Measuring the performance of knowledge resources using a value perspective: integrating BSC and ANP

Yaoguang Hu, Jingqian Wen and Yan Yan



Yaoguang Hu, Jingqian Wen and Yan Yan are all based at the Department of Manufacturing Engineering, Beijing Institute of Technology, Beijing, China.

Abstract

Purpose – *This paper aims to provide insight into how knowledge resources in R&D organizations can be effectively and separately measured for knowledge sharing and transfer. Knowledge is recognized as a durable strategic resource to obtain sustainable competitive advantage.*

Design/methodology/approach – *The paper proposes a theoretical framework integrating an analytic network process (ANP) with a balanced scorecard (BSC) to measure the performance of knowledge resources under value perspective. Four indicators and three knowledge value (KV) components including labor value, technology value and utilization value are discussed. The model construction, problem structuring and calculation procedure for measuring the performance of knowledge resources based on ANP and BSC are demonstrated.*

Findings – *Despite a number of models to assess the performance of knowledge resources being proposed, they highlighted a need for separately measuring under value perspective. With the aim of filling this gap, the main finding of the paper is to clarify relevant issues, providing a better framework for assessment of the performance of knowledge resources.*

Research limitations/implications – *To handle the dynamic nature of knowledge, the research should take into account more advanced methods to measure the performance of knowledge resources. Both qualitative and quantitative methods should be utilized in future research.*

Practical implications – *The consequences of measuring the performance of knowledge resources under value perspective may help managers to organize and arrange the separate knowledge resources, improving the knowledge resources exchange between different institutions in R&D organizations.*

Originality/value – *The main contribution of this paper lies in the development of a comprehensive model, which incorporates diversified issues for conducting the performance of knowledge resources under value perspective.*

Keywords *Balanced scorecard, ANP, BSC, Analytic network process, Knowledge resource, The performance of knowledge resources*

Paper type *Research paper*

1. Introduction

Knowledge is recognized as a durable and sustainable strategic resource that aids in the acquisition and maintenance of competitive advantages (Marr *et al.*, 2004). It is one of the most vital resources for organizational competitiveness (Ahn and Chang, 2004; Hsieh *et al.*, 2009; Witherspoon *et al.*, 2013; van den Berg, 2013), particularly for R&D organizations, which focus on creating and utilizing knowledge to obtain sustainable competitive advantages. R&D organizations increasingly rely on knowledge management to complement and contribute to their own knowledge resources, which can be leveraged for competitive positioning. To gain and sustain competitive advantages in a global economy, R&D organizations need to effectively mobilize and manage their knowledge resources (Liebowitz *et al.*, 2007; Wang and Chang, 2007).

It is very important to measure knowledge resources to attain effective knowledge management. Knowledge resource evaluation is a key issue in knowledge management and sharing (Lee *et al.*, 2005; Wong *et al.*, 2014). Without valid and reliable measurement, it

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becomes very difficult to develop a comprehensive theory of knowledge or knowledge resources. However, the inherently intangible characteristic of knowledge makes its measurement difficult (Ahn and Chang, 2004; Chen *et al.*, 2009). In fact, although significant research exists in areas such as knowledge sharing and knowledge resource measurement (Edvinsson and Malone, 1997; Wilkins *et al.*, 1997; Dekker and De, 2000; Bontis, 2001; Kreng and Tsai, 2003; Carlucci and Schiuma, 2007; Chen, 2011; Schiuma *et al.*, 2012; Calabrese *et al.*, 2013; Witherspoon *et al.*, 2013; and Wong *et al.*, 2014), little is known about the applied approaches and tools available to assess the value of separate knowledge resources in R&D organizations.

Additionally, most of the metrics and methods regarding knowledge measurement that have been developed focus on measuring the performance of knowledge resources (MPKR), whereas only a few papers examine the topic of measuring the value of the knowledge resources separately within an organization (Wong *et al.*, 2014). To the best of our knowledge, no study has utilized an integrated design with an analytic network process (ANP) and a balanced scorecard (BSC) to measure the value of knowledge resources.

The current research aims to provide insight regarding how knowledge resources in R&D organizations can be effectively and separately measured with regard to knowledge sharing and transfer. Given that not all knowledge is valuable, the evaluation of knowledge resources is important and necessary in the planning phase to determine the priority of knowledge collection and dissemination (Li and Chang, 2009). A lack of proper knowledge evaluation may lead to ignorance regarding valuable knowledge or to the duplication of redundant knowledge. To achieve the aim of the current research, this paper proposes an MPKR approach to using a value perspective. This approach integrates an ANP with a BSC that consists of four perspectives, which include the customer perspective (CP), internal business perspective (IBP), innovation and learning perspective (I&LP) and financial perspective (FP). These perspectives are adopted as indicators of MPKR. The ANP used in this paper is a multi-attribute decision-making approach based on the reasoning, knowledge, experience and perceptions of experts in the field.

The remainder of this paper is organized as follows: Section 2 presents a literature review, and Section 3 develops the theoretical framework for the current research. Section 4 provides an overview of the ANP methodology as applied to one specific case study. Finally, Section 5 presents a discussion and managerial implications, and Section 6 states the major conclusions.

2. Literature review

2.1 Knowledge and knowledge resources

Knowledge has been referred to as a vital resource for organizational functioning, innovativeness, performance and competitiveness (Wong *et al.*, 2014). Knowledge is considered as intellectual capital or material, which includes useful information, intellectual property and experiences that can be used to create wealth. Fundamental to the theory of knowledge creation is that knowledge can be present in the form of both explicit and tacit knowledge (Hubert, 1996; Anand *et al.*, 2010). Explicit knowledge is characterized by information that is relatively easy to capture, articulate and share both precisely and formally. This type of knowledge is typically found in manuals, documents and standard operation procedures and is more amenable to exchange between owners and users of knowledge due to its unambiguous nature. Tacit knowledge refers to implicit and hard-to-conceptualize subjective knowledge that is part of an individual's experiences. Tacit knowledge develops interactively over time through shared experiences, and this "know-how" is embedded in a person who cannot easily express and share it (Hubert, 1996). Given that knowledge is a valuable intangible resource, it should be managed intelligently and dynamically by any organization that seeks to achieve competitive advantages (Wong *et al.*, 2014).

In recent decades, several categories of knowledge resources have been proposed in the economic and management literature (Lerro *et al.*, 2012). Wong *et al.* (2014) categorized knowledge resources into human capital, knowledge and information capital and intellectual property. Currently, there is a trend to consider knowledge resources as intangible and ignore the cognitive nature of the tangible resources. This is a significant limitation given that tangible assets can represent important codified knowledge and, as such, they should be considered as knowledge resources within an organization (Lerro *et al.*, 2012).

