A FUZZY ANALYTICAL HIERARCHY PROCESS FOR EVALUATION OF KNOWLEDGE MANAGEMENT EFFECTIVENESS IN RESEARCH CENTERS

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ABSTRACT

Measuring knowledge management (KM) effectiveness is a very important issue in organizations today. This study aims to develop a method to evaluate the effectiveness of KM under uncertainty in research centers (RCs) in Iran. To develop an evaluation, the relevant literature was reviewed to identify KM effectiveness criteria. Next, the judgments of the experts, specialists, scholars, and professionals in IT and KM systems and senior managers of Iran's RCs were determined using a pairwise comparison questionnaire. Because linguistic terms are an integral part of human judgments that will influence the results of the research, a fuzzy Analytic Hierarchy Process (AHP) called the Extent Analysis (EA) method was used for data analysis and weight determination. Accordingly, 34 subcriteria extracted from the literature that are important in the evaluation of KM effectiveness were categorized into six main criteria as follows: human resources, leadership and center structure, knowledge creation and acquisition, knowledge storage and security, knowledge sharing, and knowledge utilization and updating. The findings indicate that human resources is the most important criterion based on both the AHP and fuzzy AHP methods. The other five criteria in descending order of importance are knowledge sharing, leadership and center structure, knowledge utilization and updating, knowledge creation and acquisition and knowledge storage and security. Finally, to test the validity and reliability of the proposed framework, we evaluated the effectiveness of KM system in nine of Iran's RCs.

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v15i1.978

Keywords: knowledge management; effectiveness; Fuzzy Set Theory (FST), AHP; research centers

1. Introduction

In recent decades, organizations have shifted their focus from capital, human resources, and technology to knowledge (Wang & Chang, 2007). Moreover, managers need knowledge and information to make appropriate decisions. Therefore, the knowledge and information that comes from human resources must be organized and accessible for decision-makers whenever it is needed. As a logical result, each organization should develop a comprehensive and effective system to manage knowledge and information. Knowledge management (KM) is an appropriate tool for this purpose (Barão et al., 2017; Ogiela, 2015). Currently, KM has become increasingly important because of the growing awareness of its significance for an organization's prosperity and survival (Byukusenge & Munene, 2017). In summary, KM allows an organization to meet its needs and expectations, enhance its performance and competitiveness in the market, and develop new ideas or ways of conducting business.

KM links information supply and demand with a learning management system and consequently, improves organizational performance (Schniederjans et al., 2019). Integrating organizational knowledge from theory into practical actions is an essential function of KM. The successful implementation of KM in organizations can increase the organization's productivity by more than 30% (Kim et al., 2021). An appropriate KM system enables an organization to efficiently create, acquire, share, transform, and use knowledge, which leads to better organizational performance (Kim et al., 2021; Yap et al., 2022).

The most cited document on the topic of KM was written and published by Alavi and Leidner (2001). They indicate that companies' difficulties in maintaining, locating, and applying knowledge have led them to develop systematic procedures to manage it. Their framework of KM processes encompasses knowledge creation, knowledge storage/retrieval, knowledge transfer, and knowledge application to create value from the knowledge assets the firm possesses.

Simultaneously, the establishment of KM by research centers (RCs) has been growing in recent years (Ermine, 2010). Numerous RCs expect to achieve the capability of managing their intellectual and valuable resources and reinforce existing advantages by initiating KM. The strength of any RC highly depends on the knowledge that is in the hands of their researchers. An organization will be exposed to risk when a researcher leaves that organization. Indeed, tacit knowledge of employees at RCs is one of the most essential factors that affect business performance (Adachi, 2009; Smits & De Moor, 2004). However, the reduction in strength is preventable for RCs, like any other business, by establishing an effective KM system. Measuring the effectiveness of KM operations is one of the most challenging issues for RCs in Iran, and is also an extremely complicated matter in other countries around the world.

One limitation of the classic Analytical Hierarchy Process (AHP) approach is the use of deterministic values as the equivalent of verbal values, which removes the subjective nature of the comparisons from the calculation process. Therefore, researchers have used fuzzy AHP because fuzzy ratios help respondents include imprecise and ambiguous answers in pairwise comparisons in weight calculations which helps reduce respondents' uncertainty about their choices (Ohoitimur et al., 2021). Fuzzy AHP is one of the most popular and famous MCDM methods that has been used in various fields such as dynamic vendor selection (Koul & Verma, 2009), warehouse location selection (Kahraman et al., 2016), industrial maintenance strategy (Ohta et al., 2018), strategic management (Ohoitimur et al., 2021), software requirements selection (Nazim et al., 2022), and public transportation (Buran & Erçek, 2022).

The aim of this study is to provide a framework for evaluating KM in RCs. Nevertheless, models for evaluating and measuring the effectiveness of KM in the literature are very general and include a wide range of businesses and organizations. In this article, a specific framework for measuring the effectiveness of KM at RCs is presented. Then, both fuzzy and crisp Analytical Hierarchy Process (AHP) methods are used to prioritize the criteria and subcriteria of the proposed framework and their results are compared. The applied methods are able to assess quantitative and qualitative criteria. Among the other weight determining methods in the literature, the AHP is the most frequently applied method which indicates its critical importance. It is believed that the proposed evaluation framework is very useful for research-based organizations. This study adds precise and practical knowledge to the available literature on the evaluation and measurement of KM effectiveness by providing experts with suitable criteria to evaluate and measure KM effectiveness. These criteria would be useful especially in RCs with a fuzzy standpoint for dealing quantitatively with imprecision and uncertainty. It also helps to obtain a fuzzy prioritization of KM effectiveness measurement indicators. RCs, which are knowledge producers, have a greater need to establish a KM system at different stages in their work. The existence of a system that creates synergy in conducting research projects and optimal use of the resources of knowledge-based organizations is a matter that is directly related to the efficiency and effectiveness of conducting research projects in these centers. Therefore, in this study an attempt has been made to evaluate the influence factors of KM in RCs by presenting a model to improve the performance of the organization.

2. Literature review

2.1 Knowledge and knowledge management

Rapid changes in today's environment have led organizations to adjust and update the knowledge they possess to maintain their competitive advantage (Ale et al., 2014). Knowledge is recognized as a core competency and a primary source of value creation for organizations around the world (Liu et al., 2020). It is the only asset in an organization that completes technology, strategy, process, and structure as a whole (Breznik, 2018). Knowledge has an inherent value that needs to be managed, applied, developed, and exploited. It can be seen as an asset that raises traditional asset questions to management, such as when, how much, and what to invest in (Mardani et al., 2018). Knowledge has different meanings and concepts and is referred to by different terms, such as expertise, experience, skill, intelligence, and insight, depending on the subject area. The KM literature has not reached a consensus on the definition of knowledge (Anjaria, 2020). As the combination of experiences, values, contextual information and expert insights, knowledge provides a framework for combining experiences and inferring new knowledge (Donate & Sánchez de Pablo, 2015; Kusumastuti et al., 2021; Kokkaew et al., 2022).

