18b)$$

$$\sum_{i=1}^{n} x_{ij} \le c_j, j = 1,2,...,m \qquad (18c)$$

$$x_{ij} \in \{0,1\}, i = 1,2,...,n; j = 1,2,...,m \qquad (18d)$$

where $c_{ij} = \eta_S v_{ij} + \eta_D \bar{v}_{ij} + \eta_B \bar{\bar{v}}_{ij}$, η_S, η_D, η_B are, respectively, the weight for the suppliers, users, and the broker, reflecting their importance in the actual two-sided matching decision process. These weights are typically determined through a three-party consultation process or unilaterally determined by a dominating party, and $\eta_S + \eta_D + \eta_B = 1$.

Model (18) can be transformed to a standard assignment model that can be solved by using the Hungarian method. It is easy to see that the feasible region is nonempty and, hence, optimal solutions exist for (18). For such a model, if it is not too big, an optimal matching solution can be obtained by employing different software packages such as Lingo, Matlab, and WinQB2.0.

4.3 Solution procedure

The aforesaid discussions allow us to summarize the solution procedure of the proposed decision method for two-sided matching technological knowledge supply and demand as follows:

Step 1: Determine evaluation matrices *A* and *B* by using (1) and (2) based on the suppliers' and users' evaluations of the other party and criteria weights;

Step 2: Find the positive and negative ideal users and suppliers as per Definition 2 and 3, and calculate positive and negative relational coefficients of the suppliers and users by using the grey relational analysis method;

Step 3: Obtain prospect values and prospect matrices for the suppliers and users based on the positive and negative relational coefficients of the suppliers and users as per Eqs. (8) and (14); Compute the broker's prospect values and prospect value matrix as per (16);

Step 4: Establish the multi-objective optimization model (17), and convert it to a single-objective optimization model (18) by using the weighted average method;

Step 5: Solve the optimization model (18) to obtain the optimal matching pairs.

5 A case study

This case study takes Jia Yong Technology Trade Centre as a representative broker to facilitate matching technological knowledge supply and demand in Nanjing, Jiangsu in China. Numerous higher education and research institutions are located in Nanjing. On the one hand, these research institutions produce a large quantity of technological knowledge, which fails to reach right users in industry to realize its economic benefit. On the other hand, many large-scale state-owned enterprises and numerous small and medium enterprises in the region have been actively seeking for open innovation opportunities by acquiring technological knowledge. This mis-match has significantly affected the commercialization of technology innovations and the innovation capability of the enterprises [Jian and Liu, 2012]. Therefore, it has become an urgent issue to better match suppliers and users of technological knowledge so that suppliers can commercialize their research results and contribute to the betterment of the general society, and users can benefit from open innovation and improve their competitiveness. In the meantime, the broker can collect commissions by providing value-added matching services. From an open innovation lens, this can be treated as a broker-assisted MFT.

According to statistical data, there exist 405 brokers in the MFT to facilitate effective matching between suppliers and users in Nanjing. Jia Yong Technology Trade Center is one of these organizations and is selected as a representative broker to illustrate how the proposed model can incorporate different stakeholders' psychological considerations into the two-sided matching process. To facilitate matching the needs of enterprises (users) and technology owners (suppliers), Jia Yong has been actively collecting relevant supply and demand information on technological knowledge. In March 2014, the broker received matching requests from four enterprises and five patent owners, denoted by $(S_1, S_2, ..., S_5)$ and $(D_1, D_2, ..., D_4)$. The five suppliers assess the four enterprises based on three criteria: patent technology transfer income (A_1), technological level of the enterprise (A_2) and the speed of patent technology transfer (A_3). The four enterprises evaluate the five patents on five criteria: market prospect (B_1), potential economic value (B_2), patent cost (B_3), technology complexity (B_4), and technology advancement level (B_5). After evaluating actual needs and soliciting domain expert opinions, the three criterion weights for the enterprises (users) and the five criterion weights for the patents (suppliers) are, respectively, obtained as follows:

$(0.45, 0.30, 0.25)$ and $(0.3, 0.18, 0.22, 0.15, 0.15)$.

