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LEADER IDENTIFICATION IN A RESEARCH COLLABORATIVE NETWORK

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There is considerable empirical evidence on the advantages of interorganizational research collaborative networks across societies and research institutes such as research and development (R&D) centers and universities. Identifying a leader in this contexts is important both theoretically for doing leadership studies, and practically for effective governmental funding allocation and private investments. Inconsistent definitions and non-homogeneous attributes with unidimensional measurement approaches such as subjective measuring of power or considering a central company as the leader made the previous efforts inefficient for identifying leaders in an interorganizational setting. This research aims to identify a leading organization among a set of homogenous R&D centers in a research collaborative network context through implementing the main leader's attributes in different dimensions. The article presents a multidimensional common weight model based on the data envelopment analysis (DEA) approach in a parallel system with several operational dimensions each of which consumes a set of inputs (budget, lecturers, and students) to produce a set of outputs (scientific meetings and conferences, national and international papers). Centrality and visibility are two main leaders' attributes combined with efficiency influence the contributions and outcomes of each collaborative network partner. It is demonstrated how the proposed model performs its high-efficiency score in the most influential R&D center named the "leader" among 47 R&D centers in medical universities in Iran. The comparative analysis of managerial results showed that reputation has a greater impact on leader identification than centrality. The results based on mathematical calculations showed a robust discriminating power for efficiency measurement of the proposed model.

Keywords: research collaborative network, leader, data envelopment analysis, common weights, non-discretionary variables, efficiency, network centrality, reputation.

INTRODUCTION

The COVID-19 pandemic has demonstrated the importance of cross-border research collaborative networks to create a safe and effective COVID-19 vaccine [Lee,

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Haupt, 2020]. While there are different definitions of the collaborative network in the literature [Thomson, Perry, 2006], the two main elements of working together and sharing knowledge directed many scholars to define it as a network consisting of a variety of entities (organizations and people) that are largely autonomous, geographically distributed, heterogeneous in terms of their operating environment, culture, social capital, and goals, but work together toward common and compatible goals [Tsimiklis, Makatsoris, 2019]. Organizations are interested in collaboration to share research and development (R&D) costs and risks, accelerate new products or processes introduction, or gain new markets and skills accessibility [Powell, Koput, Smith-Doerr, 1996] by exploitation of external resources, capabilities, and competencies [Müller-Seitz, Sydow, 2012]. This research addresses an example of collaborative networks which is named "research collaboration network" particularly among a set of R&D centers in universities that work together for doing joint research (e.g., [Chen et al., 2020]).

In these research collaborative networks identifying the leader is important because R&D centers are interested in direct collaboration with the leader and imitating its strategies and behaviors to enhance their visibility, legitimacy, and survival chance [Haveman, 1993]. Leader selection is regarding the collaborative partner selection as a research direction among interested scholars in this realm (e.g., [Kalesnikaite, Neshkova, 2020]) based on the persistent belief that leaders are sources of knowledge and expertise [Haveman, 1993], right decision-makers, and successful in accessing higher levels of resources [Mehra et al., 2006] that can influence the collective actions, behaviors, and performance [Mehra et al., 2006; Mokhtar et al., 2019b]. Finding a leader among collaborative R&D centers in universities is also important for governmental funding allocation and for achieving a high reputation within the research community. The leader's reputation can attract highly qualified foreign students and indirectly lead to society's welfare through attracting foreign R&D centers to collaborate and invest. In addition, organizations are more interested in collaboration with leading R&D centers in universities for doing industry-university research for improving national innovative capabilities [Zhang et al., 2016; Chen et al., 2020].

However, despite the growing attention and studies devoted to the leader in an interorganizational setting, the term is characterized by relatively inconsistent definitions with non-homogeneous attributes and measurements which lead to a rather incoherent picture of leader for identification [Müller-Seitz, Sydow, 2012; Mokhtar et al., 2019b]. Previous studies also do not explicitly focus on identifying leaders in networks and have targeted dyads in a buyer-supplier relationship and a focal company as a leader (e.g., [Mokhtar et al., 2019a; Shin, Park, 2021]). Further, leadership studies in an interorganizational context have paid little attention to the heterarchical networks, i.e., consisting of more or less independent partners without a formally legitimated leading position such as collaborative networks. In other words, the focus of this marginal and diverse body of works has been on the leadership styles of behavior (see [Mokhtar et al., 2019b]), and less attention has been paid to unanimously and comprehensively characterize the leaders and their attributes in interorganizational setting like research collaborative networks. Therefore, this study aims to answer the following two research questions.

Research question 1. What central attributes of leaders in an interorganizational context can be implemented to identify leaders in research collaborative networks?

Research question 2. How we can identify a leader in a research collaborative network among a set of R&D centers?

To address these two questions, this study contributes to the body of knowledge on this topic in two ways. Firstly, we articulate the main leaders' attributes by the review of the previous works and focusing on the leader as an organization at the network level of analysis. To this aim, this research focuses on the most recent relevant studies (e.g., [Mokhtar et al., 2019b; Zenkevich, Kazemi, 2020]) and defines a research collaborative network leader as *an organization that based on its influence on other collaborative partners demonstrates a higher level of efficiency*. Secondly, we address a call for research by S. Kazemi with coauthors [Kazemi et al., 2021] to identify a leading organization in a multidimensional way by developing a multidimensional common weight model (MDCW) based on the data envelopment analysis approach for identifying the leader in a more holistic way among a set of collaborative R&D centers in medical universities.

The remainder of this paper is organized as follows. The second section introduces the most important attributes of a leading organization. The third section presents the development of the model. The problem description, data collection, and model application are presented in the fourth section. Finally, the paper concludes by providing some directions for future research.

LITERATURE REVIEW

Research collaborative network. The importance of interorganizational collaborations has motivated particularly innovative organizations to form collaborative networks where they can exchange information, ideas, and other critical resources with each other (e.g., [Zhang et al., 2016]). Collaborations among these innovative organizations or research institutes facilitate the integration of internal and external knowledge and enable them to be more productive and efficient in producing innovative outcomes [Chen et al., 2020].

Research institutes such as R&D centers in universities as the critical actors in research collaborative networks are important for the economic development and competitiveness by promoting cutting-edge research in science and technology through acquisition, implementation, creation, and transfer of knowledge among collaborative partners [Zhang et al., 2016]. These actors which are usually independent organizations in a different operating environment with unique resources, capabilities, and competencies form research collaborative networks to take advantage of each other for achieving competitive advantages and higher performance [Tsimiklis, Makatsoris, 2019; Chen et al., 2020]. They can share investment costs and risks and access to complementary resources toward a higher innovative performance [Guan, Zhang, Yan, 2015].

However, there is a paradoxical situation in which interorganizational collaborations while having so many advantages for the research institutes such as R&D centers [Zhang et al., 2020], the majority of these collaborations fail to meet the expectations [Ospina, Saz-Carranza, 2010]. In this regard, the role of leaders can be highlighted based on the persistent belief that leaders can enhance collective performance [Mehra et al., 2006]. In these contexts, a leading organization has been viewed from three perspectives:

1) evaluating leaders among operationally heterogeneous organizations (e.g., [Shu et al., 2019]);
2) evaluating leaders among operationally homogenous organizations (e.g., [Li et al., 2018]);
3) evaluating leaders among a set of operationally homogenous and heterogenous organizations (a network form) (e.g., [Hao, Feng, Ye, 2017]).

This study with considering a research collaborative network consisting of a set of R&D centers in universities with homogenous operations addresses the identification of the leader in the second form, among a set of operationally homogenous decision-making units (DMUs) based on the major attributes of the leader in the literature and corresponding theoretical basis. Also, a fundamental assumption of DEA models in measuring the efficiency of DMUs is based on their homogenous operations, which limits our choice to consider the identifying leader among a set of homogenous DMUs.