In the literature, knowledge is divided into tacit and explicit forms. Tacit knowledge is produced by information processing in an individual's mind and acquired through experience (Ale et al., 2014; Schniederjans et al., 2020). It is deeply rooted in action, commitment, and involvement and thus is very difficult to formalize, communicate, and share with other people. In contrast, explicit knowledge can be expressed in words and numbers. It is produced by the articulation and communication of tacit knowledge and captured in a code or language that facilitates its communication in libraries, archives, and databases (Schniederjans et al., 2020). This knowledge is codified and transmittable in formal, systematic language and thus is able to be captured (Ale et al., 2014). There is a permanent interaction between tacit and explicit knowledge that moves across individuals, groups, organizations, and back to individuals (Nonaka & Toyama, 2003).

The theory of knowledge creation proposes that knowledge is created over an endless cycle and, thus, increases organizational knowledge via externalization (conversion of tacit to explicit knowledge), socialization (creation of tacit knowledge from shared tacit knowledge), combination (creation of knowledge through the combination and exchange of explicit knowledge), and internalization (conversion of explicit to tacit knowledge) (Ale et al., 2014; Curado & Bontis, 2011). In the current knowledge economy, knowledge is an essential strategic resource that enables firms to sustain a competitive advantage in a dynamic market environment. Because it is intangible, knowledge is a complex concept to understand and share among the departments of the organization. Using knowledge effectively and consistently is an important way to succeed (Rabeea et al., 2019; Martins et al., 2019).

As the necessary intangible resource for any organization, knowledge should be effectively managed (Mardani et al., 2018). In the literature, there are many authors who point out the role played by KM as an increasingly important capability for an organization to be successful in both public and private sectors (Al Ahbabi et al., 2018; Gaviria-Marin et al., 2019; Gonzaga de Albuquerque et al., 2018; Martins et al., 2019). Duhon (1998) defined KM as a discipline for promoting the identifying, capturing, evaluating, retrieving, and sharing of the organizations' information, systematically. To this aim, some assets such as procedures, policies, expert and experienced workers, documents, databases and computerized systems must be used. Since its introduction in 1990s, the concept of KM has become an important area of research in modern management and leadership for academics and practitioners. There is a consensus among researchers that KM can be seen as a collaborative and integrated approach that facilitates the creation, capture, organization, access, and use of the intellectual asset for long-term sustainability and strategic advantage in organizations (Al Saifi, 2015; Hussinki et al., 2017; Peng et al., 2007; Prusak, 2014; Martins et al., 2019). KM bridges information demand and supply on behalf of learning processes, and consequently, organizational performance improvement (Curado & Bontis, 2011; Schniederjans et al., 2020).

2.2 Knowledge management effectiveness

In the 21st century, business environments have become increasingly knowledge-based, leveraging this knowledge to innovate (Urban & Matela, 2022). Knowledge is essential to the organization because it is essential to its survival in the competitive market. It is the main engine of economic growth and the catalyst for technological progress and productivity (Abusweilem & Abualous, 2019). Knowledge creates value only when it is applied by organizations to create capabilities and take effective actions. Therefore, support and enhancement of knowledge use in organizations should be one of the major focuses of KM initiatives (Yun, 2013).

KM refers to the range of practices and techniques used by organizations to identify and distribute knowledge, know-how, expertise, intellectual capital and other forms of knowledge for leveraging, reusing and transferring knowledge and learning across the organization. It can be defined as the practice of using prior knowledge to make decisions that affect the current and future effectiveness of the organization (Ale et al., 2014). Indeed, KM directs organizational innovation processes toward a competitive advantage (Mardani et al., 2018; Vaio et al., 2021) and helps organizations improve their effectiveness by strengthening their decision-making capabilities. The view that regards knowledge as a source of competitive advantage comes from the resource-based perspective of organizations, which stems primarily from the theory of internal resources and capabilities. Scholars have argued for the relevance of KM in increasing organizational effectiveness. Indeed, KM plays a significant role in organizations that are seeking ways to reach their goals and strategic plans more efficiently and effectively. Therefore, it is a key factor for survival in the turbulent international market because KM makes knowledge delivery at all layers of an organization possible (Ping et al., 2009; Albassam, 2019).

Innovative firms such as RCs need sophisticated KM that gives close attention to the special requirements of interactive knowledge. Particularly in knowledge-based organizations such as RCs, effectiveness is highly dependent on how well knowledge is shared between individuals, teams, and units (Alavi & Leidner, 2001). The incentive for the search, absorption, and sharing of knowledge has contributed considerably to the achievement of organizational goals (Martin et al., 2019). It has been argued that knowledge-sharing behaviors contribute to the generation of various organizational capabilities such as innovation, which is vital to a firm's performance (Mardani et al., 2018).

According to Wu and Lee (2007) and Kamara et al. (2002), KM is the organizational optimization of knowledge to achieve superior productivity through a variety of techniques. KM is a systematic approach to managing knowledge in organizations for competitiveness (Wu & Lee, 2007). It is useful to consider the relationship between data, information, knowledge, and wisdom to have a clear view of KM. Data and information are the foundation of knowledge and have hierarchical relationships based on the studies of Arthur Anderson Business Consultant in 1999 (Wen, 2009). Dóci et al. (2022) studied KM in transfer management, and the results showed that the problem is due to the lack of knowledge integration.

Wen (2009) established a model with five major constructs including staff, information, data, knowledge, wisdom, and 30 indices to measure the effectiveness of the KM process. According to the research, several problems would be solved by establishing an assessment model for KM effectiveness such as multiple objectives, evaluation difficulties, and fuzzy behavior of KM. In other research, Tseng (2008) proposed a new metric measure for assessing the performance of a KM system based on financial and

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v15i1.978

non-financial criteria. The study presented the critical factors to improve the quality of the KM system. Furthermore, the study claimed that appropriate IT can significantly enhance the effectiveness and efficiency of implementing a KM system.

As previous studies indicate, many factors affect the prosperity of KM projects with leadership and center structure being the most important (Chang et al., 2009; Cabrera & Cabrera, 2005; Hislop, 2003). Moreover, among these factors, human resources is regarded as a key lever of competitive advantage in the current global, dynamic, and complex business environment, particularly in the context of KM (e.g., Chen & Huang, 2009; Oltra, 2005; Hislop, 2003; Martinsons, 1997; Davis & Botkin, 1994; Ulrich, 1998; Winch & Schneider, 1993). Ode and Ayavoo (2020) investigated the relationship between KM practices and firm innovation by the mediating role of knowledge application. Their findings showed that knowledge generation, storage, and application have significant effects on firm innovation. Kim et al. (2021) studied the impact of KM strategies on firm performance by categorizing KM portfolios into four patterns. The findings indicate that unrelated diversity portfolio strategies show substitutable effects on firm performance, while the effects of related diversity portfolios strategies are complementary. Abbas and Sağsan (2019) studied the impact of KM practices on green innovation and corporate sustainable development. Based on the results, KM significantly impacts green innovation and corporate sustainable development activities.