By collecting and assessing relevant suppliers and users information, the five suppliers furnish their evaluation on the four users based on the three criteria as shown in Table 1, and the four users assess the five suppliers as per the five criteria as given in Table 2. Given their limited financial resources and technological capability, the four users set up their upper limits of the maximum number of patents that they can possibly take as 2,2,1,1, respectively. By examining its pools of suppliers and users, the broker estimates its commission revenue by providing the 20 possible matching pairs as shown in Table 3 (in millions of RMB), and its expected value of each successful matching pair is 4 million RMB.

Table 1 Evaluation values of the suppliers (patent owners) with respect to the users (enterprises)

A	S/D	D_1	D_2	D_3	D_4
A_1	S_1	0.90	0.82	0.55	0.78
	S_2	0.78	0.89	0.84	0.58
	S_3	0.85	0.69	0.76	0.80
	S_4	0.70	0.78	0.88	0.54
	S_5	0.65	0.80	0.74	0.90
A_2	S_1	0.86	0.78	0.64	0.82
	S_2	0.73	0.90	0.88	0.65
	S_3	0.87	0.75	0.74	0.82
	S_4	0.69	0.75	0.86	0.63
	S_5	0.57	0.82	0.76	0.88
A_3	S_1	0.85	0.66	0.60	0.75
	S_2	0.75	0.85	0.82	0.66
	S_3	0.88	0.84	0.79	0.65
	S_4	0.59	0.74	0.85	0.74
	S_5	0.76	0.68	0.82	0.87

Table 2 Evaluation values of the users (enterprises) with respect to the suppliers (patent owners)

B	D/S	S_1	S_2	S_3	S_4	S_5
B_1	D_1	0.84	0.78	0.65	0.89	0.53
	D_2	0.66	0.84	0.75	0.49	0.88
	D_3	0.86	0.64	0.72	0.81	0.78
	D_4	0.65	0.78	0.85	0.80	0.65
B_2	D_1	0.88	0.74	0.77	0.84	0.65
	D_2	0.72	0.88	0.79	0.64	0.92
	D_3	0.84	0.76	0.66	0.88	0.74
	D_4	0.73	0.69	0.88	0.78	0.64
B_3	D_1	0.84	0.78	0.75	0.79	0.69
	D_2	0.78	0.82	0.74	0.65	0.88
	D_3	0.87	0.75	0.69	0.90	0.63
	D_4	0.82	0.57	0.88	0.75	0.71
B_4	D_1	0.88	0.72	0.62	0.77	0.64
	D_2	0.75	0.86	0.68	0.74	0.81
	D_3	0.82	0.70	0.77	0.88	0.71
	D_4	0.79	0.64	0.89	0.74	0.69
B_5	D_1	0.84	0.65	0.68	0.78	0.72
	D_2	0.76	0.89	0.75	0.71	0.83
	D_3	0.85	0.64	0.76	0.89	0.69
	D_4	0.78	0.68	0.85	0.72	0.65

Table 3 Revenue of the broker for the matching pairs

S/D(r_{ij})	D_1	D_2	D_3	D_4
S_1	4.4	4.8	6	5.4
S_2	4.3	1	4.5	5.6
S_3	3.5	5	2.8	5.2
S_4	5.6	6	3.4	5.3
S_5	4.4	3.9	5.3	5.1

Given the aforesaid decision input, one can execute the procedures laid out in Section 4.3 as follows.

Step 1: Given the suppliers' evaluations of the users in Table 1 and the users' assessments of the suppliers in Table 2 as well as the associated criteria weights, one can obtain the overall evaluation values based on formulas (1) and (2) as shown in Table 4.

Table 4 Mutual satisfaction evaluation values of the suppliers and users

D/S	S_1	S_2	S_3	S_4	S_5
D_1	（0.8532,0.8755）	（0.7443,0.7575）	（0.8245,0.8635）	（0.8245,0.6695）	（0.6318,0.6535）
D_2	（0.7257,0.768）	（0.8533,0.883）	（0.7445,0.7455）	（0.6227,0.761）	（0.8692,0.776）
D_3	（0.8511,0.5895）	（0.6948,0.847）	（0.7161,0.7615）	（0.8649,0.8665）	（0.7158,0.766）
D_4	（0.7423,0.7845）	（0.6816,0.621）	（0.868,0.7685）	（0.7644,0.617）	（0.6674,0.8865）

Step 2: Based on the overall evaluations, the positive and negative ideal users and suppliers are, respectively, determined as follows:

$$D_0^+ = (0.8755, 0.883, 0.8665, 0.8865)\,;\, D_0^- = (0.6535, 0.7455, 0.5895, 0.617)$$

$$S_0^+ = (0.8532, 0.8533, 0.868, 0.8649, 0.8692)\,;\, S_0^- = (0.7257, 0.6816, 0.7161, 0.6227, 0.6318)$$

Plugging these values into formulas (5), (6), (11) and (12), the positive and negative relational coefficients of the suppliers and users can be determined, which are omitted here for the sake of brevity.