The leader in collaborative networks and its main attributes. Most of the leadership studies in interorganizational settings tried to address leaders as focal firms mostly in a dyadic buyer-supplier relationship (e.g., [Mokhtar et al., 2019a; Shin, Park, 2021]). In addition, leadership studies at the network level of the analysis demonstrate inconsistent definitions using non-homogenous attributes for defining and characterizing leaders. For example, a leader has been defined as "an organization capable of greater influence, readily identifiable by its behaviors, creator of the vision, and that establishes a relationship with other supply chain organizations" [Defee, Stank, Esper, 2010, p. 766], "formal and informal influence a hub firm exerts over partner firms" [Hao, Feng, Ye, 2017, p. 652], "a firm which influences and orchestrates the actions and behaviors of its own partners" [Mokhtar et al., 2019b, p. 257], etc. While there are different definitions of the leader, the majority of these definitions emphasize that the leader must stand out from followers through its higher capacity for influence [Shamir, 1999].

Also, following the neo-institutional theory and imitation isomorphism, every leading organization should demonstrate a higher level of success and performance to convince other organizations to follow its orders [Müller-Seitz, Sydow, 2012]. In other words, in a research collaborative network, it is expected that a leading company not only has a higher level of influence comparing other collaborative partners but also can demonstrate higher efficiency in using lower levels of inputs and producing higher levels of outputs. Therefore, a research collaborative network leader is defined as an organization that based on its influence on other collaborative partners demonstrates a higher level of efficiency [Li et al., 2018; Mokhtar et al., 2019b; Zenkevich, Kazemi, 2020; Kazemi et al., 2021].

In this definition, influence is a central factor and is defined as *the ability of a company to induce a change in the decision and behavior of another company* [Reber, Berger, 2006]. The manner in which the influence is exerted can be different by which we are able to differentiate between different types of leaders and followers in interorganizational contexts. For example, a market leader influences through its reputation and visibility which are derived from possessing a higher market share in a particular market segment [Hora, Klassen, 2013], and a network leader which we name a non-market leader that exerts influence through several mechanisms stemming from its reputation [Shu et al., 2019] and positional advantages or centrality [Fernandez, Gould, 1994]. This research focuses on the non-market leader in research collaborative networks and tries to articulate these two main attributes by which leaders exert higher influence on other collaborative partners.

Reputation: A source of leaders' influence. Companies with higher reputations serve as a target of imitation and reference point for other companies and rivals to obtain the desired performance level [Hora, Klassen, 2013]. Many studies (e.g., [Mehra et al., 2006]) argue that reputation is one of the main attributes of a leader to be observable and distinguishable from followers. For example, in [Shu et al., 2019] authors indicated that companies with better reputations and popularity among consumers are more likely to become leaders. Although corporate reputation has been defined and measured differently in the literature (see [Lange, Lee, Dai, 2011]), different empirical works have revealed the association between corporate reputation and for example better efficiency and performance (e.g., [MacLeod, 2007]). Corporate reputation also affects the accessibility of resources and outcomes. In other words, past studies have demonstrated that the reputation of organizations affects their attractiveness to other organizations which finally results in higher access to resource providers (e.g., [Vanacker, Forbes, 2016]).

In [Lange, Lee, Dai, 2011] authors explain that a company's reputation stems from different sources, such as visibility and higher success levels in achieving goals and performance. The influential role of corporate visibility on corporate reputation has been investigated by several empirical works which in turn can provide the company with the capacity to influence other companies and eventually modify their decisions [Fernandez, Gould, 1994]. On the one hand, organizations are more likely to imitate and follow a more visible company as they consider this company with successful performance and superior information [Haveman, 1993]. On the other hand, the level of a company's success and performance as a signal of quality and competence is related to a leading company's prestige and reputation [Fernandez, Gould, 1994].

Therefore, following these arguments, the organization's reputation not only is a source of influence for leaders but also affects the efficiency of organizations through influencing on flows of resources. In a research collaborative network among R&D centers in universities, the most obvious indicator of reputation is the rank of the university in the world. This research will consider this indicator as a proxy for measuring reputation.

Centrality: A source of leaders' influence. In the research collaboration context, co-authorship is the most visible and accessible indicator of collaborative network analysis [Milojevic, 2010]. In this context, the network theory is a dominant perspective and argues that the position of actors within the network affects the economic actions of actors, resource accessibilities, and their performance [Freeman, 1979; Zaheer, Gözübüyük, Milanov, 2010]. The main idea is that the pattern of relationships among actors is unique, provides the opportunity for sharing resources, affects the behavior and performance of actors, and potentially confers competitive advantage [Zaheer, Gözübüyük, Milanov, 2010].

Many scholars (e.g., [He et al., 2018]) indicate that an actor's positional advantages in the network, such as centrality, contribute to its influence on other actors. For example, J. Moody [Moody, 2004] indicates that actors with higher centrality gain higher prestige and connections that affect the decision of new actors to be the main target of collaboration more than other collaborative partners. Organizations in the central positions with a large number of ties have information advantages and can influence other collaborative network partners through lowering their level of uncertainty, providing necessary resources such as knowledge, etc. [Powell, Koput, Smith-Doerr, 1996]. Although there are several different measures of centrality in the literature such as degree centrality, Katz-Bonacich centrality and betweenness centrality [Freeman, 1979], Katz-Bonacich's centrality, used by several studies on identifying the leader (e.g., [Zhou, Chen, 2016]), is more efficient in measuring centrality relative to the entire network (see [Ballester, Calvó-Armengol, Zenou, 2006]). Organizations occupying a central position in networks can acquire non-redundant and diverse information more quickly than others. Central organizations also have better access to the resources and capabilities (e.g., [Powell, Koput, Smith-Doerr, 1996]) and are able to have better outcomes such as innovation and performance. L. Freeman [Freeman, 1979] also emphasizes network centrality as an important structural feature that affects efficiency.

Therefore, based on this argument network centrality as the second main attribute of leaders in a research collaborative network is considered to identify a leader. The combination of reputation and centrality increases the attractiveness of a company as a non-market leader in a research collaborative network for other collaborative partners.

Efficiency measurement for identifying a research collaborative leader. There are different efficiency analysis approaches in the literature, including deterministic frontier analysis (DFA), stochastic frontier analysis (SFA) [Aigner, Lovell, Schmidt, 1977], and data envelopment analysis (DEA) [Charnes, Cooper, Rhodes, 1978]. This research will focus on the DEA approach as the most widely used method in this regard, with advantages over DFA and SFA [Hjalmarsson, Kumbhakar, Heshmati, 1996]. It provides a simple method to deal with multiple inputs and outputs in examining relative efficiency and handles large numbers of variables, constraints, and data [Charnes, Cooper, Rhodes, 1978; Kiani Mavi, Kazemi, Jahangiri, 2013].

DEA is a non-parametric fractional mathematical modeling as a ratio of a weighted sum of the outputs to a weighted sum of the inputs for measuring the relative efficiency of a homogeneous group of DMUs by multiple inputs and outputs [Charnes, Cooper, Rhodes, 1978]. Many additional theoretical developments in the field have adapted the models to deal with different problems in practice [Adler, Friedman, Sinuany-Stern, 2002]. Since the advent of DEA in 1978, there has been extensive growth in theoretical developments and applications in its basic models, focusing on the various models, data, status of variables, and approaches to incorporating restrictions on multipliers [Kao, 2009].