2.2 Knowledge resource evaluation in R&D organizations

Knowledge resource evaluation plays an important role in knowledge management in R&D organizations. The assessment of knowledge resources has two main managerial purposes, as follows: the governance of an organization's value creation dynamics and the communication of the value generated and/or incorporated by an organization (Lerro *et al.*, 2012). First, knowledge resource evaluation aims to maximize the utilization of the knowledge resources to create value among organizations. Many types of knowledge resources are articulated in digital documents in R&D organizations, including experiences, cases, models, best practices, papers, patent files and many others. To strengthen the sharing and exchanging of these knowledge resources, the first step is to identify and evaluate them (Marr *et al.*, 2004). Second, assessing the value of knowledge resources contributes to four operations regarding knowledge in R&D organizations, as mentioned by Karl *et al.* (1997), which are developing (e.g. buying, learning programs and machine learning with databases), distributing (e.g. manuals and network connections), combining (e.g. finding synergies and reusing existing knowledge) and consolidating (e.g. preventing knowledge from disappearing and offering tutoring programs) the knowledge. Knowledge resource evaluation also maintains the appropriate equilibrium among knowledge resources in R&D organizations (Lev, 2003). When measuring knowledge resources, many authors emphasize focus on the soft side, which is human capital, whereas others support evaluating the intellectual property and knowledge capital. Wong *et al.* (2014) summarized the measurement metrics for knowledge resources, as shown in Table I (Wong *et al.*, 2014).

According to Table I, there are no scholars conducting research on MPKR according to the value perspective. In this context, knowledge resources are measured in R&D organizations as separate and as having cross-purposes instead of as integrated intellectual assets, such as human assets or customer assets, as in Edvinsson's Skandia Navigator (Edvinsson and Malone, 1997). Although the existing and related research (Edvinsson and Malone, 1997; Kreng and Tsai, 2003; Carlucci and Schiuma, 2007; Lerro *et al.*, 2012) is useful, it does not aid in measuring the value of separate knowledge resources compared to the overall value of the knowledge resources in R&D organizations.

3. Theoretical framework

3.1 General framework

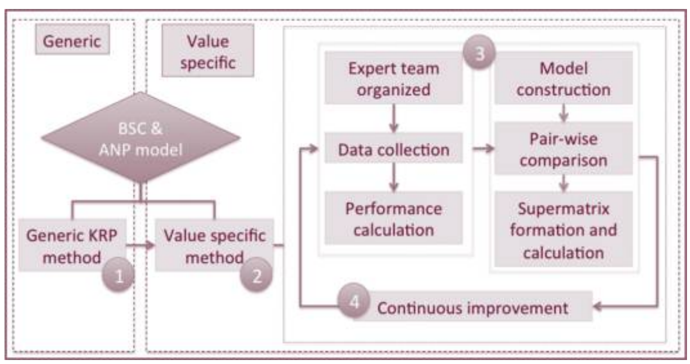
The aim of the proposed MPKR framework (Figure 1) is to relate the generically defined MPKR methods with the value-specific measurements for the environment and knowledge management strategies of an organization. This would allow for the development of a value-specific method for MPKR. The proposed framework presented in Figure 1 consists of the following four major steps:

1. argue the generic MPKR methods;
2. based on these methods, theorize measurement indicators and components of MPKR according to the value perspective;
3. calculate the performance of knowledge resources based on the developed ANP methodology and model; and
4. continuously improve this model by redefining knowledge resources according to the knowledge management environment.

Table I Metrics for measuring the performance of knowledge resources

Category	*Metric*	*Author*
Human capital	Number of years in the profession	Sveiby (1997)
	Growth in average professional experience	
	Education level	
	Training and education costs	
	Grading of executives	
	Professional turnover	
	Proportion of professionals in the company	
	Value added per professional	
	Relative pay position	
	Professional turnover rate	
	Percentage of managers with advanced degrees	Edvinsson and Malone (1997)
	Percentage of annual turnover of staff	
	The human capital value of the firm in currency unit terms	Bontis *et al.* (1999)
	Number of staff trained	Gooijer (2000)
	Number of experts in each function	Arora (2002)
	Number of employees	Ahn and Chang (2004)
	The proportion of skilled workers	Wu *et al.* (2009)
	Retention of technicians	
	The average level of employees' education	
	Average level of education	Minonne and Turner (2009)
Knowledge and information capital	Number of central processing unit (CPU)-information technology (IT) capacities	Edvinsson and Malone (1997)
	Number of communities in database	Shannak (2009)
	Number of topics in communities in database	
	Number of taxonomies in database	
	Number of contributions in systems per community	
Intellectual property	Number of average age of patents	Edvinsson and Malone (1997)
	Number of successful product launches	Ahn and Chang (2004)
	Possession of technological achievements	Wu *et al.* (2009)

Figure 1 Framework for measuring the performance of knowledge resources



This paper focuses on the first three steps of the proposed methodology, given that previous MPKR research identifies these as the ones with the most potential for improvement.

3.2 Knowledge resource evaluation approaches

The approaches to measuring the value of knowledge resources can be divided into the following two types: macro approaches and micro approaches. Macro approaches aim to measure the overall value of the knowledge resources in an organization, whereas micro approaches aim to measure the value of separate knowledge resources (Dekker and De, 2000). This section discusses a number of representative macro and micro approaches.

3.2.1 Macro approaches. Most researchers in the field of knowledge management examine macro evaluation approaches, with studies divided into two subject groups: static and dynamic. The most representative macro approaches in the static group are the Skandia Navigator by Edvinsson and Malone (1997) and the Technology Broker by Brooking (1996). The Skandia Navigator represents the holistic intellectual capital reporting model. The strength of the Skandia Navigator is that it provides broader coverage of organizational structural factors; yet, it only offers a snapshot in time and cannot represent the dynamic flows of an organization (Bontis, 2001). In contrast, the Technology Broker defines intellectual capital as a combined amalgam. The strength of the Technology Broker is that it aids in identifying value and in leveraging the intellectual capital of an organization. However, the main weakness of the Technology Broker is that there is a considerable leap from the qualitative results that this questionnaire provides to the actual dollar values for knowledge resources.

However, a number of researchers focus on the dynamic value of knowledge resources. One representative dynamic model was constructed by Kreng and Tsai (2003) to forecast knowledge value (KV). Other researchers have focused their studies on generating a knowledge map, which is a popular method for assessing the value of knowledge resources across a period of time. For example, Carlucci *et al.* (2004) proposed the knowledge assets value map (KAVM), which is a tool for assessing the associations between knowledge assets and a company's business performance (Carlucci and Schiuma, 2007). Furthermore, Giovanni and Daniela (2007) presented the KAVM as a thinking-based approach for assessing knowledge assets dynamics. Dynamic approaches are useful for evaluating the value of knowledge resources across a period of time. However, these dynamic models provide only a fuzzy evaluation of undefined knowledge resources.

3.2.2 Micro approaches. Although macro approaches are both practical and popular, they are less helpful when examining knowledge resources at a level lower than the organization as a whole. Micro approaches are better suited for addressing these cases and are divided into two subject groups: monetary and non-monetary. In the monetary group, Wilkins *et al.* (1997) proposed a method that describes valuing knowledge assets at a specific level of detail. Then, Dekker and De (2000) constructed an extension and enhancement of Wilkins *et al.*'s (1997) model. Both micro approaches evaluate knowledge resources in a monetary way. The indicators and metrics of a company's monetary nature provide financial information that supports the negotiation, exchange or transfer of knowledge assets in the market. However, monetary approaches assume that an organization has described its knowledge areas and has negotiated a price for its products on the market. In the current study, we assume that knowledge resources in R&D organizations are protected and cannot be sold in the market. This condition limits the usability of monetary approaches, which often require complicated calculations.

Furthermore, non-monetary metrics support defining and describing the properties and specific features of organizational knowledge assets, both from qualitative and quantitative perspectives (Lerro *et al.*, 2012). Nevertheless, the evaluation results cannot provide market prices for knowledge resources.