Step 3: To apply the prospect theory given in [Kahneman and Tversky, 1979; Tversky and Kahneman, 1992], the three parameter values $\alpha, \beta,$ and θ must be obtained first. As mentioned earlier, stakeholders from different geographical locations may possess distinct risk profiles, corresponding to different parameter values. To calibrate the model with our case study, experiments were conducted to estimate the three parameter values for $\alpha, \beta,$ and θ. To accomplish this task, 380 scientific and technological employees and government officials in Nanjing (180 males and 200 females) were commissioned and their opinions were solicited. Then, an SPSS nonlinear regression model is exploited to estimate the model parameters [Kahneman and Tversky, 1979; Tversky and Kahneman, 1992], resulting in $\alpha = 1.18, \beta = 1.12, \theta = 2.25$. A further chi-square test was conducted to confirm that these parameter values are greater than 1 at a significant level of 1%. Compared with the parameter values in the literature [Kahneman and Tversky, 1979; Tversky and Kahneman, 1992], these values are relatively small, indicating that the scientific and technological employees and government officials in Nanjing tend to display gradual sensitivity to risk according to the prospect theory. Plugging the positive and negative relational coefficients of the suppliers and users into (7) and (13), one can calculate the positive and negative prospect values of the suppliers and users, thereby determining their prospect value matrices based on (8) and (14) as shown in Table 5. According to the possible revenues in Table 3 and the broker's expected value for each successful matching pair, the prospect value matrix of the broker is computed based on (15) and (16) and shown in Table 6.

Table 5 a. The prospect value matrix of the suppliers

D/S	D_1	D_2	D_3	D_4
S_1	-1.9266	-0.3060	0.3426	-0.8203
S_2	-0.6120	-1.8068	-1.6519	0.2886
S_3	-1.7135	-0.0394	-0.8103	-0.7102
S_4	0.0681	-0.2266	-1.9765	0.3291
S_5	0.2293	-0.3944	-0.8420	-1.9705

Table 5 b. The prospect value matrix of the users

D/S	D_1	D_2	D_3	D_4
S_1	-1.8220	-0.0054	-1.7748	-0.2270
S_2	-0.4852	-1.8972	0.0036	0.1629
S_3	0.1715	-0.3629	-0.0875	-1.9010
S_4	-1.3154	0.3426	-1.9763	-0.7427
S_5	0.3327	-1.9721	-0.3628	-0.0124

Table 6 Prospect values of the broker

D/S	D_1	D_2	D_3	D_4
S_1	0.0409	0.0928	0.2735	0.1796
S_2	0.0292	-1.0352	0.0533	0.2102
S_3	-0.1391	0.1207	-0.3710	0.1497
S_4	0.2102	0.0181	-0.1707	0.1645
S_5	0.0409	-0.0229	0.1645	0.1351

Step 4: Based on the prospect values of the suppliers, users and broker, a multi-objective optimization model (17) can be constructed. According to the status and importance of the suppliers, users and broker in the actual matching situation, the weights of the suppliers, users and broker could be determined by consultation as $\eta_S = 0.35, \eta_D = 0.45, \eta_B = 0.20$, (17) can then be converted to a single-objective optimization model (18) by using the weighted average method, and the coefficient matrix $\left[c_{ij}\right]_{n\times m}$ is determined and shown in Table 7. To facilitate comparison

with the matching result without psychological behaviours, the coefficient matrix of model (18) is obtained by directly taking the weighted average of matrices *A*, *B* in Table 4 and *H* by using (15), and this matrix is displayed in Table 8.