Na et al. (2017) developed a knowledge-based advisory expert system using the AHP to investigate the late-life structural ambiguity of fixed jacket platforms in the selection of the best practicable decommissioning method. In their study, the effects and ranking of key factors on the decommissioning planning process were numerically computed. Castrogiovanni et al. (2016) determined the sources of knowledge that have the greatest effect on financial entities' knowledge acquisition and management using the Analytic Hierarchy Process (AHP). The results showed that human resources and new technology adoption are the most effective sources of knowledge acquisition and management. Patil and Kant (2014) prioritized the solutions of KM adoption in an Indian hydraulic valve manufacturing organization supply chain to overcome its barriers. They proposed a framework based on fuzzy AHP and fuzzy TOPSIS to identify and rank the solutions for KM adoption in the supply chain and overcome its barriers. The AHP was used to determine the weights of the barriers as criteria, and the fuzzy TOPSIS method was used to obtain the final ranking of the solutions of KM adoption in supply chain.

Fan et al. (2009) proposed a fuzzy linguistic method based on a 2-tuple linguistic representative model with seven attributes. They stated that knowledge creation, knowledge acquisition, knowledge storage, security, and knowledge utilization have a strong effect on KM capability (Wen, 2009). Also, the capability of KM depends on two other factors: infrastructure capability and process capability (Fan et al., 2009; Chuang, 2004; Gold et al., 2001). Cui et al. (2005) also mentioned that KM capabilities consist of the following three interrelated processes: knowledge acquisition, knowledge conversion, and knowledge application (Liao & Wu, 2010). Some important studies in KM effectiveness measurement with their proposed criteria are mentioned in Table 1.

Table 1
Research on KM effectiveness measurement

Source	Proposed Criteria
Tseng (2010)	Technology; Structure; Culture; Acquisition; Conversion; Application; Security; Market share; New green product competitiveness; Monitoring market forces; Specialized market units; Export percentage; Success rate of R&D green products; Self-generated innovative products; Number of patents; R&D intensity; Percentage of researchers to overall employees; Degree of innovation of R&D green products; Intensity of collaboration with others; R&D knowledge sharing ability; Forecasting and evaluation of technological innovation; Entrepreneurial innovation initiatives.
Tan and Nasurdin, (2011)	Acquisition; Sharing; Application; Innovation.
Fan et al. (2009)	Technology; Structure; Culture; Acquisition (obtaining knowledge); Conversion (Make existing knowledge useful); Application (Actual use of the knowledge); Security.
Chang and Wang (2009)	Strategy; Employee traits; Superintendent traits; Audit and assessment; Organizational culture; Operation procedure; Information technology.
Hsieh et al. (2009)	KM strategy; KM promotion; KM assessment; Intellectual capital; Knowledge identification and classification; Knowledge sharing; Knowledge capture; Knowledge store; Knowledge application; Knowledge creation and innovation; Knowledge protection; Knowledge learning and training; Best practices; Communities of practice (CoPs); IT infrastructure; KM system.
Wen (2009)	Human resources; Information; Data; Knowledge; Wisdom.
Oltra (2005)	Motivation; Participation; Human resources; Integration IT infrastructure; Technical customization; Past experiences.
Smits and De Moor (2004)	Use of knowledge resources; Development of knowledge resources; Level of KM; Level of maintenance KM.
Hoy and Miskel (2001)	Knowledge adaptation effectiveness; Knowledge achievement effectiveness; Knowledge integration effectiveness; Knowledge potential effectiveness
Mehdibeigi et al. (2016)	Customer KM; Organizational agility; Organizational effectiveness
Adaileh et al. (2020)	Knowledge capturing; Knowledge sharing; Firm performance; Knowledge acquisition; Knowledge application
Kavalić et al. (2021)	Organizational culture; T-shaped skills: Human resources; Information technology; Knowledge acquisition process; Knowledge conversion process; Process of applying knowledge; Knowledge protection process; Competition advantage; Organizational culture
Darvishi and Darvishi (2019)	Knowledge creation; Knowledge accumulation; Knowledge sharing; Knowledge utilization; Knowledge internalization

2.3 Knowledge management in research centers (RCs)

In the most common classification of knowledge, the concept is divided into two categories, tacit and explicit (Li & Chandra, 2007). Since encouraging employees to share their tacit knowledge is crucial in a research environment, the role of KM would be more obvious in these types of organizations (Joseph et al., 2005; Okemwa, 2006; Smits and De Moor, 2004; Astrid, 2003). RCs face varied and challenging projects which require knowledgeable and experienced staff to manage. In most cases, the greater portion of knowledge and experience that staff gain during their work and research is tacit not explicit. Due to the strategic role of knowledge in RCs, measuring the effectiveness of KM in these centers has been recognized by academics and practitioners (Chin et al., 2010).

Tacit knowledge is a valuable resource for future projects and highly depends on the presence of staff. If researchers leave the RC, the tacit knowledge will disappear; this issue is the most important concern of RCs. Indeed, this situation illustrates the critical role of effective KM. Undoubtedly, to have effective KM criteria must be customized to measure the KM effectiveness of RCs (Okemwa, 2006). Because of the importance of RCs in producing and developing knowledge, researchers focus on different aspects of them. For instance, Adachi, (2009) attempted to answer the four following questions in his studies about RCs:

- How is knowledge transferred to each task in the planning stage?
- What are the problems in the planning stage and how do you eliminate them?
- How does KM work in the planning stage of a public research organization?
- What kinds of knowledge are created, shared, utilized, and accumulated in the planning stage of a public research organization?

Smits and De Moor (2004) asked “when is KM effective?” and “are measurements necessary to realize the effectiveness of KM?” The answers to these questions were “it depends on the level of KM” and “for a successful KM, sufficient attention must be paid to the selection of key aspects, instead of trying to measure everything”, respectively. Joseph et al. (2005) studied the need for and impact of a KM system in a research organization and how it would help the researcher’s work/output and institutional values. Moreover, research was done by the International Atomic Energy Agency (IAEA) of Australia (2006) to determine the essential criteria for an effective KM system. Agostino et al. (2012) presented a system for performance measurement of the R&D activities in public research centers in Italy. Due to the multiple stakeholders with different needs, they concluded that managers should balance the multiple goals and integrate their different performance indicators. Several researchers also studied the main performance indicators for assessing R&D performance in public sector research centers (Leitner & Warden, 2004; Chu et al., 2006; Secundo et al., 2010; Agostino et al., 2012). This research stream is based on intellectual capital (IC) reporting models.

Wang et al. (2016) found that the consistency of the three dimensions of IC (i.e. human capital, structural capital, and relational capital) and KM strategies facilitates both operational and financial performance of high-tech firms. Similarly, knowledge strategy was found to moderate the relationship between IC and organizational performance (Asiaei et al., 2018). There are also two research streams in the private sector; one focuses on the choice of performance indicators and assessment of the R&D department (Bremser & Barsky, 2004; Schiuma & Neely, 2004; Mettänen, 2005) and the other concentrates on the design of the performance measurement system in R&D firms and their characteristics, objectives and contextual variables (Chiesa & Frattini, 2007). Based on these considerations, some key performance indicators were defined to measure the effectiveness of the RCs. The effectiveness indicator makes it possible to evaluate the RCs’ outputs based on the level of achievement of their research objectives (Agostino et al., 2012). As Steiner and Nixon (1997) mentioned, this aspect is related to a key issue of “what is the output of a research center” and “how do you measure it”.