3.3 The balanced scorecard

Kaplan and Norton (1992) developed a BSC framework using a combination of measures related to four perspectives (originally defined as financial, customer, internal business processes and innovation and learning) to align individual, organizational and cross-departmental initiatives. With regard to the value of knowledge resources, the BSC aimed to help R&D organizations test and update their knowledge management strategies and meet their customers' needs and their shareholders' objectives. Kaplan and Norton (1992) posited that the BSC balanced the following four perspectives:

1. short-term and long-term objectives;
2. financial and non-financial measures;
3. lagging and leading indicators; and
4. internal and external performance perspectives.

Zhang (2010) applied the BSC to measure knowledge management performance and verified its effectiveness, yet observed that the BSC method does not explain the procedures for conducting evaluations of the key areas. Gooijer (2000) implemented the BSC to examine knowledge management performance measurement and mapped the knowledge management objectives across the four key areas.

To measure performance, managers should concentrate on financial measures and take into account non-financial criteria. When factors are carefully integrated in a balanced manner, this "scorecard" provides managers with a brief yet comprehensive and timely view of their business (Braam and Nijssen, 2004). The BSC serves as a means for communicating long-term strategic initiatives to business-units and achieving long-term financial success (Chen *et al.*, 2009). It combines important concepts and practices from various theories and disciplines into a single performance measurement system with the purpose of improving performance (Davis and Albright, 2004). An important contribution of the BSC is its explicit consideration of multiple performance perspectives as opposed to providing a strictly FP. However, the BSC also brings complexity to the measurement of performance, particularly with regard to information overload, judgment biases and the need to reach some synthetic judgment that summarizes and makes sense of the BSC's multiple perspectives and indicators. Chan (2006) argued that information overload and judgment biases are some issues identified with the implementation of the BSC and showed that the analytic hierarchical process (AHP) is a valuable tool, as it can assist management in developing priorities for performance indicators, as the BSC includes performance indicators as the highest priority. The ANP, as an extension of the AHP, allows management to synthesize information from the BSC into a composite measure. Moreover, the algorithm for the ANP accounts for all of the performance measures included in the BSC (i.e. common, unique, financial and non-financial) in the decision-making process. This alleviates the negative influence of judgment biases when decision-makers use the BSC as part of their performance management.

3.4 Developing KV components according to the value perspective

The performance indicators for knowledge resources can be classified into different categories viewed from various perspectives. With regard to the value perspective, three sets of knowledge resources performances are described next.

The first set of knowledge resources is labor value (LV). In accordance with the labor theory of value, the value of knowledge resources results from human labor and is determined by socially necessary labor time (Mossoff, 2012; Murphy, 2012). In a practical application, Brooking (1996) aimed to calculate a dollar value for the non-tangible parts of an organization. She used the cost-based approach, which determines the value of an asset by ascertaining its LV. Wilkins *et al.* (1997) also proposed a method using added value and the cost of a knowledge asset as the main contributors to its value.

The second set is technology value (TV). A number of researchers have argued that TV contributes to the evaluation of knowledge resources. For example, the Advanced Technology Program in the USA noted the significance of technological knowledge evaluation (Wang *et al.*, 2010) and researched this topic for several years. A more recent knowledge evaluation factor model developed by Chen (2011) also indicated that TV should be added to the assessment of knowledge resources.

The third set is utilization value (UV). UV of knowledge resources is a critical determinant of knowledge transfer. In previous knowledge management literature, perceived value (i.e.

UV) of knowledge resources is a critical determinant of knowledge transfer (Alavi and Leidner, 2001; van den Berg, 2013), knowledge sharing (Fullwood *et al.*, 2013) and knowledge consumption (Desouza *et al.*, 2006). The set of knowledge resources that includes usefulness and the benefits gained from knowledge utilization contribute to the creation of knowledge (Desouza *et al.*, 2006).

This review of relevant research revealed a number of problems and deficiencies. Due to as-yet undefined standards regarding how to quantify the knowledge resources of R&D organizations according to financial terms, non-monetary metrics are more frequently adopted in operational practices and are therefore more suitable to examine in this paper. Although research examining the micro approach has been performed with monetary groups, there has been less research examining the micro approach with non-monetary groups. As previously noted, the aim of the current paper is to manage knowledge resources and develop them into continuous performance improvements for organizations; our aim is not to communicate their real value to the market. Therefore, we propose a micro approach to evaluate the non-monetary value of knowledge resources in R&D organizations.

3.5 Analytic network process

The AHP proposed by T.L. Thomas prioritizes decision alternatives and may be the most widely used technique for multi-criteria decision-making (MCDM) (Malcolm, 2002). The ANP is an extension of the AHP, in which the assumption of independent criteria is not valid (Saaty, 1996). In the current paper, the ANP is used to derive ratio scales for the performance indicators of the knowledge resources from paired comparisons within the multilevel network structures.

The advantages of the ANP indicate why it is believed to be the most suitable to measure the value of knowledge resources. First of all, the ANP is a proven strategic decision support method which is used in many applications (Ravi *et al.*, 2005; Jharkharia and Shankar, 2007; Partovi, 2006; Verdecho *et al.*, 2012). Based on expert knowledge of the decision-maker, both quantifiable and non-quantifiable parameters can be incorporated into the methodology. Moreover, the ANP allows for a more complex relationship among the decision levels and attributes, as it does not require a strict hierarchical structure, whereas the AHP models a decision-making framework that assumes a unidirectional hierarchical relationship among the decision levels. In addition, the ANP allows for the consideration of interdependencies among and between levels of criteria and thus is an attractive MCDM tool. This feature makes it superior to the AHP, which fails to capture interdependencies among different enablers, criteria and sub-criteria. Finally, the ANP uses pairwise comparisons to derive priorities among the considered criteria in the decision process, and provides synthetic scores that are considered a crucial indicator of the relative ranking of different alternatives available to the decision-maker. In this way, decision-makers gain knowledge and insight into the problem when performing the process of comparison between the different criteria.

Previous research has addressed the joint applications of the ANP with the BSC. Wong *et al.* (2014) argued that the ANP supports the ability to model complex and dynamic environments. Moreover, they argued that the ANP is a theory of measurement that has tangible and intangible criteria and is well-suited for group decision-making, given that it offers numerous benefits as a synthesizing mechanism. Chen *et al.* (2009) proposed an approach that integrated the ANP and BSC to measure knowledge management performance using a competitive perspective. Joseph (2003) concluded that the ANP has a number of advantages, including ease of use, over-specification of judgment, built-in consistency tests, use of proper measurement scales and applicability in the elicitation of utility function. Yüksel and Dağdeviren (2010) developed a framework by integrating the BSC approach with the fuzzy ANP technique to determine the performance level of a business based on its vision and strategies. The applications of the ANP within the BSC framework also appeared:

- in Chen *et al.* (2008), who discussed the BSC using the ANP with a sensitivity analysis that was constructed to prioritize the relative importance of multiple criteria and the preferences of new product mixes by generalizing experts' opinions;
- in Tseng (2010), who proposed a hybrid approach using the ANP and BSC to evaluate the performance of a university in Taiwan; and
- in Tjader *et al.* (2014), who combined the ANP and BSC to build a cohesive decision model to determine a firm's level of IT outsourcing strategy.