According to the proposed definition of a leader in a research collaborative network, the leader will be a company with higher efficiency based on the two main attributes of centrality and reputation. As above-mentioned, these two attributes affect particular types of resources and outcomes of organizations in interorganizational relationships. Therefore, it is required to consider these two attributes in different dimensions with related inputs and outputs. Accordingly, this research aims to develop an MDCW based on DEA to calculate efficiency scores by proposing a full ranking of organizations through implementing the common weight (CW) approach [Kiani Mavi, Kazemi, Jahangiri, 2013]. The proposed model will realize its high-efficiency score on the most influential leading organization in a research collaborative network based on the two main attributes including the network centrality and reputation.

Restrictions and variables. Typically, there are two basic structures in production systems of DMUs including series processes and parallel processes [Kao, 2009], which constitute two important parts of DEA studies known as "Network DEA" (e.g., [Zhang, Chen, 2018]) and "Parallel DEA" (e.g., [Kao, 2009]). For example, L. Zhang and Y. Chen [Zhang, Chen, 2018] have used the input-oriented additive two-stage network DEA model with predetermined weights and compared two approaches for solving this model. However, weights have been applied directly by the decision-maker in a series process of network DEA.

This study focuses on the parallel systems as DMUs usually use various sets of inputs, which separately lead to various outputs through parallel functions toward outcomes (see Figure 1).

There are no clearly defined and agreed-on input and output relationships in many cases for implementing multiple inputs and outputs. This issue highlights the importance of classifying inputs versus outputs in separate dimensions and determining their extent in efficiency measurement to better discriminate among DMUs. Accordingly, measuring efficiency based on only some dispersed criteria with different significance for the managers may lead to inaccurate and unsatisfactory results. This system is following our proposed leader's attributes as we argued that the reputation and centrality affect related inputs and outputs of each organization in n separate dimensions.

Incorporating appropriate sets of inputs and outputs is critical for the managers to decide how to consume inputs and produce outputs efficiently while they are taking the advantages of reputation and network centrality. However, some inputs are exogenously fixed and beyond managers' discretionary control [Banker, Morey, 1986].

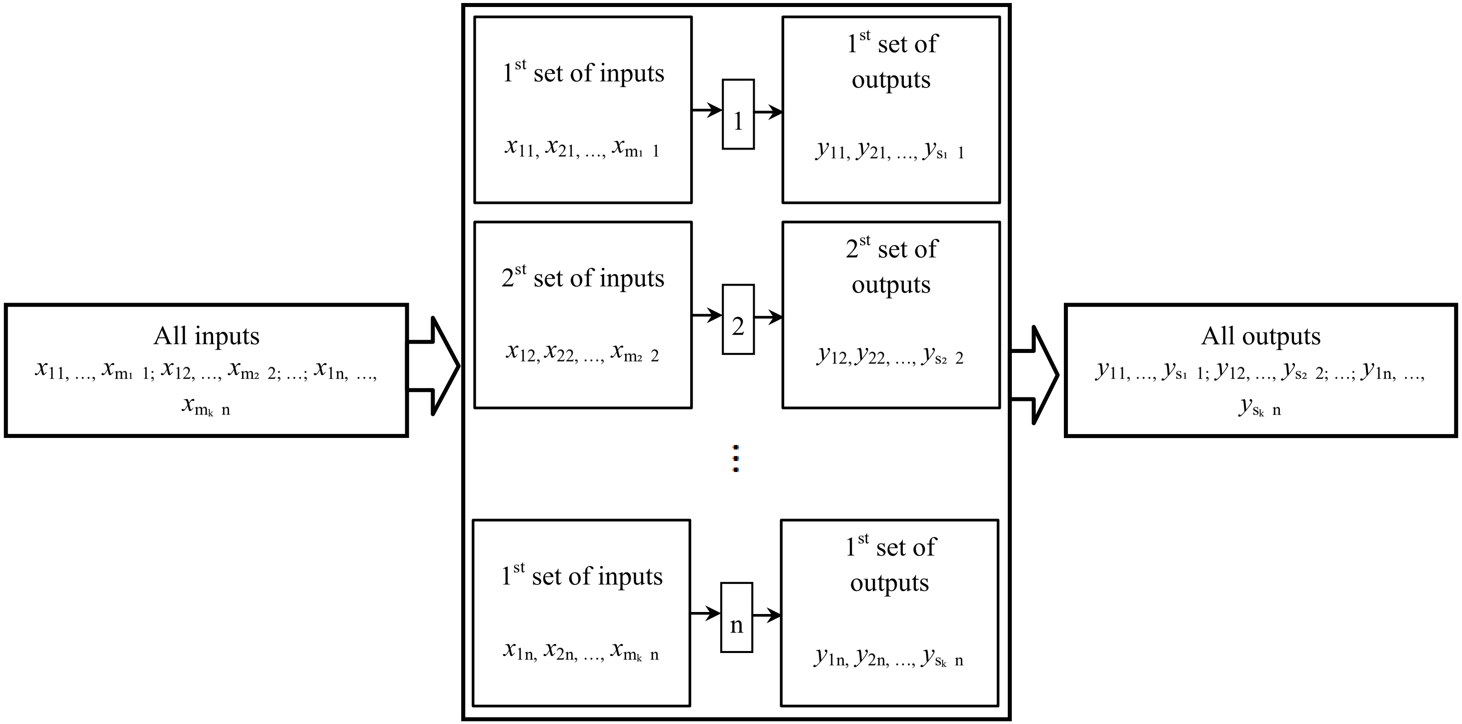

Figure 1. A general parallel system of operations for each DMU

Notes: x — input; y — output.
Adapted from: [Kao, 2009, p. 1108].

These inputs, which are known as non-discretionary (ND) variables, affect the efficiency score indirectly and have been studied in several studies to enhance efficiency measurement (e.g., [Banker, Morey, 1986]). Non-discretionary variables affect organizations' efficiency scores by contributing to their resources and outcomes, such as age and size [Haveman, 1993]. This research also considers this type of data to enhance the accuracy of the efficiency measurement.

MODEL DEVELOPMENT

A common weight model with an ideal point approach. While the efficiency scores of DMUs using basic DEA models are between zero and one inclusively, it is impossible to reach a full rank of DMUs when some are efficient with the efficiency scores of one [Kiani Mavi, Kazemi, Jahangiri, 2013]. N. Adler with coauthors propose a review of the studies and techniques which focus on the differential capabilities of DEA to rank both effcient and ineffcient DMUs fully [Adler, Friedman, Sinuany-Stern, 2002]. However, several studies (e.g., [Kiani Mavi, Kazemi, Jahangiri, 2013]) have mentioned that CW models are the most popular approach for assessing and fully ranking all DMUs. These models focus on an identical criterion to select the most favorable set of weights and reduce the flexibility of weights assigned to all inputs and outputs of DMUs [Kiani Mavi, Kazemi, Jahangiri, 2013]. Several methods have been developed in the DEA literature for obtaining common weights (CWs) for DMUs, which have led to a wide range of contributions in this realm and reviewed by several studies (e.g., [Sun, Wu, Guo, 2013]).

This research focuses on the ideal point (IP) method introduced by [Sun, Wu, Guo, 2013] for driving CWs as it is always feasible and provides a better insight into the main purpose of developing a model to find the leader as the best performing DMU. Also, as we mentioned before, the ND inputs will be implemented in model development to enhance the accuracy of the efficiency measurement.

Therefore, this research will focus on the proposed model by [Kiani Mavi, Kazemi, Jahangiri, 2013] as a common weight model with an ideal point method and implementing ND inputs (CW-IP-ND model). In this regard, we first assume that there are a set of J DMUs and each DMU_j, $j = 1, \ldots, J$ produces s different discretionary outputs y_{jr}, $r = 1, \ldots, s$ with consuming m different discretionary inputs x_{ji}, $i = 1, \ldots, m$ and t different non-discretionary inputs z_{jl}, $l = 1, \ldots, t$. In the next step, we define an ideal point DMU as follows.