According to Okemwa (2006)’s study of the International Livestock Research Institute (ILRI), establishing KM for a research organization is necessary to determine how knowledge should be generated, shared, transferred and integrated into their day-to-day operations. Although different studies have been done in the field of KM in RCs, the studies did not pay enough attention to determining and prioritizing criteria of KM effectiveness. Therefore, this article fills this gap in the literature. Many RCs exist that are very important for the production of knowledge in various fields of science. KM helps improve performance and processes in organizations by discovering, collecting, and using technical knowledge. In this research, considering the importance and role of KM in RCs, the influence factors of KM were evaluated using the fuzzy AHP method. By evaluating the influence factors of KM in RCs, the gap in knowledge production in this sector is filled.

3. Research methodology

The present study was conducted in three main phases. The first stage included an exploratory literature review on KM effectiveness criteria through the study of relevant articles in scholarly journals. The results are summarized in Table 1. These criteria were investigated by conducting interviews with KM experts and senior managers of nine research centers in Iran (phase 1). In this phase, the experts were asked to judge the main criteria and sub-criteria of the hierarchical structure until a consensus was reached. The second phase involved collecting data through a pairwise comparison questionnaire, which was analyzed by the AHP using simple additive weighting techniques and fuzzy AHP (Chang's method). Finally, in the third phase, the validity of the proposed framework was tested by measuring the KM effectiveness of nine RCs (Research Institute of Petroleum Industry, Iranian Research Institute for Information Science and Technology, Center of Strategic Research, Institute for Cognitive Science Studies, IPM Institute for Research In Fundamental Sciences, Institute for Management and Planning Studies, Iran Standard and Industrial Research Institute, Chemistry & Chemical Engineering Research Center of Iran, and Iran Management & Productivity Study Centre (IMPSC)). Although the population of the study included all of Tehran's RCs, only nine agreed to take part in the research. It should be noted that in each RC, the manager of the R&D department or the assistant director was selected as the organization's representative. MADM methods, especially the AHP/fuzzy AHP, do not have any limitation on the number of experts, according to the consistency rate of each expert's responses.

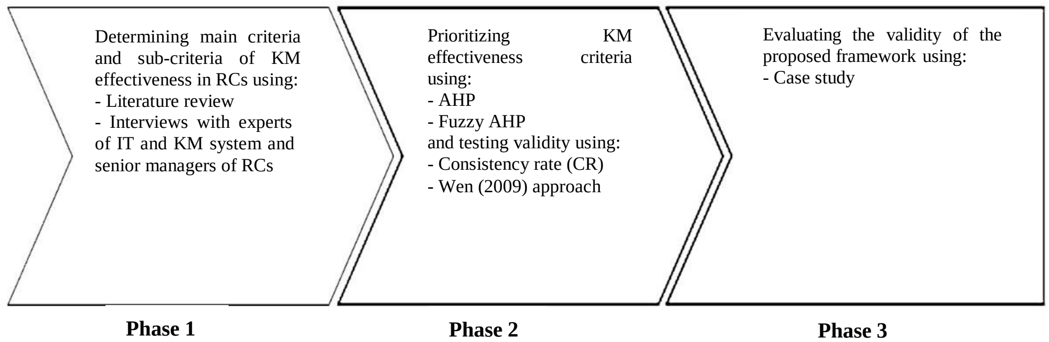

Figure 1 Research phases

As the analytical part of the research, a Multiple Attribute Decision Making (MADM) method was applied. Most MADM techniques resort to either the ordinal scale or the interval scale as an easy way to transform qualitative criteria into the numerical scale (Hatefi, 2021). There are several techniques for dealing with MADM problems in the literature. A comprehensive literature review was conducted by Toloie-Eshlaghy and Homayonfar (2011) who reviewed MCDM methodologies and applications from 1999 to 2009. Based on their study, the AHP is the most widely used and popular method among all of the MADM methods. The AHP method, which was first introduced by Saaty (1980), divides a complex system into a hierarchical structure, where decision elements are placed at the final (bottom) level, decision criteria and sub-criteria are placed at intermediate levels, and the goal is placed at the first level (Ozan, 2008; He et al., 2022). According to Lee et al. (2008), the AHP has six fundamental steps:

1. Identify the problem and determine the objectives and outcomes.
2. Divide the compound problem into a hierarchical structure with decision elements (criteria, subcriteria, and alternatives).
3. Conduct pairwise comparisons among decision elements and form comparison matrices.
4. Use the eigenvalue method to calculate the relative weights of the decision elements approximately.
5. Check the consistency of the matrices to ensure that the judgments of the decision-makers are consistent.
6. Aggregate the relative weights of the decision elements to gain an overall rating of the alternatives.

In order to solve the ambiguity and subjectivity of human judgments in the decision-making process and to express linguistic variables, fuzzy numbers are replaced with linguistic values in fuzzy AHP, as the second method of data analysis. Using the fuzzy AHP method reduces vague judgments and increases accuracy in the calculations (Liu et al., 2020). Many fuzzy AHP methods have been proposed by researchers such as van Laarhoven and Pedrycz, (1983); Buckley (1985); Boender et al. (1989); Chang (1996). In this study, Chang's EA method (Chang, 1996) is preferred because its steps are relatively easier than the other fuzzy AHP approaches and are similar to the conventional AHP (Bozbura et al., 2007).

Chang's extent analysis method can be represented as below (Rezaee Kelidbari et al., 2016):

Let X = {$x_1, x_2, \ldots, x_n$} be an object set, and G={$g_1, g_2, \ldots, g_n$} be a goal set. Then, the fuzzy synthesis extent values for each object are as the following:

$$M^1{}_{gi}, M^2{}_{gi}, \ldots, M^m{}_{gi} \qquad ; \qquad i = 1, 2, \ldots, n \tag{1}$$

In the above equation, $M^j{}_{gi}$ (j = 1, 2 . . . m) are triangular fuzzy numbers (TFNs) whose parameters are l, m, and n, which show pessimistic, the most likely, and optimistic values, respectively. The steps to measure Chang's fuzzy synthesis extent can be given as follows:

Step 1. The value of fuzzy synthetic extent with respect to the ith object is defined as:

$$S_i = \sum_{j=1}^{m} M_{gi}^{j} \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j}\right]^{-1} \tag{2}$$

To obtain$\sum_{j=i}^{m} M_{gi}^{j}$, the fuzzy addition operation of m extent analysis values for a particular matrix is performed such that

$$\sum_{j=i}^{m} M_{gi}^{j} = \left(\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j\right) \qquad i = 1, 2, \ldots, n \tag{3}$$

To obtain$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j}\right]$, the fuzzy addition operation of $M_j g_i$ (j = 1, 2, ... , m) values is performed such that

$$\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j} = \left(\sum_{j=i}^{m} l_j, \sum_{j=i}^{m} m_j, \sum_{j=i}^{m} u_j\right) \tag{4}$$

Then, the inverse of the vector in Equation 4 is calculated such that

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i}\right) \tag{5}$$

Step 2. The possibility degree of M2 = (l2, m2, u2) ≥ M1 = (l1, m1, u1) is defined as

$$V(M_2 \geq M_1 = \sup\left[\min(\mu_{M_1}(x), \mu_{M_2}(x)\right] \tag{6}$$

and can be equivalently expressed as follows:

$$V(M_2 \geq M_1) = hgt(M_1 \otimes M_2) = \mu_{M_2}(d) = \tag{7}$$

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v15i1.978

$$\begin{cases} 1 & \text{if } M_2 \geq M_1 \\ 0 & \text{if } l_1 \geq u_2 \\ \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)} & \text{otherwise} \end{cases}$$

where d is the ordinate of the highest intersection point, D, between μM1 and μM2 (see Figure 2). To compare M1 and M2, we need both the values of V (M1 ≥ M2) and V (M2 ≥ M1).