4. Methodology and case study

In the current paper, we propose a theoretical framework (Figure 1) that integrates the ANP and BSC to measure the performance of knowledge resources within an organization according to the value perspective. First, an experienced expert team was organized in the relevant area. Second, we utilized sufficient time and manpower to collect data. Finally, we adopted useful tools to calculate and form pairwise comparison matrices, which will be discussed in Section 4.2.

4.1 A decision group

The present study applied the proposed methodology within a large R&D organization with a background in the aerospace industry, specifically the research and development of large spacecraft. This organization consisted of 16 research institutions in Beijing, China, with each research institution composed of ten professional research units. This R&D organization was facing the following two critical problems:

1. a lack of innovation competence, and
2. disorganization of knowledge resources.

To survive, an R&D organization has to retain competitive advantages in the current hypercompetitive environment. Given that knowledge is a critical factor related to business competitiveness, an R&D organization with superior performance should increase its competitive advantage. Therefore, MPKR according to the value perspective is a critical task for R&D organizations. As such, the current research examined the selected aerospace R&D organization, which is the case organization, to explore the performance of knowledge resources.

In the ANP approach, the accuracy of the results for the pairwise comparisons depends on the involved expert's knowledge. Therefore, organizing an experienced expert team with appropriate knowledge in the relevant area is critical (Chen *et al.*, 2009). A decision group was organized in the case organization with 16 members, as follows: six knowledge managers, six chief engineers, the director of the R&D center and three professional technologists from the R&D center. The decision group had to measure the performance of the knowledge resources within the case organization to obtain useful information that supports decision-making.

Forman and Peniwati (1998) discussed several possible ways to aggregate information during group decision-making. Two of the methods that have been widely used are the aggregation of individual judgments (AIJ) and the aggregation of individual priorities (AIP). These authors proposed that the choice of method depends on whether the group acts together as a unit or as separate individuals, with AIJ being appropriate for the former, whereas AIP is appropriate for the latter. Bentes *et al.* (2012) argued that there were two paths for aggregating individual responses in terms of group responses, as follows:

1. simple averaging across assessments that are produced independently by the evaluating judges (e.g. AIJ and AIP); and

2. an agreement-building approach whereby evaluating judges reach some consensus about the value of priorities and performance levels.

Grošelj *et al.* (2015) proposed that groups will try to reach a consensus during a meeting, first by developing a hierarchy and then by generating pairwise comparisons. If the group cannot reach a consensus regarding a particular judgment, the members of the group can vote or try to reach a compromise. Some researchers use the averaging approach (Chou *et al.*, 2004; Javalgi *et al.*, 1989), whereas others prefer the agreement-building approach (Fletcher and Smith, 2004; Shahin and Mahbod, 2007; Kumar and Bhagwat, 2007; Bentes *et al.*, 2012). Morgan and Krueger (1993) concluded that group effects generate valuable data that are derived from both the consensus and diversity of the participants. The present study utilizes the agreement-building approach and organizes several face-to-face meetings to construct comparison matrices.

This research project took approximately one year to complete, with two months required for data collection. Four meetings with the managers occurred during the first semester of 2013. During the first meeting, consistent with instructions, the 16 executives and knowledge employees discussed performance indicators as the basis for the subsequent analysis. Based on the ANP method, senior knowledge managers and experts from the 16 research institutions within the R&D organization were interviewed to determine the major indicators. These were deemed the detailed indicators for evaluating performance according to the value perspective. The second meeting was a brainstorming session, during which all 16 participants suggested indicators. The researchers addressed issues concerning the adequacy of the indicators and their classifications within the value perspectives. During the third meeting, the group fine-tuned the performance indicators and discussed goals. Finally, during the fourth meeting, the group reached a consensus as to which performance indicators to use.

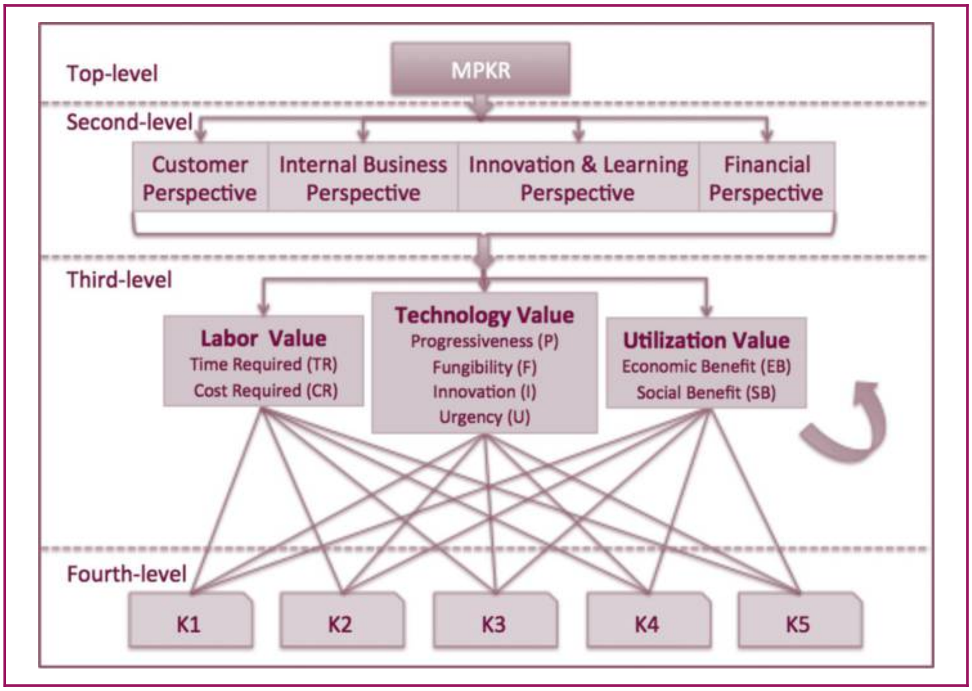
4.2 Application of the ANP methodology

4.2.1 Step 1: the ANP network and problem formulation. In the ANP methodology, the decision problem should be transformed into a network structure, which was built based on the comprehension of the decision problem and the associations between the different factors related to the decision problem. According to Horenbeek and Pintelon (2014), the network structure is composed of different clusters (i.e. groups of elements) and these elements are connected with each other. These connections represent the different relationships that exist between the clusters and elements in the decision problem. The ANP network allows for inner and outer dependence (Horenbeek and Pintelon, 2014). The different components in a network structure include source components (i.e. no incoming arrows), sink components (i.e. no leaving arrows), recurrent state (i.e. falls in a cycle) and transient states. Based on the literature overview presented in Section 2 and our previous discussion of the theoretical frameworks in Section 3, a generic network structure for MPKR is presented in Figure 2.

The first step was to structure a performance measurement of knowledge resources according to its basic components. The relevant indicators and alternatives, which were selected based on our review of the previous literature and discussions with individuals in industry and academia, were structured in the form of a control hierarchy (Figure 2). The overall objective was to evaluate the performance of the knowledge resources within the case organization.