Definition 1. The ideal DMU is a DMU that its inputs are at the minimum level, and its outputs are at the maximum level among all DMUs and are shown by $\overline{DMU} = (\underline{X}, \underline{Z}, \overline{Y})$ where $\underline{X}$, $\underline{Z}$, and $\overline{Y}$ respectively denote the discretionary inputs, non-discretionary inputs, and discretionary outputs of the ideal unit, $\underline{x}_i = \min_j\{x_{ji}\}$, $\underline{z}_l = \min_j\{z_{jl}\}$, and $\overline{y}_r = \max_j\{y_{jr}\}$, $j = 1, \ldots, J$. Finally, the CW-IP-ND model is presented as Model (1) [Kiani Mavi, Kazemi, Jahangiri, 2013]:

$$\min \theta = \sum_{j=1}^{J}\left[\sum_{i=1}^{m} v_i (x_{ji} - \underline{x}_i)\right] + \sum_{j=1}^{J}\left[\sum_{l=1}^{t} q_l (z_{jl} - \underline{z}_l)\right] + \sum_{j=1}^{J}\left[\sum_{r=1}^{s} u_r (\overline{y}_r - y_{jr})\right]$$

s.t.

$$\sum_{r=1}^{s} u_r y_{jr} - \sum_{i=1}^{m} v_i x_{ji} - \sum_{l=1}^{t} q_l z_{jl} \le 0,\ j = 1,\ \ldots,\ J;$$

(Model 1)

$$\sum_{i=1}^{m} v_i \underline{x}_i = 1;$$

$$\sum_{r=1}^{s} u_r \overline{y}_r - \sum_{l=1}^{t} q_l \underline{z}_l = 1;$$

v_{ik}, u_{rk}, $q_l \ge \varepsilon\ \forall i, \forall r, \forall l$,

where $(v, u, q) \in R^{(m+s+t)}$ is the common set of weights and the constraints $\sum_{i=1}^{m} v_i \underline{x}_i = 1$ and $\sum_{r=1}^{s} u_r \overline{y}_r - \sum_{l=1}^{t} q_l \underline{z}_l = 1$ ensure that the ideal DMU is efficient. Finally, the efficiency score of DMU_j (E_j) is measured by implementing the following ratio: $E_j = \dfrac{\sum_{r=1}^{s} u_r^* y_{jr}}{\sum_{i=1}^{m} v_i^* x_{ji}}$.

We will develop this model based on a parallel system of multiple operating dimensions and two separate weights which we will describe in the model development section.

Developing a multidimensional CW-IP-ND model (MDCW-IP-ND). In this section, a multidimensional common weight model with ideal point method (CW-IP) and ND inputs is proposed as a newly developed version of the model (1) by considering the following five steps.

Step 1. According to the traditional denotations in DEA, we consider a set of k homogeneous DMUs, denoted DMU_j, $j = 1, \ldots, J$. However, instead of assuming that these DMUs consume multiple inputs to produce multiple outputs [Charnes, Cooper, Rhodes, 1978], we will define inputs and outputs in n separate dimensions (equivalent to the parallel system) and a particular weight assigned to each dimension to show the importance of each dimension. Accordingly, we consider that DMU_j consumes m different inputs, x_{jik}, $i = 1, \ldots, m_k$, to produce s different outputs, y_{jrk}, $r = 1, \ldots, s_k$, in k different dimensions, $k = 1, \ldots, n$.

Step 2. We implement a weight (D_k) to control the importance of each dimension over other dimensions which have been proposed in step 1 for efficiency measurement. This will illustrate the importance of the decision-maker in characterizing the leader.

Step 3. In the next step of development, we multiplied a weight (W_{jk}) to each DMU's inputs and outputs in each dimension while $\sum_{j=1}^{J} W_{jk} = 1, \forall k.$

These weights contribute to discriminating between DMUs regarding better influencing other collaborative network partners through implementing the network centrality and reputation. In other words, a leader should take advantage of network position and visibility in accessing inputs and producing outputs efficiently.

Step 4. Considering the previous definition of ideal DMU, we will define an ideal DMU based on multiple dimensions and the defined weights as follow.

Definition 2. The ideal DMU is a virtual DMU that possesses minimum discretionary and non-discretionary inputs and maximum discretionary outputs among all DMUs. It is shown by $DMU = (\underline{X}^k, \underline{Z}, \overline{Y}^k)$, where $\underline{X}^k$ and $\overline{Y}^k$ respectively denote the vector of discretionary inputs and outputs of the ideal unit in each dimension and $\underline{Z}$ refers to the vector of non-discretionary inputs without having a particular dimension. Accordingly, we have $\underline{X}^N = (\underline{x}_{11}, \ldots, \underline{x}_{m_1 1}; \underline{x}_{12}, \ldots, \underline{x}_{m_2 2}; \ldots; \underline{x}_{1n}, \ldots, \underline{x}_{m_k n})$, $\underline{x}_{ik} = \min_j \{W_{jk}.x_{ji}\}$, j = 1, …, J,

$\overline{Y}^k = (\overline{y}_{11}, \ldots, \overline{y}_{s_1 1}; \overline{y}_{12}, \ldots, \overline{y}_{s_2 2}; \ldots \overline{y}_{1n}, \ldots, \overline{y}_{s_k n})$ $\overline{y}_{rk} = \max_j \{W_{jk}.y_{jrk}\}, j = 1, \ldots, J$, and $\underline{z}_l = \min_j \{W_{jk}.z_{jl}\}$.

Step 5. Different modifications have been made to develop corresponding models for controlling non-discretionary variables (e.g., [Banker, Morey, 1986]). R. Banker and R. Morey [Banker, Morey, 1986] were the first scholars who addressed ND variables by proposing different alterations to the original DEA models for measuring technical efficiency. Their approach has become the standard way of controlling ND inputs in DEA [Golany, Roll, 1993], which is considered in this research as z_{jl}, $l = 1, \ldots, t$.

Therefore, after following these five steps, we will have the final model as follow:

$$\min\theta = \sum_{j=1}^{J}\left[\sum_{k=1}^{n} D_k\left(\sum_{i=1}^{m_k} W_{jk}.v_{ik}.x_{jik} - \sum_{i=1}^{m_k} v_{ik}.\underline{x}_{ik}\right)\right] + \sum_{j=1}^{J}\left[\left(\sum_{l=1}^{t} q_l.z_{jl} - \sum_{l=1}^{t} q_l.\underline{z}_l\right)\right]$$

$$+\sum_{j=1}^{J}\left[\sum_{k=1}^{n} D_k\left(\sum_{r=1}^{s_k} u_{rk}.\overline{y}_{rk} - \sum_{r=1}^{s_k} W_{jk}.u_{rk}.y_{jrk}\right)\right] \qquad \text{(Model 2)}$$

s.t.

$$\sum_{k=1}^{n} D_k\left(\sum_{i=1}^{m_k} W_{jk}.v_{ik}.x_{jik}\right) + \sum_{l=1}^{t} q_l.z_{jl} - \sum_{k=1}^{n} D_k\left(\sum_{r=1}^{s_k} W_{jk}.u_{rk}.y_{jrk}\right) \geq 0, j = 1, \ldots, J$$

$$D_k\left(\sum_{i=1}^{m_k} v_{ik}.\underline{x}_{ik}\right)=1,\quad k=1,\ldots,n$$

$$D_k\left(\sum_{r=1}^{s_k} u_{rk}.\overline{y}_{jrk}\right)-\sum_{l=1}^{t} q_l.\underline{z}_l=1,\quad k=1,\ldots,n$$

$$v_{ik}, u_{rk}, q_l \geq \varepsilon;\ k = 1, \ldots, n;\ l = 1, \ldots, t;\ i = 1, \ldots, m_k;\ r = 1, \ldots, s_k,$$

where ε is a non-Archimedean infinitesimal epsilon that is imposed to avoid ignoring any factor in calculating efficiency [Kiani Mavi, Kazemi, Jahangiri, 2013]. The calculated weights of v_{ik} and u_{rk} are the assigned weights to the discretionary input i and output r, respectively in dimension k. The weight of q_l is also the calculated weight assigning to non-discretionary input l by the model.