Table 7 Coefficient matrix with psychological behaviours

S/D(r_{ij})	D_1	D_2	D_3	D_4
S_1	-1.4860	-0.0910	-0.6240	-0.3533
S_2	-0.4267	-1.6931	-0.5659	0.2164
S_3	-0.5504	-0.1530	-0.3972	-1.0741
S_4	-0.5261	0.0785	-1.6152	-0.1861
S_5	0.2382	-1.0301	-0.4250	-0.6682

Table 8 Coefficient matrix without psychological behaviours

S/D(r_{ij})	D_1	D_2	D_3	D_4
S_1	0.7037	0.6220	0.6560	0.6553
S_2	0.6101	0.7930	0.6258	0.5774
S_3	0.6310	0.6293	0.6288	0.6996
S_4	0.6587	0.5532	0.7125	0.6033
S_5	0.5264	0.6661	0.6335	0.6473

Step 5: Different software packages such as Lingo, Matlab13.0, and WinSQB can be applied to solve the optimization model (18) with and without psychological considerations, and the matching results are derived and shown in Table 9.

Table 9 Matching results with and without accounting for psychological behaviour

Two-sided matching method	Matching results				
without psychological behaviours	(S_1,D_1)	(S_2,D_2)	(S_3,D_4)	(S_4,D_3)	(S_5,D_2)
with psychological behaviours	—	(S_2,D_4)	—	(S_4,D_2)	(S_5,D_1)

The matching results in Table 9 demonstrate that all suppliers will be matched with a user with (S_1, D_1), (S_2, D_2), (S_3, D_4), (S_4, D_3), and (S_5, D_2) being the five matching pairs if the stakeholders' psychological behaviours are not considered. However, once psychological considerations are introduced via the prospect theory, matching results have been significantly changed. As a matter of fact, none of the previous successful matching pairs survives: suppliers 1 and 3 cannot be matched with any user now. Although suppliers 2, 4, and 5 can still be matched with users, but their matching partners differ from the previous solution without psychological considerations. The matching results without psychological behaviours are derived based on perfect rationality. However, stakeholders have their expected assessments on potential matching pairs. The relative gains/losses with respect to these reference points will understandably affect the stakeholders' overall evaluations of the matching results. By incorporating the prospect theory with the calibrated model parameters α, β, and θ through a field study, the final solution properly reflects what happened in reality: Although the broker, Jia Yong Technology Trade Center, aims to match the patents from the five research groups with the four enterprises, it fails to find matching partners for suppliers 1 and 3 as well as user 3.

From a policy implication perspective, those stakeholders without recommended matching partners fail to meet the expectations and needs of the other stakeholders. At the macro level, national and local governments should introduce appropriate regulations and policies to promote the exchange and cooperation between the universities, research institutions and enterprises. In so doing, universities and research institutions can better understand the needs and expectations of enterprises to create readily transferrable technological knowledge, and enterprises can obtain necessary attributes of technological knowledge that is of their interests, and the brokers can have policy and funding support to provide better matching service between universities and enterprises. At the micro level, all stakeholders should better understand the expectations of the other parties: the suppliers should provide more detailed information on their technology innovations, the users should elaborate more on their specific needs and expectations, and the brokers should establish a more convenient platform to facilitate information exchange between the users and suppliers in order to improve matching efficiency.

The key contributions of this research are threefold: 1) It furnishes a novel theoretical model for matching supply and demand in a broker-assisted MFT; 2) Methodologically, the proposed model can effectively capture market participants' psychological considerations; 3) The case study demonstrates that, by properly calibrating model parameters, the proposed approach can be applied to real-world technological knowledge trading in an MFT and yields matching results that are consistent with the reality.

6 Conclusions

In the process of technological knowledge exchange, matching subjects (suppliers and users) and the broker are typically agents with limited rationality. By employing the prospect theory and grey relational analysis, this paper develops a two-sided matching decision framework for matching supply and demand of technological knowledge. The proposed method is conceived to account for stakeholders' psychological considerations in the decision process, thereby deriving more realistic matching results. A real-world case analysis is employed to demonstrate how the proposed model can be applied to solve a two-sided matching problem in technological knowledge exchange in a broker-assisted MFT. Analytical results show that this approach with psychological considerations is able to generate matching pairs that are more consistent with what happened in reality. This research improves and extends the applications of the two-sided matching theory to the MFT in the open innovation paradigm.

The proposed model has its limitations. For example, it does not differentiate the types of knowledge exchanged (established vs. novel, tacit vs. codified, general vs specialized) [Ardito et al. 2016, Nielsen and Nielsen 2009]. Moreover, the model focuses on incorporating psychological behaviour of the MFT participants and does not consider their other characteristics. These issues warrant further studies in the future.

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