We confirmed the second-level indicators based on the BSC according to the determinants of the performance of the knowledge resources, including the CP, IBP, I&LP and FP. Martinsons *et al.* (1999) argued that the goal of the CP is to achieve an organization's vision by delivering value to its customers. The CP indicates the direction for knowledge management (Zhang, 2010). To enhance knowledge sharing and utilizing within an organization, it is necessary to periodically conduct customer service surveys across different departments. Abran and Buglione (2003) stated that several measures that reflect

Figure 2 The ANP network structure for measuring the performance of knowledge resources



successful outcomes of an organization's strategy, such as customer satisfaction and retention, can serve as outcome indicators for the CP. According to the process-based view, the aim of internal business processes is to satisfy the knowledge users by promoting efficiency and effectiveness in the internal business processes that have the greatest impact on customer satisfaction to achieve an organization's financial objectives. According to the future view, the aim of learning and growth processes is to achieve an organization's vision by sustaining its innovation and change capabilities based on knowledge sharing and utilization through continuous improvement and preparation for future challenges. The aim of the FP is to achieve financial success by delivering value to users within different departments in R&D organizations. Intellectual assets are a general term similar to knowledge-related assets. The evaluation of an organization's intellectual assets organization can supplement traditional financial statements that are available to shareholders as well as other resources.

The third level of the hierarchy has three sub-criteria that are referred to as the value components of the model. These components support all of the indicators at the second level relative to the performance of the knowledge resources. The components are LV, TV and UV, and they were defined in Section 3.4 as the KV components of the performance of the knowledge resources. LV is the basic criteria considered by providers of knowledge resources. To measure LV, two critical factors are the time and cost required to introduce and develop the knowledge resources (Mossoff, 2012; Murphy, 2012; Dekker and De, 2000). One critical criterion influencing knowledge resource evaluation is TV, which is perceived by both the providers and users of knowledge resources. When the knowledge generated through management activities has no TV, it is not beneficial for future decision-making needs. LV and TV are interdependent to some degree. One instrument that assesses TV utilizes the following four constructs:

1. progressiveness (Karahanna *et al.*, 1999; Wang *et al.*, 2010);
2. fungibility (Chen, 2011);

3. innovation (Venkatesh *et al.*, 2003); and
4. urgency (Wang *et al.*, 2010).

Before researching knowledge resources, knowledge users should consider UV as a vital contribution to knowledge resource evaluation. The degree of UV depends on constructs such as economic benefit and social benefit (Lerro *et al.*, 2012; Marr *et al.*, 2004; Brooking, 1996; Desouza *et al.*, 2006; Ford and Staples, 2006). The determinants of knowledge resources (i.e. customer, internal business, innovation and learning and financial), which are the indicators of the performance of the knowledge resources, are modeled to have dominance over the value dimensions of knowledge resources. The KV components are the enablers of the performance of the knowledge resources. The enablers are dependent on achieving the controlling value dimension of the knowledge resources. There are a number of interdependencies among the enablers, which justifies the arrow arching back to the enabler's decision level (Figure 2).

The fourth level of the hierarchy consists of five types of knowledge resources available in the case organization. According to van den Berg (2013), organizational knowledge may be categorized as belonging to one of three classifications, which are tacit, codified and encapsulated knowledge. Tacit knowledge must be learned, acquired and accumulated through experience (Nelson and Winter, 1982; Winter, 1987; Boisot, 1998; van den Berg, 2013). Wong *et al.* (2014) stated that intellectual property includes inventions, patents, trademarks, industrial designs, trade secrets and copyrights according to the World Intellectual Property Organization (WIPO, 2004). Scarf (1997) expressed concern with the mathematical modeling of maintenance rather than the management processes related to maintenance. Batanov *et al.* (1993) discussed algorithms and mathematical models as declarative knowledge in a knowledge-based system that could be used to develop maintenance management. Lerro *et al.* (2012) argued that reporting should be used to collect, aggregate and represent data that were collected using measurements to disclose and communicate important information. Research reports can be categorized as internal reporting, which communicates information internally to an organization, whereas external reporting discloses information to the public domain. The output of knowledge creation is referred to as knowledge assets, which include patents, copyrights and scientific publications (Kuah *et al.*, 2012). Lu *et al.* (2014) argued that there are three types of output that are generally deemed as the final output of the R&D production process. Published scientific articles are concrete outputs of technological and academic research, which are one of the most important knowledge resources in R&D organizations.

Based on the literature reviewed previously, we posit that the following five knowledge resources are the primary achievements from recent major research projects at the case institution: the experience (Nelson and Winter, 1982; Winter, 1987; Boisot, 1998; van den Berg, 2013) of maintenance for a specific type of machine (K1), an invention patent (Wong *et al.*, 2014; WIPO, 2004) (K2), a mathematical model (Batanov *et al.*, 1993; Scarf, 1997) (K3), a research report (Lerro *et al.*, 2012; Li *et al.*, 2011) (K4) and a scientific article (Kuah *et al.*, 2012; Lu *et al.*, 2014) (K5). The current research examines these five types of knowledge resources at the case organization to verify the proposed ANP model (Figure 2). Following two months of data collection and classification, we organized the pairwise comparisons with regard to relevant meetings for MPKR using the ANP approach.

4.2.2 Step 2: pairwise comparisons. After transforming the decision problem into the appropriate business-specific network structure, pairwise comparisons of the elements at each level were performed to derive the overall priorities. In this step, the members of the expert team were asked to respond to a series of pairwise comparisons in which two components were simultaneously compared regarding an upper-level "control criterion". The decision-makers judged the comparisons according to the fundamental AHP scale (i.e. a ratio scale from 1-9), which was developed by Saaty (1990). The numerical values that represented the judgments of the comparisons were arranged in a matrix for further analysis.

All influences should be considered according to the same criterion to derive the overall priorities; therefore, all comparisons should be made with regard to one criterion, which is the control criterion for the ANP network. A pairwise comparison matrix was constructed for each correlation between the elements defined in the network structure. The number of pairwise comparisons that should be performed for a $n \times n$ pairwise comparison matrix equals $n \times (n-1)/2$, in which n is the number of elements that need to be compared. The pairwise comparison number a_{ij} is the number from the fundamental scale (Saaty, 1990) that approximates the ratio w_i/w_j, in which w_i is the weight or priority of the *ith* element (row element) and w_j is the weight or priority of the *jth* element (column element). As such, a score of 1 on the defined ratio scale indicates the equal importance of the two elements given the control criterion, whereas a score of 9 indicates the overwhelming dominance of the *ith* element compared to the *jth* element. The comparison Matrix A to compare n elements is $A = [a_{ij}]$ (in which $a_{ij} = w_i/w_j = 1/a_{ji}$, $a_{ii} = 1, 1 \le i \le n$, *and* $1 \le j \le n$). Following the completion of the pairwise comparisons, the local priority vector W was computed as follows (Laura, 1998):

$$AW = \lambda_{max} W, \tag{1}$$

$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{i1} & a_{i2} & \cdots & a_{in} \\ \vdots & \vdots & \vdots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}$ and $W = \begin{bmatrix} W_1 \\ \vdots \\ W_i \\ \vdots \\ W_n \end{bmatrix}$, in which A is defined as the matrix of the pairwise comparisons values (Tables II-V), W is the priority vector of the weights and λ_{max} is the maximum or principal eigenvalue of Matrix A. The principal eigenvector represents the priority rating of each element in the pairwise comparison matrix. This eigenvector becomes the local priority vector when normalized. An associated local priority vector was

Table II Pairwise comparisons of knowledge resource performance indicators

MPKR	*CP*	*IBP*	*I&LP*	*FP*	*Priorities*	*CR*
CP	1	1/2	1/4	2	0.143	0.008
IBP	2	1	1/2	3	0.264	
I&LP	4	2	1	5	0.507	
FP	1/2	1/3	1/5	1	0.086	