The objective function of the model measures the total virtual distances between each DMU and the $\overline{DMU}$ [Kiani Mavi, Kazemi, Jahangiri, 2013] based on the given inputs and outputs and the corresponding weights. In other words, the total horizontal distances will be

$$\sum_{j=1}^{J}\left[\sum_{k=1}^{n} D_k\left(\sum_{i=1}^{m_k} W_{jk}.v_{ik}.x_{jik}-\sum_{i=1}^{m_k} v_{ik}.\underline{x}_{ik}\right)\right]+\sum_{j=1}^{J}\left[\left(\sum_{l=1}^{t} q_l.z_{jl}-\sum_{l=1}^{t} q_l.\underline{z}_l\right)\right]$$

for both discretionary and ND inputs, and the total vertical distances will be

$$\sum_{j=1}^{J}\left[\sum_{k=1}^{n} D_k\left(\sum_{r=1}^{s_k} u_{rk}.\overline{y}_{rk}-\sum_{r=1}^{s_k} W_{jk}.u_{rk}.y_{jrk}\right)\right].$$

In this model, the external weights of each dimension (D_k) can be in two states, including variable states, with determining their optimal scores by the Model (2) and parameter states to determine their scores by the manager. The amount of internal weight for each DMU and its inputs and outputs in each dimension (W_{jk}) are parameters that will be defined and predetermined based on the case study and two main interorganizational and network characteristics of DMUs. As the assumptions mentioned above, these weights are essential in leaders characterizing and discriminating between DMUs regarding resource accessibility. Previous studies have used external weights in the network DEA (e.g., [Zhang, Chen, 2018]).

Finally, after calculating variables by Model (2), we need to calculate each DMU's efficiency score. Following [Kiani Mavi, Kazemi, Jahangiri, 2013], the following definition will complete this efficiency measurement procedure.

Definition 3. The efficiency of DMU_j is better than other DMUs if its objective function which measures the distance in Model (2) is less than the objective function of other DMUs. In other words, the distance between the DMU_j and $\overline{DMU}$ is less than the other distances. The purpose of Model (2) is to obtain an optimal solution of ($D_1, \ldots, D_k$; $v_1^*, \ldots, v_{ik}^*$; $u_1^*, \ldots, u_{rk}^*$; $q_1^*, \ldots, q_l^*$) to make the total distances between all

DMUs and $\overline{DMU}$ as short as possible [Sun, Wu Guo, 2013]. Afterward, we can calculate the efficiency of each DMU_j with the optimal CWs using Equation (1) [Kiani Mavi, Kazemi, Jahangiri, 2013]:

$$E_j^* = \frac{\left[\left(\sum_{k=1}^{n} D_k \sum_{r=1}^{s_k} W_{jk}.u_{rk}^*.y_{jrk}\right)\right] - \left(\sum_{l=1}^{t} q_l^*.z_{lj}\right)}{\left(\sum_{k=1}^{n} D_k \sum_{i=1}^{m_k} W_{jk}.v_{ik}^*.x_{jik}\right)}. \tag{1}$$

The DMU with a higher value of E_j^* will be considered as the leader in the horizontal network among a set of homogenous and related organizations.

ILLUSTRATIVE CASE STUDY

In this section, the developed Model (2) is applied to evaluate the performance of R&D centers' as the numerical example for the leader investigation.

Problem description. This research focuses on R&D networks as an example of a research collaborative network, which has received increasing academic interest in recent years (e.g., [He et al., 2018]) to illustrate the applicability of the proposed model for identifying the leader. Shortcomings in fundamental technologies and technological and scientific capabilities highlight the importance of R&D efficiency improvement [He et al., 2018]. Therefore, R&D leaders' role is becoming increasingly important to find, invest in, and pay greater attention to different network levels for establishing R&D policy and resource allocation. This study identifies a leader among 47 R&D centers in medical universities in Iran where lecturers, researchers, and budget will be employed to deliver scientific outcomes in terms of meetings and new knowledge in the form of papers. In this regard, we implemented our proposed model, the network structure, and collected data to investigate a leading DMU by measuring the efficiency of DMUs based on the network centrality and reputation as two leader's attributes.

To define the network structure, we have investigated strategic collaborative relationships based on joint papers published by these R&D centers (Figure 2).

Accordingly, ***G*** is defined as the symmetric adjacency matrix of research collaborative relationships between R&D centers. Elements of $g_{jj'}$ in matrix **G** are the link between DMU_j and $DMU_{j'}$ and defined with a value of 1 if DMU_j has collaborated with $DMU_{j'}$ and 0 otherwise, also g_{jj}=0 which indicates there is no self-loop.

Data collection. For the data analysis, the input and output variables are selected based on the literature (e.g., [Qin, Du, 2018; Yang, Fukuyama, Song, 2018]). For example, S. Zemtsov and M. Kotsemir [Zemtsov, Kotsemir, 2019] presented a literature review on the most applicable inputs and outputs for measuring the efficiency of innovation systems and R&D centers. In this research, Human Capital inputs including R&D research staff and researchers, and R&D and education expenditures are two main categories of inputs, and Patents and Publications are two main categories of outputs