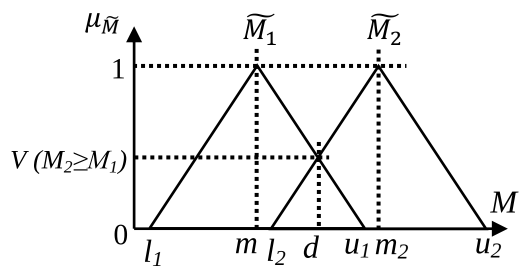

Figure 2 Intersection between $\widetilde{M}_1$ and $\widetilde{M}_2$

Step 3. The possibility degree for a convex fuzzy number to be greater than k convex fuzzy numbers Mi (i = 1, 2 . . . k) can be defined by

$$\begin{aligned} &V(M \geq M_1, M_2, \ldots, M_k) = \\ &V[(M \geq M_1) \; and \; (M \geq M_2) and \ldots and (M \geq M_k)\\ &\qquad = \min V(M \geq M_i) \qquad \text{i= 1, 2, 3, …, k} \end{aligned} \tag{8}$$

assuming that

$$\acute{d}(A_i) = minV(S_i \geq S_k) \tag{9}$$

For k= 1, 2, …, n; k≠i then the weight vector is given by

$$\acute{W} = (\acute{d}(\acute{A}_1), \acute{d}(\acute{A}_2), \ldots, \acute{d}(\acute{A}_n))^T \tag{10}$$

where Ai (i = 1, 2 . . . n) are n elements.

Step 4. The normalized weight vectors are

$$W = (d(A_1), d(A_2), \ldots, d(A_n))^T \tag{11}$$

where W is a non-fuzzy number.

Measuring consistency in the fuzzy AHP method is the same as in the traditional AHP; however, it consists of two parallel procedures. According to the Gogus and Boucher (1998), each fuzzy matrix should be divided into two matrices: (1) the matrix formed from the geometric mean of the upper (optimistic) and lower (pessimistic) values (A^g), and (2) the matrix formed from the most likely value (A^m). Then, the consistency ratio of both of them must be calculated based on Saaty's method. The steps for calculating the consistency ratio are as follows:

Step 1: As mentioned above, in the first step, the fuzzy triangular matrix was divided into two matrices A^m and A^g. Suppose the fuzzy triangular number as a_{lmu} , then

$$A^m = \left[a_{ijm}\right] \;\; ; \quad A^g = \sqrt{a_{iju}.a_{ijl}} \tag{12}$$

Step 2: The weight vector of each matrix should be calculated using Equation 13:

$$\begin{gathered} w_i^m = \frac{1}{n}\sum\nolimits_{j=1}^{n} \frac{a_{ijm}}{\sum_{i=1}^{n} a_{ijm}}\; w^m = \left[w_i^m\right] \\ w_i^g = \frac{1}{n}\sum\nolimits_{j=1}^{n} \frac{\sqrt{a_{iju}.a_{ijl}}}{\sum_{i=1}^{n}\sqrt{a_{iju}.a_{ijl}}}\; w^g = \left[w_i^g\right] \end{gathered} \tag{13}$$

Step 3: In the next step, the highest eigen value for each matrix was calculated using Equation 14:

$$\begin{gathered} \lambda_{max}^m = \frac{1}{n}\sum\nolimits_{i=1}^{n}\sum\nolimits_{j=1}^{n} a_{ijm}\left(\frac{w_j^m}{w_i^m}\right) \\ \lambda_{max}^g = \frac{1}{n}\sum\nolimits_{i=1}^{n}\sum\nolimits_{j=1}^{n} \sqrt{a_{iju}.a_{ijl}}\left(\frac{w_j^g}{w_i^g}\right) \end{gathered} \tag{14}$$

Step 4: Then, the consistency ratio was calculated using Equation 15:

$$\begin{gathered} CI^m = \frac{(\lambda_{\max}^m - n)}{(n-1)}; CI^g = \frac{(\lambda_{\max}^g - n)}{(n-1)} \\ CI^m = \frac{(\lambda_{max}^m - n)}{(n-1)} \;\; ; \quad CI^g = \frac{(\lambda_{max}^g - n)}{(n-1)} \end{gathered} \tag{15}$$

Step 5: The consistency index (CI) was divided by the random index (RI) to calculate the consistency rate (CR) using Equation 16.

$$CR^m = \frac{CI^m}{RI^m} \;\; ; \quad CR^g = \frac{CI^g}{RI^g} \tag{16}$$

If the CR index is lower than 0.1, the matrix is considered consistent and the experts' judgments are reliable. In fuzzy AHP, since the numerical values of fuzzy comparisons are not always integers, and the geometric mean generally converts them to non-integer numbers even if the 1 to 9 scale was used, the RI table provided by Saaty is not applicable. Table 2 shows the random index of both fuzzy AHP and AHP.

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v15i1.978

Table 2
Consistency ratio in AHP and Fuzzy AHP

Size of the Matrix	RI^n	RI^o	RI
1	0	0	0
2	0	0	0
3	0.4890	0.1796	0.58
4	0.7937	0.2627	0.90
5	1.0720	0.3597	1.12
6	1.1996	0.3818	1.24
7	1.2874	0.4090	1.32
8	1.3410	0.4164	1.41
9	1.3793	0.4348	1.45
10	1.4095	0.4455	1.49
11	1.4181	0.4536	1.51
12	1.4462	0.4776	1.54
13	1.4555	0.4691	1.56
14	1.4913	0.4804	1.57
15	1.4986	0.4880	1.58

The process of measuring the consistency ratio in this method is the same as the in classic AHP method, with the only difference being that two rates of consistency, namely, consistency ratio of the matrix of mean values (CR_n) and the consistency ratio of the matrix of geometric means of lower and upper bounds (CR_o) should be measured for each fuzzy pairwise comparison matrix. The matrix is consistent if both CR values are 0.1 or less than 0.1.

4. KM effectiveness evaluation framework

4.1. Hierarchical structure to prioritize KM effectiveness measures in RCs

As mentioned in the previous section, in phase 1 of the research 34 sub-criteria were finalized for measuring the KM effectiveness in RCs through a literature review and interviews with experts. These subcriteria were then divided into six main criteria, as follows: human resources, leadership and center structure, knowledge creation and acquisition, knowledge sharing, knowledge storage and security, and knowledge utilization and updating. It should be noted that, by investigating the technical documents of the RCs, some subcriteria were added to this list. Figure 3 illustrates the decision tree of the extracted factors.