Table III Pairwise comparisons of the KV components under customer perspective

Customer perspective	*LV*	*TV*	*UV*	*Priorities*	*CR*
LV	1	1/3	1/5	0.109	0.004
TV	3	1	1/2	0.309	
UV	5	2	1	0.582	

Table IV Pairwise comparison matrix for knowledge resources under MPKR, CP and LV cluster

Labor value	*K1*	*K2*	*K3*	*K4*	*K5*	*Priorities*	*CR*
K1	1	1/3	3	1/2	1/5	0.104	0.074
K2	3	1	2	3	1/3	0.233	
K3	1/3	1/2	1	1/2	1/5	0.072	
K4	2	1/3	2	1	1/3	0.134	
K5	5	3	5	3	1	0.457	

Table V Priority Matrix A for the KV components under CP over the knowledge resources

Matrix A	*LV*	*TV*	*UV*
K1	0.104	0.135	0.411
K2	0.233	0.477	0.181
K3	0.072	0.089	0.087
K4	0.134	0.074	0.266
K5	0.457	0.225	0.054

calculated for each pairwise comparison matrix. The derived local priority vectors for the pairwise comparison matrices are shown in Tables II-V.

During the evaluating process, there may be an issue with the consistency of the pairwise comparisons. To check this consistency, we calculated the consistency ratio, CR, as follows:

$$CR = \frac{CI}{RI}, \tag{2}$$

in which:

$$CI = \frac{\lambda_{max} - n}{n - 1}, \tag{3}$$

in which *CI* is the Consistency Index, *RI* is the Random Index and *n* is the size of Matrix *A*. The CR for each pairwise comparison matrix was calculated using the previous formula and these ratios are shown in Tables II-V. A CR of less than 0.10 or 10 per cent is acceptable (Saaty, 1990). When the *CR* is greater than this value, the decision-makers were consulted again to fine-tune their pairwise comparisons.

As discussed in Section 4.1, this study utilizes the agreement-building approach to reach a consensus regarding the value of priorities and performance levels. Rather than having the participants define the weights individually, 16 members jointly discussed why a given indicator would be more or less important than another and the degree of this difference. By utilizing an agreement-building approach, weights may reflect a more balanced perception of the relative importance of the indicators and perspectives. The expert team members' discussions had the additional benefit of forcing the participants to provide explicit justifications for their reasoning. Participants were also aware of aspects (due to comments from other participants) that they may otherwise have overlooked had the open discussion not occurred (Bentes *et al.*, 2012). Given that the ANP network structure (Figure 2) had four levels, we constructed four pairwise comparisons that will be described next.

4.2.2.1 Pairwise comparisons of the four performance indicators of the knowledge resources. To start, the pairwise comparisons of the four performance indicators of knowledge resources were conducted. Table II presents the pairwise comparison matrix for the indicators with the responses from the members of the decision group. Table II shows that the I&LP is viewed as more important than the CP. The priorities (also referred to as the local priority vector) are the weighted priorities of the performance indicators of the knowledge resources, as shown in the last column of the matrix. The I&LP is the most important indicator (priority = 0.507) of the four indicators. These priorities are used in Table X to calculate the overall weighted index of MPKR for the case organization. From Table II, the results of the comparisons (priorities) of the indicators for MPKR are shown as P_j in Table X.

4.2.2.2 Pairwise comparisons of the KV components. To examine one performance indicator of knowledge resources, a pairwise comparison matrix was generated for the KV components. Table III shows the pairwise comparison matrix for the KV components according to the CP. In Table III, the relative importance of the TV compared to the LV is three, according to the CP. The UV is the most influential (priority = 0.582) with regard to the CP when evaluating the performance of the knowledge resources, whereas the LV has the least amount of influence (priority = 0.109). The number of pairwise comparison matrices depends on the number of indicators. Therefore, four pairwise comparison matrices were formed for the four indicators. The priorities obtained from these matrices are presented as A_{kj} in Table X.

4.2.2.3 Pairwise comparisons of the knowledge resources. Pairwise comparisons were made for the relative impact of each of the knowledge resources on the KV components that influenced the knowledge indicators and MPKR. One example of a comparison matrix is shown in Table IV. This matrix represents the results for the MPKR-CP cluster with LV as the control KV component for the knowledge resources. Table IV shows that the K5 (priority = 0.457) has the greatest impact on the MPKR-CP cluster with LV as the control KV component for the knowledge resources in the case organization. Additionally, the impact of the K3 was minimal (priority = 0.072). Therefore, the K5 is the most relevant component for LV in the MPKR-CP cluster at the case organization. With regard to the performance indicators of the knowledge resources, there will be three such matrices and 30 pairwise comparisons at this level of relationship. For a KV component, such as LV, there will be four such matrices according to the following four clusters: the MPKR-CP cluster, the MPKR-IBP cluster, the MPKR-I&LP cluster and the MPKR-FP cluster. Table V presents the priority Matrix *A* for the KV components according to the CP regarding the knowledge resources in the case organization.

4.2.2.4 Pairwise comparisons of the KV components for the knowledge resources. The local priority weights for the relative impacts of the KV components for each knowledge resource at the case organization were calculated. Table VI presents an example of the impact of an experience of maintenance on a certain type of machine (K1) in the case organization with regard to various KV components. Note that the UV (priority = 0.637) influences the knowledge resources of the case organization more than any other component. Additionally, the impact of the LV on the knowledge resources of the case organization was minimal (priority = 0.105). Each of the five knowledge resources has a priority weight, and, taken together, these vectors form Matrix *B*, as shown in Table VII.

4.2.3 Step 3: calculating the performance of the knowledge resources. The performance of the knowledge resources was calculated using a super-matrix formation and the "desirability index". A super-matrix is a two-dimensional matrix consisting of all of the elements for the different clusters (rows and columns). The super-matrix represents the influence priority of an element at the left of the matrix (row) with regard to another element at the top of the matrix (column). Each local priority vector that was derived from the pairwise comparison matrices is presented in the right column of the super-matrix. In this model, there are four super matrices for the four indicators of the hierarchy network,

Table VI Pairwise comparisons of the KV components under K1 of the case organization

An experience of maintenance for a certain type of machine (K1)	*LV*	*TV*	*UV*	*Priorities*	*CR*
LV	1	1/3	1/5	0.105	0.04
TV	3	1	1/3	0.258	
UV	5	3	1	0.637	

Table VII Priority Matrix B for the case organization over the KV components under CP

Matrix B	*K1*	*K2*	*K3*	*K4*	*K5*
LV	0.105	0.249	0.163	0.528	0.157
TV	0.258	0.594	0.297	0.333	0.249
UV	0.637	0.157	0.540	0.140	0.594

which is the factor to be evaluated. For example, a super-matrix *V-CP*, as shown in Table VIII, presents the results regarding the relative importance of each knowledge resource for each component of the KV according to the CP indicator of MPKR. Matrix *A* in Table V and Matrix *B* in Table VII are combined to form the super-matrix *V-CP*, as shown in Table VIII.