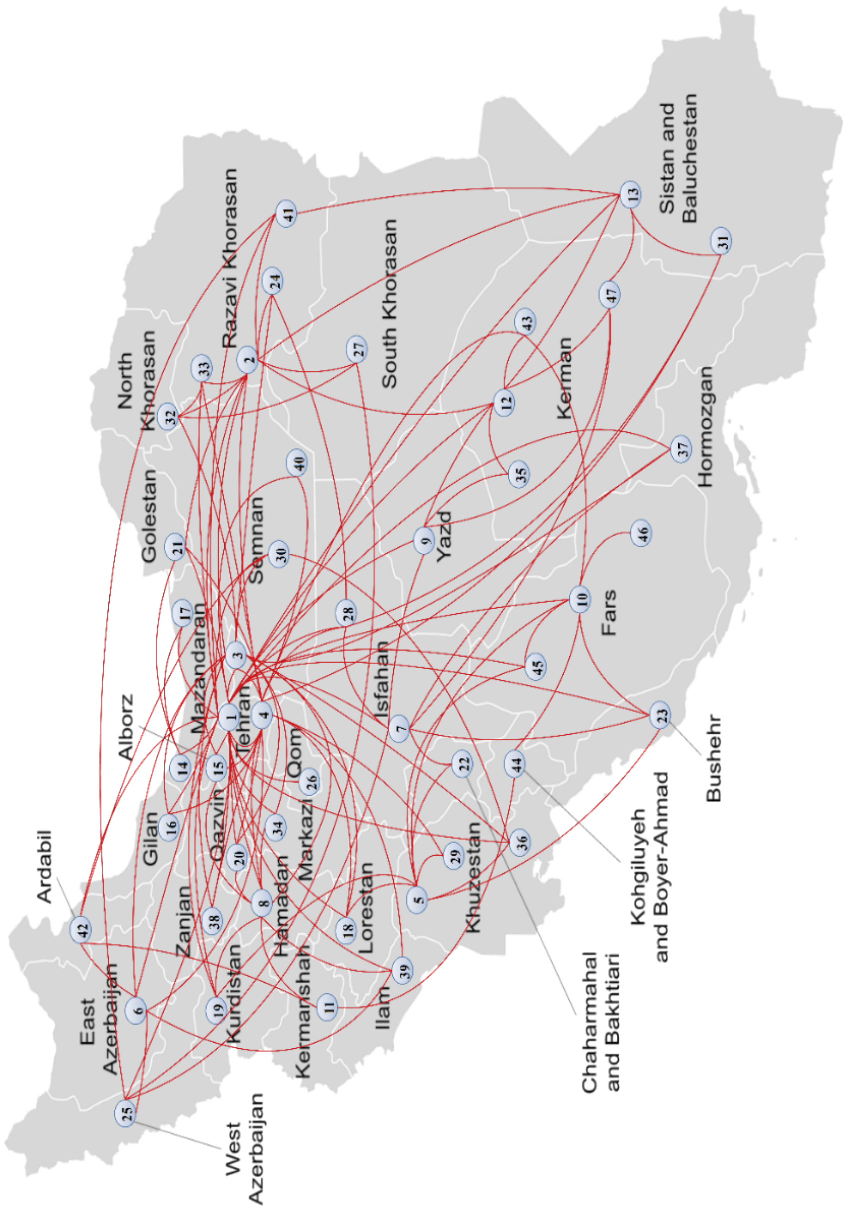

Figure 2. The research collaborative network of 47 medical R&D centers

based on the previous literature. In this research, according to the particular strategies of R&D centers in Iranian Universities and the available data, the categorizing inputs and related outputs in different dimensions is exclusively related to current research that can be different in other collaborative research networks in other countries.

Hence, we assume that the operations of these medical R&D centers are based on two parallel sets of inputs and outputs as two dimensions. In the first dimension, it is assumed that the budget of R&D centers[1] (input) leads to their scientific meetings and conferences (output). In other words, R&D centers in universities consume their budget to hold scientific meetings and conferences as an important attribute of knowledge level and productivity indicator of scientists in R&D centers [Lopes, Lanzer, 2002]. In the second dimension, we assume that students and lecturers (input) in each R&D center contribute to the national and international published articles (output) that is based on the dominant strategy to increase publications in Iranian universities by students and lecturers [Kharabaf, Abdollahi, 2012].

These dimensions can be different in other similar networks for different countries. The efficiency of individual scientists also can be inferred in terms of consuming their knowledge and creativity to develop knowledge in terms of publications. We have also considered universities' age as a non-discretionary factor as it is an uncontrollable input for managers and affects level of prior knowledge in R&D centers and their efficiency [Beier, Ackerman, 2003]. The corresponding data was collected from the UniRef[2] database and the universities' website in 2018 (Appendix).

However, for collecting data regarding the other defined variables, we will perform as bellow:

- the reputation of universities affects some parts of their resources and, accordingly, the relevant outcomes. The high reputed universities cause managers to enhance their budget for holding scientific meetings. This research used universities' ranking[3] to measure their reputation and normalized them as the ratio to the sum of the rankings. In this way, the sum of reputation scores of universities is one;
- there are several measures of centrality in the literature [Freeman, 1979]. However, Katz-Bonacich's centrality is more popular for finding the leader in the networks (e.g., [Zhou, Chen, 2016]), and is more efficient in measuring centrality relative to the whole network [Ballester, Calvó-Armengol, Zenou, 2006]. The Katz-Bonacich centrality of a DMU counts the number of paths that stem from the DMU exponentially discounted based on the length of paths [Ballester, Calvó-Armengol, Zenou, 2006] and is calculated using the network structure and the following Equation (2) in the matrix form:

[1] All universities are public universities and they have annual budget, which is approved by the Ministry of Science.

[2] Database www.uniref.ir introduces and ranks Iranian universities based on clear and documented data from internal conference and journal papers as well as published papers in international journals indexed by Science Citation Index (SCI).

[3] From www.webometrics.info

$$w = [I - \delta G]^{-1} \delta G 1 \quad (2)$$

where w is the vector of centralities, **1** is the J-dimensional vector of *1*s, and $\boldsymbol{I}$ denotes the identity matrix [Ballester, Calvó-Armengol, Zenou, 2006]. Also, δ is a discount factor between 0 and the inverse of the largest eigenvalue, $1/(\lambda_{\text{Max}}(\mathbf{G}))$ to compute the discounted sum of walks emanating from the node j to $j^{'}$ ($g_{jj'}$) Finally, after calculating the centrality of each university, the values have been normalized by the sum of centralities.

Results and discussion. This part presents the efficiency scores derived from the formulating developed model using GAMS software and collected data from 47 R&D centers in medical universities. In this regard, we presumed that there are two dimensions of inputs and outputs regarding each DMU for the leader's investigation. Also, for differentiating between outputs of R&D centers in terms of produced paper, we considered that the weight of international papers (u_{22}) is more than double the weight of internal papers (u_{12}).

Furthermore, the optimization technology in the GAMS software adjust the weights of dimensions (D_k) with the weights of inputs (v_{ik}) and outputs (u_{rk}) for solving the proposed model. This adjustment leads to similar rankings of DMUs for different status of D_k (to be as a parameter or variable). To prevent such adjusting weights, we measure the efficiency scores through two rounds of calculation. In the first round of efficiency calculation, we derive the optimal weights of inputs and outputs where the status of D_k is variable (Table 1).

Table 1. **Optimal weights of inputs and outputs**

Variable	With D_k and W_{jk}	Without D_k and W_{jk}
v_{11}^{*}	0.42E-4	0.08E-5
v_{12}^{*}	38.7374	0.01587
v_{21}^{*}	0.01E-4	0.01E-4
u_{11}^{*}	1.82915	0.72E-4
u_{21}^{*}	1.82915	0.03571
u_{22}^{*}	0.01561	0.00014
q_1	0.01E-4	0.01E-4

For efficiency calculation, we selected a non-maximum value arbitrarily for the epsilon (ε=10^{-6})) to achieve feasible solutions due to the existence of large values. Then, through fixing these weights as the optimal results for v_{ik}, u_{rk}, and q_l we recalculate the efficiency scores in the second round of efficiency measurement. Here, a sensitivity analysis also on the values of D_k has been performed for a better understanding of its impact on efficiency scores (Table 2).

Finally, we compared the results of this proposed model with a simple situation where there is no D_k and W_{jk} in the model. We also implemented the normalization of the efficiency scores to produce efficiencies between 0 and 1 with at least one efficient unit. Based on the efficiency calculations and sensitivity analysis in Table 3, the following results can be inferred:

a) the comparison between the cases in which there are different weights of D_k for each dimension (the first and third columns of efficiency scores) and the case without considering weights of dimensions (the last column of efficiency scores) or with equal weights (the second column of efficiency scores) illustrates that the external weights of dimensions (D_k) or the manager's preferences increase the discrimination power of the moedel in order to have a more precices and fair efficiency scores concerning each DMU;
b) the comparison between the case in which there is a simple CWs model with ND inputs without considering D_k and W_{jk} (the last column of efficiency scores) and the case without considering weights of dimensions or with equal weights (the second column of efficiency scores) demonstrates that internal weights (W_{jk}) affect efficiency scores;
c) the results confirm that ignoring the above weights in this research (D_k and W_{jk}) for measuring efficiency based on DEA may cause inaccurate and biased results. Consequently, the leader can vary based on managers' preferences and the external network characteristics that affect the resource availability and outcomes of DMUs;
d) the results demonstrate that the leader will be the R&D center in Tehran University of Medical Sciences (DMU 1), one of the reputable universities with the highest reputation among other medical universities in Iran. However, this university's efficiency decreases compared to other universities when we incorporate the considerably higher weight of reputation compared to the centrality in the model. In other words, the University of Tehran, with its high reputation compared to the other universities, is not efficient in exploiting its reputational advantages to produce higher levels of outcomes;
e) finally, the R&D spillover is not completely evident. On the one hand, social media and electronic communications will facilitate joint research and papers without the barrier of distance. On the other hand, the magnitude of different levels of reputation and centrality of universities in the same province creates competition between these DMUs. Only those universities which have high and relatively close knowledge accessibility, reputation, and mutual dependency (for example, universities number 1 with 4, 28 with 7) have more tendency to create mutual strategic relations to keep their competitiveness and not to lose their power advantages. The competition among these universities for higher reputation and centrality to gain a higher budget and other valuable resources is for higher knowledge and innovation creation. Therefore, competition among universities to gain a leading position is linked to their network efficiencies.