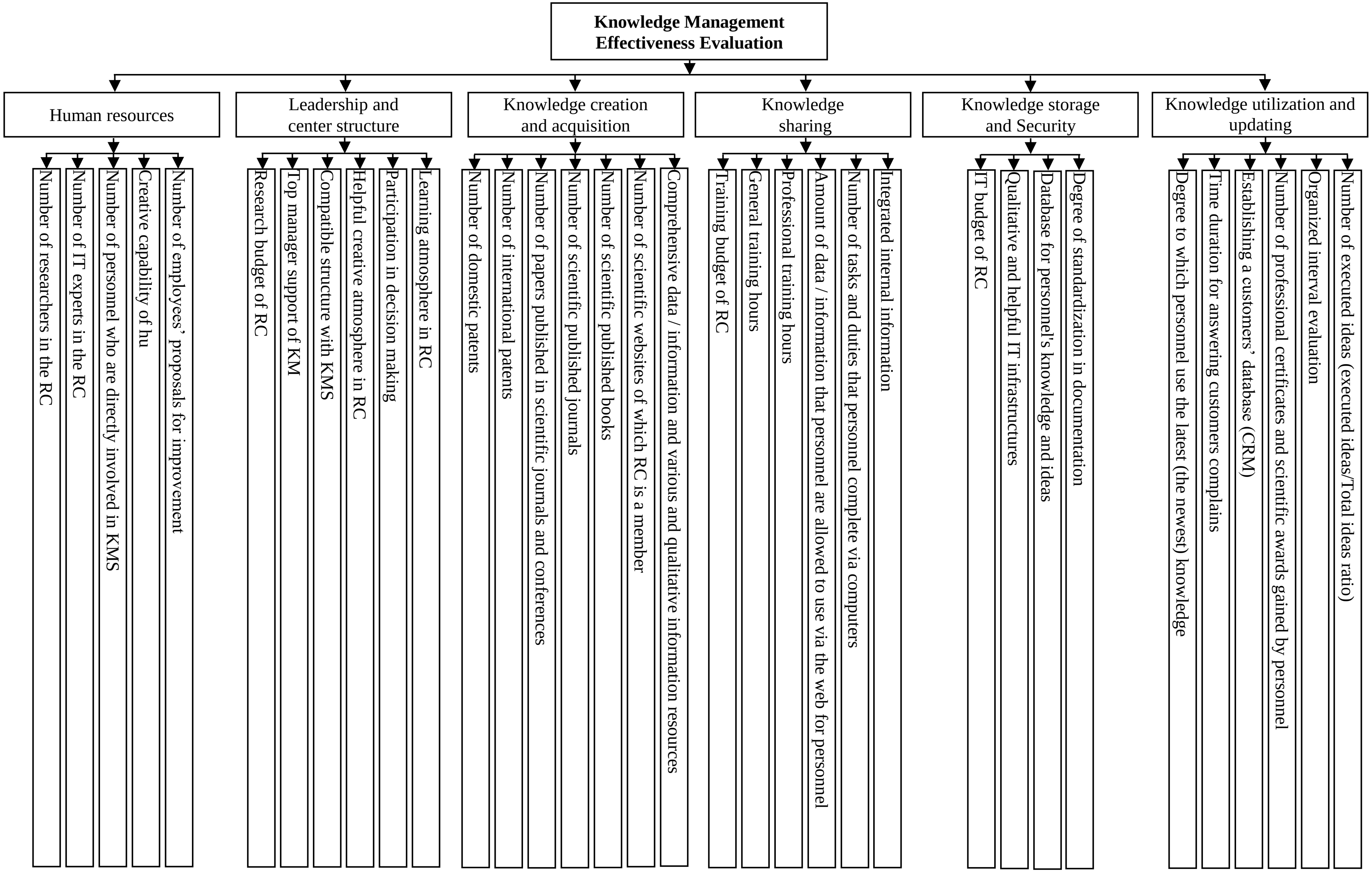

Figure 3 Decision making hierarchy

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v15i1.978

Table 3
KM effectiveness measures for research centers

Criteria	Sub-Criteria	Sym.
Human resources	Number of researchers in the RC- (Researchers/total staff ratio)	H1
	Number of IT experts in the RC- (IT experts/total staff ratio)	H2
	Number of personnel who are directly involved in KMS - (KM personnel/total staff ratio)	H3
	Creative capability of HR (Creative human resources)	H4
	Number of employees' proposals for improvement – (improving/non improving proposals ratio)	H5
Leadership and center structure	Research budget of RC (Research budget/total budget ratio)	L1
	Top manager support for KM	L2
	Compatible structure with KMS	L3
	Helpful and creative atmosphere in RC	L4
	Participation in decision making	L5
	Learning atmosphere in RC (Incentives for motivating personnel to learn more)	L6
Knowledge creation and acquisition	Number of domestic patents (Per capita domestic patents)	C1
	Number of international patents (Per capita international patents)	C2
	Number of papers published in scientific journals and conferences (Per capita papers)	C3
	Number of scientific published journals	C4
	Number of scientific published books	C5
	Number of scientific web sites of which RC is a member	C6
	Comprehensive data and information and various and qualitative information resources	C7
Knowledge storage and Security	IT budget of RC (IT budget/total budget ratio)	S1
	Qualitative and helpful IT infrastructures	S2
	Database for personnel's knowledge and ideas	S3
	Degree of standardization in documentation	S4
Knowledge sharing	Training budget of RC (Training budget/total budget ratio)	T1
	General training ratio (General training hours/total training hours)	T2
	Professional training hours (Professional training hours/total training hours ratio)	T3
	Amount of data and information that personnel are allowed to use via the web (Intranet, extranet and internet).	T4
	Number of tasks and duties that personnel complete via computers (E-tasks and duties)	T5
	Integrated internal information	T6
Knowledge utilization and Updating	Degree to which personnel use the latest (the newest) knowledge	U1
	Time to answer customers' complains	U2
	Establishing a customer database (CRM)	U3
	Number of professional certificates and scientific awards gained by personnel	U4
	Organized interval evaluation	U5
	Number of executed ideas (Executed ideas/Total ideas ratio)	U6

In past studies about prioritizing KM effectiveness criteria, the same weights were attributed to all criteria; however, in this study, the criteria do not have the same weights. Weights can be derived by pairwise comparison of the criteria based on the AHP methodology. In this research, decision-makers used linguistic terms to demonstrate the significant weights of the factors given in Table 4.

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v15i1.978

Table 4
Linguistic terms for importance weights of factors

Linguistic scale for importance	**Triangular fuzzy scale**	**Triangular fuzzy reciprocal scale**
Just equal	(1,1,1)	(1,1,1)
Equally important	(1/2,1,3/2)	(2/3,1,2)
Weakly important	(1,3/2,2)	(1/2,2/3,1)
Strongly more important	(3/2,2,5/2)	(2/5,1/2,2/3)
Very strongly more important	(2,5/2,3)	(1/3,2/5,1/2)
Absolutely more important	(5/2,3,7/2)	(2/7,1/3,2/5)

To achieve the results, the experts (managers of R&D department or their assistant directors) were asked to fill in the AHP pairwise comparisons matrix based on the linguistic values in Table 4. Then, the nine resulting individual matrices were fuzzified and merged based on the arithmetic mean. Table 5 illustrates the resulting group matrix for the main criteria.