Generally, each column of this matrix is not normalized or equal to 1, making it an un-weighted super-matrix. For convergence to occur, the super-matrix needs to be column stochastic. The weighted super-matrix is formed after normalization. The final step in obtaining the global priority vector is to reach synthesis by raising the weighted super-matrix to large powers, as follows (Meade and Sarkis, 1999):

$$W_{limit} = \lim_{x \to \infty} (W_{weighted})^{x} \text{ or } (W_{weighted})^{2k+1} \quad (4)$$

in which k is an arbitrarily large number. Raising the weighted super-matrix to these large powers is necessary to obtain stabilization or convergence. The resulting matrix is the limit super-matrix that is shown in Table IX, which contains the global priority vector. The super-matrix is raised to large powers to synthesize all of the transitive relationships between the clusters and elements in the network structure. Therefore, all of the effects of interdependence in the network are reflected in the global priority vector.

According to Table IX, the relative importance weights for the various KV components (LV, TV and UV) for the knowledge resources of the case organization are 0.117, 0.187 and 0.196, respectively. The relative performance scores for the various knowledge resources (K1, K2, K3, K4 and K5) with regard to the KV components are 0.118, 0.152, 0.042, 0.082 and 0.106, respectively.

4.2.4 Step 4: analyze the performance of the knowledge resources. Calculating the "desirability index" is the final analysis. The performance of the knowledge resources at the case organization can be analyzed using the results from the performance calculation of the knowledge resources. The implications of these results aid in the case organization's knowledge sharing and decision-making. The overall performance analysis of the knowledge resources depends on the calculation of the "desirability index" for a knowledge resource *i* within the case organization (*Di*). The equation for *Di* is defined by equation (5) (Saaty, 1999), as follows:

Table VIII Super-matrix *V-CP*

Matrix V	*LV*	*TV*	*UV*	*K1*	*K2*	*K3*	*K4*	*K5*
LV	0.000	0.000	0.000	0.105	0.249	0.163	0.528	0.157
TV	0.000	0.000	0.000	0.258	0.594	0.297	0.333	0.249
UV	0.000	0.000	0.000	0.637	0.157	0.540	0.140	0.594
K1	0.104	0.135	0.411	0.000	0.000	0.000	0.000	0.000
K2	0.233	0.477	0.181	0.000	0.000	0.000	0.000	0.000
K3	0.072	0.089	0.087	0.000	0.000	0.000	0.000	0.000
K4	0.134	0.074	0.266	0.000	0.000	0.000	0.000	0.000
K5	0.457	0.225	0.054	0.000	0.000	0.000	0.000	0.000

Table IX Limit super-matrix for MPKR of the case organization

Matrix W	*LV*	*TV*	*UV*	*K1*	*K2*	*K3*	*K4*	*K5*
LV	0.117	0.117	0.117	0.117	0.117	0.117	0.117	0.117
TV	0.187	0.187	0.187	0.187	0.187	0.187	0.187	0.187
UV	0.196	0.196	0.196	0.196	0.196	0.196	0.196	0.196
K1	0.118	0.118	0.118	0.118	0.118	0.118	0.118	0.118
K2	0.152	0.152	0.152	0.152	0.152	0.152	0.152	0.152
K3	0.042	0.042	0.042	0.042	0.042	0.042	0.042	0.042
K4	0.082	0.082	0.082	0.082	0.082	0.082	0.082	0.082
K5	0.106	0.106	0.106	0.106	0.106	0.106	0.106	0.106

$$Di = \sum_{j=1}^{J} \sum_{k=1}^{K} P_j A_{kj} B_{kj} R_{ikj}, \tag{5}$$

in which P_j is the relative importance weight of the performance indicator j, A_{kj} is the relative importance weight of the component k of the KV on the performance indicator j, B_{kj} is the stabilized relative importance weight of the component k of the KV on the performance indicator j, R_{ikj} is the relative importance weight of the knowledge resource i on the component k of the KV for the performance indicator j, K is the index set of component k of the KV and J is the index set of performance indicator j. Table X shows the desirability indices for the case organization's performance measurements of its knowledge resources. These indices are based on the MPKR hierarchy using the relative weights obtained from the pairwise comparisons of the knowledge resources, KV components, indicators and weights of the KV components from the converged super-matrix. These weights were used to calculate a score for the knowledge resources overall weighted index (KROWI) for each knowledge resource being compared. Table X presents the values from the second column of Table II. These values were obtained by comparing the relative impacts of the indicators on MPKR. The values of the fourth column are from the pairwise comparisons of the KV components for the knowledge indicators and MPKR. The fifth column of Table X presents the stable independent weights of the KV components that were obtained through the converged super-matrix (Table IX). The next five columns are from the pairwise comparison matrices showing the relative impact of each knowledge resource on the components. The final five columns represent the weighted values for the knowledge resources ($P_j \times A_{kj} \times B_{kj} \times R_{ikj}$). For example, the value that corresponded to the knowledge resource K1 for the case organization with regard to the LV according to the CP was 0.000190 ($0.143 \times 0.109 \times 0.117 \times 0.104 = 0.000190$). A summary of these results is shown in the final row of Table X. These results indicate that the knowledge resource of an invention patent (K2) with a value of 0.050477 had the maximum score, whereas the knowledge resource of a mathematical model (K3) with a value of 0.015182 had the minimum score for MPKR. Table XI, which was extracted from Table X, provides a summary of the MPKR analysis with regard to the three KV components for the case organization.

4.3 The discussion of the final results

A re-analysis of Table XI allowed for the creation of the radar graph presented in Figure 3. For the five types of knowledge resources, the value score for invention patent (K2) was the highest, followed by research reports (K4), scientific articles (K5), experience (K1) and mathematical models (K3). Therefore, invention patents from specific research projects should be paid more attention when organizations identify and manage knowledge resources, as these patents may have greater benefits. Regarding the practical process of

Table X Desirability index calculation for MPKR

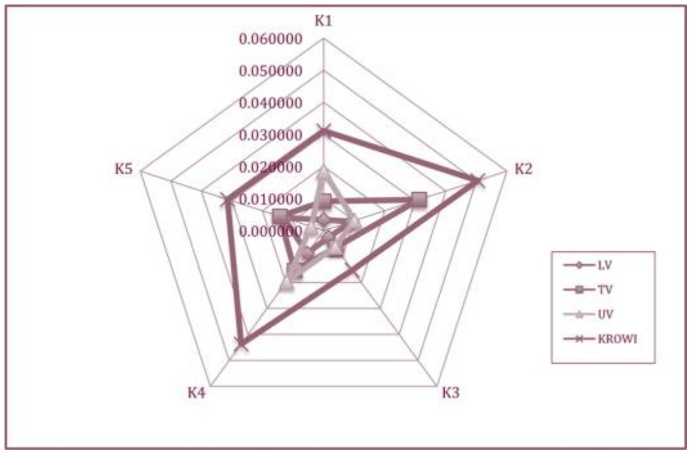
Indr	P_j	*CP*	A_{kj}	B_{kj}	R_{ik1}	R_{ik2}	R_{ik3}	R_{ik4}	R_{ik5}	*K1*	*K2*	*K3*	*K4*	*K5*
CP	0.143	LV	0.109	0.117	0.104	0.233	0.072	0.134	0.457	0.000190	0.000425	0.000131	0.000244	0.000833
	0.143	TV	0.309	0.187	0.135	0.477	0.089	0.074	0.225	0.001116	0.003941	0.000735	0.000611	0.001859
	0.143	UV	0.582	0.196	0.411	0.181	0.087	0.266	0.054	0.006704	0.002953	0.001419	0.004339	0.000881
IBP	0.264	LV	0.540	0.139	0.079	0.150	0.068	0.277	0.426	0.001575	0.002969	0.001338	0.005488	0.008446
	0.264	TV	0.163	0.183	0.158	0.435	0.070	0.222	0.115	0.001243	0.003422	0.000553	0.001749	0.000907
	0.264	UV	0.297	0.177	0.304	0.161	0.096	0.364	0.074	0.004221	0.002236	0.001339	0.005057	0.001025
I&LP	0.507	LV	0.109	0.139	0.106	0.369	0.085	0.232	0.207	0.000815	0.002835	0.000657	0.001785	0.001591
	0.507	TV	0.582	0.192	0.111	0.400	0.084	0.214	0.191	0.006311	0.022638	0.004781	0.012109	0.010815
	0.507	UV	0.309	0.169	0.266	0.173	0.121	0.362	0.078	0.007051	0.004577	0.003210	0.009582	0.002056
FP	0.086	LV	0.648	0.136	0.110	0.385	0.061	0.160	0.284	0.000833	0.002919	0.000463	0.001212	0.002153
	0.086	TV	0.230	0.189	0.128	0.336	0.094	0.240	0.203	0.000479	0.001255	0.000350	0.000897	0.000758
	0.086	UV	0.122	0.175	0.314	0.168	0.112	0.330	0.076	0.000576	0.000309	0.000205	0.000606	0.000140
										0.031113	0.050477	0.015182	0.043680	0.031464