Table 2. **The comparison of efficiency scores**

DMU	**D_k and W_{jk} are both parameters (a sensitivity analysis on D_k)**						**D_k is variable and W_{jk} is parameter**		**Without D_k and W_{jk}**	
	E_j^* ($D_1 = 0.01$, $D_2 = 0.99$)	**Rank**	**E_j^* ($D_1 = 0.5$, $D_2 = 0.5$)**	**Rank**	**E_j^* ($D_1 = 0.99$, $D_2 = 0.01$)**	**Rank**	**E_j^* ($D_1 = 0.9$, $D_2 = 0.1$)**	**Rank**	**E_j^***	**Rank**
1	2	3	4	5	6	7	8	9	10	11
1	1.0000	1	0.5741	4	0.5461	9	0.2523	15	1.0000	1
2	0.7408	3	0.5122	6	0.7506	4	0.3614	8	0.8022	3
3	0.7300	4	0.4407	9	0.5049	11	0.2294	16	0.7344	4
4	0.0747	40	0.1114	39	0.6196	5	0.1709	21	0.5277	7
5	0.5203	11	0.2880	18	0.0852	30	0.0994	30	0.2621	24
6	0.9183	2	0.5807	3	0.4945	12	0.3236	9	0.6611	5
7	0.7034	5	0.4318	10	0.2823	22	0.2173	17	0.4403	10
8	0.5368	9	0.3447	14	0.4201	14	0.2084	18	0.5154	8
9	0.4579	13	0.2759	19	0.1611	27	0.1310	25	0.2943	21
10	0.2934	28	0.4583	7	0.9847	2	0.5981	2	0.6301	6
11	0.5956	7	0.2883	17	0.0048	37	0.0467	33	0.2800	22
12	0.4451	15	0.3040	16	0.3836	18	0.2058	19	0.4290	12
13	0.3636	22	0.2223	28	0.1591	28	0.1127	27	0.2520	25
14	0.4483	14	0.3583	13	0.2994	21	0.2614	12	0.3202	17
15	0.4426	16	0.2749	20	0.1681	24	0.1395	23	0.2439	26
16	0.2736	33	0.2261	26	0.3089	20	0.1934	20	0.2786	23
17	0.4872	12	0.4181	11	0.5719	8	0.3686	7	0.5038	9
18	0.3138	27	0.1583	34	0.0053	35	0.0322	37	0.1227	38
19	0.3738	21	0.2401	25	0.1658	25	0.1322	24	0.2301	29
20	0.3329	24	0.1707	33	0.0094	32	0.0388	35	0.1882	33
21	0.2873	29	0.2741	22	0.4105	16	0.2655	11	0.3341	16
22	0.0518	42	0.0240	44	0.0001	47	0.0031	46	0.0243	44

End of the Table 2

1	2	3	4	5	6	7	8	9	10	11
23	0.2870	30	0.1431	36	0.0036	38	0.0272	38	0.1170	40
24	0.6782	6	0.5681	5	1.0000	1	0.5179	3	0.8141	2
25	0.3629	23	0.2249	27	0.0984	29	0.1050	29	0.1589	35
26	0.2786	31	0.1368	38	0.0027	40	0.0238	40	0.1289	36
27	0.3824	20	0.1914	32	0.0051	36	0.0371	36	0.2310	28
28	0.5373	8	0.2747	21	0.0135	31	0.0612	31	0.3035	19
29	0.4008	18	0.5930	2	0.3932	17	0.4790	5	0.3152	18
30	0.0384	44	0.0782	43	0.3186	19	0.1257	26	0.1704	34
31	0.0652	41	0.2113	29	0.4192	15	0.3043	10	0.2211	30
32	0.1939	38	0.0977	42	0.0031	39	0.0197	42	0.0991	41
33	0.4285	17	0.3279	15	0.4535	13	0.2613	13	0.4350	11
34	0.0345	46	0.0174	46	0.0004	45	0.0035	45	0.0156	46
35	0.2625	34	0.4467	8	0.5949	6	0.5095	4	0.3508	15
36	0.2765	32	0.1374	37	0.0027	41	0.0255	39	0.0937	42
37	0.0976	39	0.1073	41	0.1614	26	0.1120	28	0.1224	39
38	0.2611	35	0.2464	24	0.5374	10	0.2573	14	0.4049	14
39	0.0346	45	0.0176	45	0.0006	44	0.0037	44	0.0171	45
40	0.3888	19	0.1974	31	0.0074	34	0.0419	34	0.2203	31
41	0.5289	10	0.2667	23	0.0088	33	0.0542	32	0.2323	27
42	0.2579	36	0.2029	30	0.1998	23	0.1534	22	0.2044	32
43	0.2254	37	0.1101	40	0.0020	42	0.0187	43	0.0874	43
44	0.3146	26	0.1497	35	0.0019	43	0.0224	41	0.1287	37
45	0.3261	25	0.3797	12	0.5825	7	0.4086	6	0.4215	13
46	0.0475	43	1.0000	1	0.8045	3	1.0000	1	0.2946	20
47	0.00507	47	0.00229	47	0.00008	46	0.00023	47	0.0015	47

CONCLUSION AND FUTURE RESEARCH

An increasing interest in the investigation and identification of supply network leaders is evident in recent studies by incorporating various leadership characteristics in the literature. In this research, we focused on evaluating based on efficiency through developing a multidimensional CW model and incorporating various attributes of a leader, especially in a research collaborative network.

The proposed model can consider various importance of inputs and outputs by bearing in mind two main internal and external coefficients for each dimension. The external coefficient is to handle the significance of each dimension based on the preferences of managers. This feature illustrates that efficiency scores and types of inputs and outputs are inextricably bound up for efficiency calculation, which was not considered before. On the other hand, inputs and outputs in each dimension have a different significance for each company's network regarding their access to the resources and the market. This importance also was considered as an internal coefficient for each input and output per DMU in all dimensions.

Finally, an R&D network was selected as a numerical example to test the applicability of our proposed model and framework for leader identification among 47 R&D centers in medical universities in Iran. The results demonstrate that R&D centers with different positions in the network structure and specific popularity in terms of reputation have particular access to resources and specific capability to produce outputs. The network externality is based on the network centrality, and the reputation affects the relevant dimension of each R&D center in the network, which influences their efficiency scores. Finally, selecting a leader based on the efficiency of DMUs is sensitive to managers' preferences about the importance of each dimension.

This study offers considerable contributions in evaluating and suggest further investigation of both DEA model developments and leader identification realms. Some scholars may be interested in selecting a set of leaders. In this case, the current procedure for model development can be applied to the conventional DEA models [Charnes, Cooper, Rhodes, 1978], where some DMUs may receive higher efficiency scores. Finally, this study suggests incorporating the strength of the links among DMUs (weak and strong ties) in the next studies to gain better insights into the dependencies and knowledge spillover.