Table 5
Group pairwise comparisons matrix of KM effectiveness criteria

KM effectiveness	Human resources	Leadership and center Structure	Knowledge creation and acquisition	Knowledge sharing	Knowledge storage and Security	Knowledge utilization and updating
Human resources	(1,1,1)	(1.36,1.96,2.51)	(1.96,2.47,2.97)	(0.72,1.26,1.76)	(1.78,2.62,2.8)	(1.26,1.84,2.38)
Leadership and center Structure	(0.4,0.51,0.74)	(1,1,1)	(1.84,2.38,2.9)	(1,1.55,2.08)	(1.82,2.32,2.82)	(0.79,1.36,1.89)
Knowledge creation/ acquisition	(0.34,0.41,0.51)	(0.42,0.54,0.34)	(1,1,1)	(0.56,0.69,0.87)	(0.64,0.79,1)	(1,1.36,1.82)
Knowledge sharing	(0.56,0.79,1.39)	(0.48,0.64,1)	(1.14,1.44,1.8)	(1,1,1)	(2.32,2.82,3.32)	(1.96,2.47,2.97)
Knowledge storage and Security	(0.36,0.38,0.56)	(0.35,0.43,0.55)	(1,1.26,1.55)	(0.3,0.35,0.43)	(1,1,1)	(1.19,0.67,0.87)
Knowledge utilization and updating	(0.42,0.54,0.79)	(0.53,0.74,1.26)	(0.55,0.74,1)	(0.34,0.41,0.51)	(0.84,1.14,1.49)	(1,1,1)

The results of the implementation of the extent analysis with respect to the main criteria were calculated and summarized. The value of fuzzy synthetic extent was calculated for each criterion using Equation 2.

$$\left[\sum_{i=1}^{n}\sum_{j=i}^{m} M_{gi}^{j}\right]^{-1} = (33.63, 42.96, 53.4)^{-1} = (0.0187, 0.0232, 0.0297)$$

Then:
S_1= (8.08, 11.15, 13.42) × (0.0187, 0.0232, 0.0297) = (0.151, 0.258, 0.398)
S_2= (6.85, 9.12, 11.43) × (0.0187, 0.0232, 0.0297) = (0.128, 0.211, 0.339)
S_3= (3.88, 4.67, 5.74) × (0.0187, 0.0232, 0.0297) = (0.0725, 0.108, 0.170)
S_4= (7.46, 9.16, 11.48) × (0.0187, 0.0232, 0.0297) = (0.139, 0.212, 0.340)
S_5= (3.68, 4.29, 5.28) × (0.0187, 0.0232, 0.0297) = (0.068, 0.099, 0.156)
S_6= (3.68, 4.57, 6.05) × (0.0187, 0.0232, 0.0297) = (0.068, 0.106, 0.179)

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v15i1.978

Next, the degree of possibility for each criterion was calculated. For each pairwise comparison, the minimum degree of possibility was as follows using the Equation 8:

$V(S_1 \geq Si) = 1$; $V(S_2 \geq Si) = 0.801$; $V(S_3 \geq Si) = 0.114$; $V(S_4 \geq Si) = 0.914$; $V(S_5 \geq Si) = 0.035$, $V(S_6 \geq Si) = 0.155$

After computing the primary weight vector of the main criteria (Equations 9-10) and normalizing them, the final weights of the main criteria (Wi) were calculated using Equation 11.

W = (0.34, 0.27, 0.04, 0.28, 0.02, 0.05)

Since the use of the weight values directly depended on the consistency of fuzzy pairwise comparison matrix, the Gogus and Boucher (1998) method was used to examine the validity of the results. For the fuzzy comparison matrix of the main criteria, the CR_n and CR_o indexes were calculated as 0.03 and 0.05, respectively which indicates the consistency of the fuzzy pairwise comparison matrix of the main criteria. For each of the fuzzy pairwise comparison matrices of the subcriteria for which this ratio was computed, the consistency ratio was equal to or less than 0.1.

To conduct the classic AHP, the pairwise comparisons matrices which were previously filled in by the experts using the linguistic values of Table 4, were quantified based on Saaty's scale and merged based on the arithmetic mean. Due to the simplicity of the AHP method, its steps are not discussed in detail; however, the weights of the criteria and inconsistency ratio were calculated using the Super Decision software and illustrated in Figure 4.

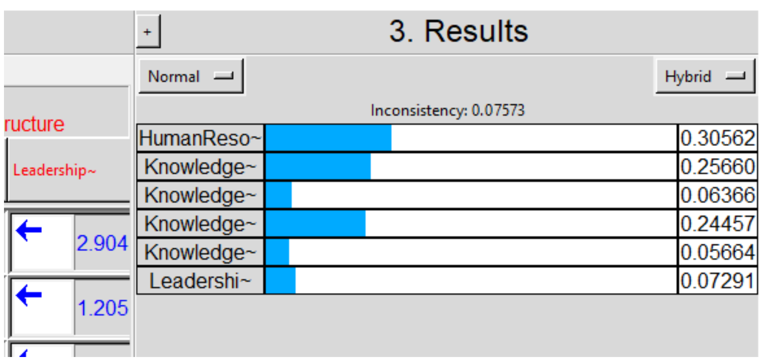

Figure 4 Results of AHP method

Table 6 shows the results of the classic and fuzzy AHP methods based on the weights of the six main criteria. The findings indicate that the weights of all criteria are relatively close in the two methods. Figure 5 also illustrates the RADAR chart for weights of the main criteria.

Table 6
Importance weights of the six criteria with using AHP and fuzzy AHP

Criteria	**AHP**	**Fuzzy AHP**
Human resources	0.31	0.34
Knowledge sharing	0.26	0.27
Leadership and center structure	0.06	0.04
Knowledge utilization and updating	0.25	0.28
Knowledge creation and acquisition	0.06	0.02
Knowledge storage and security	0.07	0.05

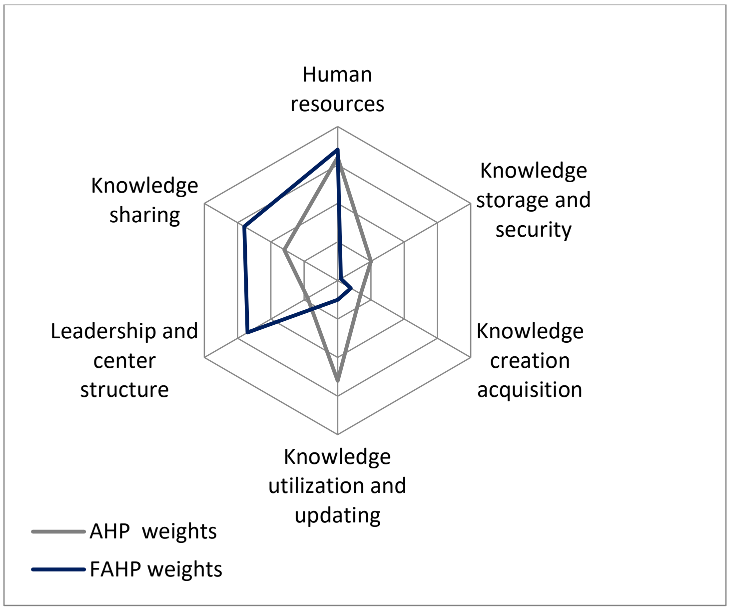

Figure 5 RADAR chart for weights of the six criteria based on AHP and fuzzy AHP methods

The weights of the subcriteria in both the AHP and fuzzy AHP were calculated and are summarized in Table 6.