Notes: Indr = Indicators; CP = Components

Table XI MPKR analysis through three KV components

Analysis item	*K1*	*K2*	*K3*	*K4*	*K5*
LV	0.003412	0.009147	0.002589	0.008729	0.013023
TV	0.009149	0.031256	0.006420	0.015367	0.014339
UV	0.018552	0.010074	0.006174	0.019584	0.004102
KROWI	0.031113	0.050477	0.015182	0.043680	0.031464
Normalized values for KROWI	0.180976	0.293616	0.088312	0.254077	0.183018
Rank	4	1	5	2	3

Figure 3 The performance of the five types of knowledge resources with regard to the KV components



knowledge management, the scores for the knowledge resources can be obtained from two representatives to simplify the calculation process, as follows: one from knowledge creators or providers, and the other from knowledge users.

Comparing the performance of the knowledge resources according to the LV, TV and UV, the performances of K2 and K5 were highest with regard to TV compared with LV and UV, suggesting that invention patents and scientific articles need more research and development efforts to accumulate, share and utilize knowledge. The performances of K1 and K4 were highest with regard to UV compared with LV and TV, suggesting that experience and research reports may benefit outside organizations.

5. Discussion and implications

The main contribution of this paper is the development of a comprehensive model that incorporates diverse issues regarding MPKR according to the value perspective. This paper examines four indicators, which were the CP, IBP, I&LP and FP, with regard to the performance of knowledge resources. The proposed ANP model guided the decision group to efficiently evaluate the performance of the knowledge resources and enabled this group to visualize the impact of various criteria when arriving at the final results. In addition, the interdependencies among the various criteria were effectively captured using the ANP technique, which has rarely been applied in the context of MPKR with regard to value.

The current results indicate that invention patents (K2) are the case organization's most important knowledge resource. The performance comparisons of the knowledge resources may be attributed to the following KV components: LV, TV and UV. In Table IX, UV (priority = 0.196) was the most important component for the performance measurement of the knowledge resources, followed by TV (0.187), and then LV (0.117).

These results shed light on how organizations can more effectively share or transfer knowledge resources and may assist knowledge workers with more effectively mobilizing and managing their knowledge resources within organizations.

Given the results regarding the performance of the knowledge resources according to the value perspective, two main managerial implications are evident from this study.

For R&D organizations, the proposed methodology reliably and effectively elicited information regarding the identification, circulation and sharing of knowledge processes to facilitate the management of all of the knowledge resources. By measuring the performance of the knowledge resources according to the value perspective, the knowledge components can be transformed into continuous performance improvements.

The users and providers of the knowledge resources are interested in participating in the construction of the evaluation methodology to comprehend how the values for the knowledge resources are evaluated. Additionally, the proposed methodology may help knowledge management managers organize and arrange the separate knowledge resources, which would improve the exchange of knowledge resources among the different institutions in R&D organizations.

In summary, the use of an integrated BSC and ANP approach to evaluate knowledge resources dynamically represents an interesting research area both theoretically and practically. From a theoretical perspective, this approach can enrich perspectives regarding the relations between strategic knowledge resources and organizations' strategic outcomes, particularly by providing a methodology to support empirical investigation. From a practical perspective, defining and evaluating the knowledge resources available in R&D organizations through an integrated BSC and ANP approach provides a solid foundation for the sharing and transferring of knowledge resources. Knowledge resources with higher evaluation scores should receive high levels of attention to be shared or transferred among organizations more effectively. In contrast, knowledge resources with lower evaluation scores should promptly be optimized to improve the utilization efficiency of these knowledge resources.

6. Conclusions

This paper presents a comprehensive methodology based on the BSC and the ANP to determine the performance of knowledge resources according to the value perspective. The proposed methodology provides an accurate assessment of the performance of knowledge resources with regard to value within R&D organizations. Following an extensive theoretical research review, an ANP model was developed to measure the performance of knowledge resources according to labor, technology and utilization dimensions.

The level of detail attained in the current study ensured that the analysis investigated the ways to increase the efficiency of the identification and management of the knowledge resources available in R&D organizations. This detailed approach clearly differentiates the proposed method from macro approaches, which address the overall value of the knowledge resources.

Organizations face increasing external and internal pressures to apply emerging business initiatives to sustain their competitiveness. Knowledge resources, which are recognized as the origin of competition in R&D organizations, should be evaluated using both qualitative and quantitative methods. Future research examining MPKR should focus on associations with other quantitative evaluation methodologies, such as the activity-based costing method (Wilkins *et al.*, 1997; Dekker and De, 2000). In addition, knowledge is stochastic, given that it constantly changes with human experience throughout the learning process (Wong *et al.*, 2014). Future work should take into account knowledge's stochastic nature and utilize more advanced methods, such as artificial intelligence systems and optimization techniques, to measure the performance of knowledge resources.

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About the authors

Yaoguang Hu holds a PhD from the University of Beihang, China. He is an Associate Professor and the Head of the Industrial and Systems Engineering Institution at Beijing Institute of Technology (BIT). His research interests focus on knowledge management, performance management and product-service systems. Contact: Department of Manufacturing Engineering, Faculty of Mechanical Engineering, Beijing Institute of Technology, 100081 Beijing, China. Tel: 86-10-68917880. Yaoguang Hu is the corresponding author and can be contacted at: hyg@bit.edu.cn

Jingqian Wen holds a PhD from the University of Beihang, China. He is a Senior Lecturer at Beijing Institute of Technology (BIT). His research interests focus on knowledge management, production and maintenance management. Contact: Department of Manufacturing Engineering, Faculty of Mechanical Engineering, Beijing Institute of Technology, 100081 Beijing, China.

Yan Yan Holds a PhD from Beijing Institute of Technology (BIT), China. She is a Professor at Beijing Institute of Technology (BIT). Her research interests focus on knowledge engineering, digital product design and manufacturing. Contact: Department of Manufacturing Engineering, Faculty of Mechanical Engineering, Beijing Institute of Technology, 100081 Beijing, China.

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