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ВЫЯВЛЕНИЕ ЛИДЕРА В СОВМЕСТНОЙ ИССЛЕДОВАТЕЛЬСКОЙ СЕТИ

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Существует множество эмпирических данных о преимуществах межорганизационных исследовательских сетей сотрудничества между обществами и исследовательскими институтами, такими как центры исследований и разработок (R&D) и университеты. Определение лидера в этих условиях важно как с теоретической (для изучения лидерства), так и с практической точки зрения (для эффективного распределения государственного финансирования и частных инвестиций). Непоследовательные определения и неоднородные атрибуты с одномерными подходами к измерению (например, субъективное измерение силы или рассмотрение центральной компании в качестве лидера) сделали неэффективными предыдущие усилия для выявления лидеров в межорганизационной среде. Поэтому настоящее исследование направлено на установление лидирующей организации среди множества центров НИОКР в контексте совместной исследовательской сети путем реализации концепции главного лидера в разных измерениях. В статье разработана многомерная модель с общими весами на основе подхода анализа свертки данных (DEA) в параллельной системе с несколькими операционными измерениями, каждое из которых потребляет набор входных данных (бюджет, преподаватели и студенты) для достижения набора результатов (научные встречи и конференции, национальные и международные документы). Центральность и видимость — два основных свойства лидеров, которые вместе с эффективностью влияют на вклад и результаты каждого сетевого партнера. Показано, как предложенная модель реализует самый высокий уровень эффективности

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в наиболее влиятельном центре НИОКР, названном «лидером», среди 47 центров НИОКР в медицинских университетах Ирана. Сравнительный анализ результатов управления показывает, что репутация в данном случае имеет большее значение при определении лидера, чем центральность. Результаты математических расчетов показали надежную различительную способность при измерении эффективности в рамках представленной модели.

Ключевые слова: совместная исследовательская сеть, лидер, анализ свертки данных, общие веса, недискреционные переменные, эффективность, центральность сети, репутация.

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APPENDIX

The input and output data from 47 R&D centers in medical universities

ID	Universities of Medical Sciences	Province	Non-discretionary input	Weight		Discretionary input			Discretionary output		
				Dimension 1	Dimension 2	Dimension 1	Dimension 2		Dimension 1	Dimension 2	
			Age	Reputation: World's rank (normalized)	Centrality (normalized)	Budget (Million Rials)	No. of lecturers	No. of students	No. of scientific meetings and conferences	National paper	International paper
1	2	3	4	5	6	7	8	9	10	11	12
1	Tehran University	Tehran	85	2.168E-02	0.0925	36044870	1650	13300	28	1175	6384
2	Mashhad University	Razavi Khorasan	73	2.161E-02	0.0403	23921622	911	8300	16	822	2434
3	Iran University	Tehran	45	2.159E-02	0.0585	20917546	980	7206	12	700	2671
4	Shahid Beheshti University	Tehran	59	2.165E-02	0.0597	22575513	1414	12600	20	675	101
5	Ahvaz Jundishapur University	Khuzestan	65	2.150E-02	0.0164	18614967	646	6400	1	576	1133
6	Tabriz University	East Azerbaijan	72	2.161E-02	0.0296	21368659	716	8500	8	568	2491
7	Isfahan University	Isfahan	73	2.159E-02	0.0236	25106905	830	8770	5	512	2209
8	Hamedan University	Hamedan	47	2.148E-02	0.0388	10359853	451	4149	4	293	875

Continuation of the Appendix

1	2	3	4	5	6	7	8	9	10	11	12
9	Yazd Shahid Sadoughi University	Yazd	37	2.147E-02	0.0175	8935700	379	5400	1	272	597
10	Shiraz University	Fars	74	2.149E-02	0.0191	25817719	898	10200	18	274	954
11	Kermanshah University	Kermanshah	52	2.149E-02	0.0076	11655656	474	4394	0	263	1064
12	Kerman University	Kerman	42	2.149E-02	0.0229	9477527	515	6136	3	227	853
13	Zahedan University	Sistan and Baluchestan	38	2.137E-02	0.0222	8495336	355	4361	1	220	435
14	Mazandaran University	Mazandaran	33	2.149E-02	0.0139	15687553	454	8200	3	198	757
15	Alborz University	Alborz	9	2.122E-02	0.0266	8787248	209	7116	1	173	304
16	Gilan University	Gilan	34	2.142E-02	0.0223	13466387	453	4805	3	162	440
17	Babol University	Mazandaran	36	2.137E-02	0.0115	4930515	297	3500	2	160	528
18	Lorestan University	Lorestan	26	2.141E-02	0.0244	9354725	279	2621	0	127	307
19	Kurdistan University	Kurdistan	33	2.143E-02	0.0223	8858326	252	2551	1	125	335
20	Qazvin University	Qazvin	36	2.136E-02	0.0266	5027122	295	2800	0	119	356
21	Golestan University	Golestan	52	2.134E-02	0.0223	10404078	305	2497	3	113	311

Continuation of the Appendix

1	2	3	4	5	6	7	8	9	10	11	12
22	Shahrekord University	Chaharmahal and Bakhtiari	33	2.144E-02	0.0049	6070802	244	2385	0	108	0
23	Bushehr University	Bushehr	37	2.141E-02	0.0169	6265364	200	2160	0	104	191
24	Gonabad University	Razavi Khorasan	33	2.094E-02	0.0134	1254249	98	1581	1	103	228
25	Urmia University	West Azerbaijan	34	2.142E-02	0.0195	16412581	313	4379	1	87	436
26	Qom University	Qom	15	2.128E-02	0.0097	5208193	206	2294	0	82	202
27	Birjand University	South Khorasan	35	2.139E-02	0.0087	2894542	197	3030	0	82	278
28	Kashan University	Isfahan	33	2.143E-02	0.0222	3622085	212	1988	0	84	440
29	Dezful University	Khuzestan	12	2.051E-02	0.0085	4341754	72	1128	1	81	79
30	Semnan University	Semnan	31	2.085E-02	0.0205	3469613	244	2756	1	77	0
31	Zabol University	Sistan and Baluchestan	14	2.132E-02	0.0117	3618462	138	1769	1	72	0
32	North Khorasan University	North Khorasan	10	2.127E-02	0.0147	4093807	195	1805	0	68	126
33	Sabzevar University	Razavi Khorasan	24	2.131E-02	0.0224	2896231	120	1783	1	65	184
34	Arak University	Markazi	33	2.141E-02	0.0203	5978916	229	3471	0	67	0

End of the Appendix

1	2	3	4	5	6	7	8	9	10	11	12
35	Rafsanjan University	Kerman	34	2.133E-02	0.0049	2661864	182	1874	1	55	170
36	Abadan University	Khuzestan	78	2.021E-02	0.0205	3367896	81	587	0	54	68
37	Hormozgan University	Hormoz	33	2.137E-02	0.0187	9125439	267	2700	1	50	84
38	Zanjan University	Zanjan	32	2.145E-02	0.0223	6774793	357	4200	3	50	366
39	Ilam University	Ilam	24	2.140E-02	0.0237	3863715	174	3826	0	47	2
40	Shahroud University	Semnan	46	2.132E-02	0.0161	2203819	130	1370	0	34	197
41	Torbat Heydarieh University	Razavi Khorasan	6	2.048E-02	0.0191	1743450	63	737	0	32	125
42	Ardabil University	Ardabil	26	2.136E-02	0.0167	7499375	235	3371	1	30	240
43	Bam University	Kerman	9	1.990E-02	0.0114	2242070	66	834	0	28	49
44	Yasuj University	Kohgiluyeh and Boyer-Ahmad	34	2.136E-02	0.0078	5435319	174	1626	0	26	219
45	Fasa University	Fars	42	2.130E-02	0.0141	2541991	95	905	1	25	117
46	Jahrom University	Fars	25	2.124E-02	0.0023	2133320	113	1091	1	25	0
47	Jiroft University	Kerman	11	2.027E-02	0.0103	4620888	90	227	0	4	0