ISSN 1936-6744
https://doi.org/10.13033/ijahp.v15i1.978

Table 6
Importance weights of subcriteria using AHP and fuzzy AHP

No.	Subcriteria	AHP	Fuzzy AHP
1	H1	0.22	0.14
2	H2	0.17	0.13
3	H3	0.18	0.24
4	H4	0.18	0.23
5	H5	0.25	0.26
6	L1	0.17	0.13
7	L2	0.29	0.19
8	L3	0.14	0.19
9	L4	0.17	0.12
10	L5	0.09	0.14
11	L6	0.14	0.23
12	C1	0.18	0.19
13	C2	0.18	0.20
14	C3	0.17	0.14
15	C4	0.16	0.16
16	C5	0.11	0.09
17	C6	0.09	0.09
18	C7	0.10	0.12
19	T1	0.03	0.12
20	T2	0.16	0.20
21	T3	0.27	0.15
22	T4	0.16	0.16
23	T5	0.22	0.21
24	T6	0.16	0.16
25	S1	0.29	0.21
26	S2	0.23	0.23
27	S3	0.21	0.26
28	S4	0.27	0.29
29	U1	0.17	0.14
30	U2	0.19	0.12
31	U3	0.10	0.20
32	U4	0.28	0.17
33	U5	0.12	0.20
34	U6	0.14	0.16

4.2 Measuring the RCs' KM effectiveness

An approach presented by Wen (2009) was used to acquire scores of KM effectiveness. According to this approach, after weighting 34 sub-criteria to obtain the standard Z value (which is between 0 and 1), we normalized the weights. Standardization makes it possible to cope with problems that arise from the fact that the measurement units of these 34 criteria are different from each other. The standard Z is used to normalize the weights. The sum of each indicator multiplied by the related weight was the standardized value of the respective criterion. The sum of each criterion multiplied by the related weight created the final score of KM effectiveness. To acquire the score of KM effectiveness in the mentioned method, the results of the fuzzy AHP were combined with the SAW method. Therefore, by using Equation 12, the score of the influence evaluation model of KM was calculated.

$$A_i = \sum W_{ij} \times Z_{ij} \tag{12}$$

Where Zij is the normalized value of the i^{th} criterion and the j^{th} index; Wij is the relative weight of the i^{th} criterion and the j^{th} index, and Ai is the score of the i^{th} criterion (Equation 13).

$$\sum_{i=1}^{5} W_{ij} \times A_i \tag{13}$$

Where Ai is the standardized value of the i^{th} criterion; Wij is the relative weight of the i^{th} criterion, and E is the total score of KM effectiveness of Iran's RCs. To execute the introduced framework, we have attempted to rank and compare nine Iranian RCs. The final results are summarized in Table 7.

Table 7
Results of ranking nine RCs in Iran

Code of RCs	Effectiveness score	Rank
RC_2	0.007226	1
RC_5	0.006598	2
RC_7	0.006446	3
RC_1	0.006435	4
RC_6	0.006429	5
RC_4	0.006236	6
RC_3	0.005710	7
RC_8	0.005341	8
RC_9	0.005264	9

5. Conclusion

Although KM effectiveness leads to an increase in efficiency in organizational performance and gives a competitive advantage, in order to manage it successfully, effectiveness measures and indicators must be identified and defined. Few systematic studies have been done regarding KM effectiveness in RCs. The AHP is the most appropriate method for this problem because of the subjective and intangible nature of the attributes that are used in the evaluation.

The opinions of experts and specialists in areas like IT and at different management levels (KM researchers, etc.) should be used to present a comprehensive model for assessing KM effectiveness in RCs. Since experts prefer natural language expressions rather than sharp numerical values in their assessments, in the present research triangle fuzzy numbers (TFNs) were used for comparison in the form of the extent analysis method. This article presents a framework with six criteria and 34 sub-criteria to evaluate the KM effectiveness in RCs.

With respect to the results derived from the fuzzy AHP, the criterion human resources (0.34) ranked first. The other five criteria in descending order of importance are knowledge sharing (0.28), leadership and center structure (0.27), knowledge utilization and updating (0.05), knowledge creation and acquisition (0.04) and knowledge storage and security (0.01). Furthermore, the number of employees' proposals for improvement subcriterion (0.26) within the criterion human resources and the learning atmosphere in RC subcriterion (0.23) within the criterion leadership and center structure, the number of international patents subcriterion (0.20) within the criterion knowledge creation and acquisition, the amount of tasks and duties that personnel complete via computers subcriterion (0.21) within the criterion knowledge sharing, the degree of standardization in documentation subcriterion (0.29) within the criterion knowledge storage and security, the establishing customers' database (0.20) and organized interval evaluation subcriteria (0.20) within the criterion knowledge utilization and updating received the highest level of importance among all of the subcriteria.

This framework can be used in any country; however, the obtained results reflect the situation of KM in Iranian RCs. Moreover, such a model could be used for a wide variety of research organizations in future research. Finally, we suggest developing this type of framework in the future using a combination of fuzzy methods and other MADM methods.

The results of the research provide some implications to consider. From a practical point of view, this research contributes to theory by providing a framework for measuring KM effectiveness in Iranian RCs. Despite the considerable attention to the evaluation of KM effectiveness, little is known about the importance of a systematic and comprehensive criteria determination and professionals' judgments, particularly in RCs. This study suggests the suitable criteria of both a qualitative and quantitative nature which promotes the validation of the KM effectiveness measurement. The applied classic and fuzzy AHP methods make it possible to analyze the sensitivity of the results and make better assessments.

From the theoretical point of view, the main criteria to measure RCs effectiveness are human resources, leadership and center structure, knowledge creation and acquisition, knowledge storage and security and knowledge sharing. Organizations that produce knowledge, especially RCs, need to measure KM performance at different stages in their life cycle. The effectiveness of the KM system strongly relies on these criteria which create synergy in conducting research projects and optimal use of the resources. Therefore, in this study an attempt was made to evaluate the influence factors of KM in RCs by presenting a model to improve the performance of this organization.

Concerning limitations, we propose conducting further analysis to identify additional variables regarding the effectiveness of the RCs performance. In addition, it may be interesting to determine RCs performance through alternative variables (e.g., number of research projects) or even study the performance as a latent variable related to multiple measured variables. For future research, we recommend defining a framework for structuring and evaluating RCs' activities according to the new approaches.

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