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Entrepreneurship policy and innovative indicators of industrial companies: Evaluation by MCDM and ANN Methods

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Abstract

The present paper presented a methodology for prioritizing the innovative and entrepreneurial indicators using Multi Criteria Decision Making (MCDM) and Artificial Neural Networks (ANNs), taking into account three individual, organizational and cultural dimensions simultaneously in decision making procedure. This methodology has two main advantages: first, the speed of operation in the accounting process and its simplification, and the other is the high precision with the elimination of errors in the calculations. Hence, a combination of findings was considered and identified in the Meta synthesis framework in the form of group categorization of indicators. Then, the entrepreneurship and innovation experts' opinion were gathered based on Meta-analysis. Next, the indicators were prioritized using Analytical Network Process (ANP) and the Decision-Making Trial and Assessment Laboratory (DEMATEL). The results obtained from Meta-analysis and multi criteria decision making methods were used as input and output data, respectively, to create an Artificial Neural Network model. Finally, the Artificial Neural Network model was designed in the form of Multi-layer Perceptron (MLP) Neural Network.

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1. Introduction

inter-organizational interaction in 700 samples, Backes-Gellner and Werner (2007) found that the entrepreneurial signaling through training is a success factor in innovative initiatives. Luke et al. (2010) studied innovative and entrepreneurship activities in the public sector. Their results showed that innovation, risk acceptance, prevention, and growth are factors usually related to entrepreneurship in the public sector and have a given impact on it.

Hunt (2011) examined immigrants in terms of the type of visa and their impact on innovation and entrepreneurship in the United States. The innovation was analyzed by Pérez-Luño et al. (2011) from two different perspectives of production or external acceptance in different companies. With the purpose of investigating the competency of the employees in innovative companies and entrepreneurs, Santandreu-Mascarell et al. (2013) examined the uniformity of competency criteria for the two groups. Gunawan et al. (2016) examined the role of extra and intra cluster ties, and entrepreneurial orientation in forming the companies' innovative performance. Bill and Fayard (2017) investigated the way of creating the entrepreneurial and innovative culture in an academic context. Sa'ari et al. (2018) found that enhancing innovative behavior is one of the results of obtained from entrepreneurship skills in Malaysian higher education.

Reviewing the literature shows that no aggregation of comments has been done yet utilizing the Meta-synthesis methodology; hence, the present paper is a field study of literature trying to collect assessment indicators in individual, organizational and cultural dimensions. The main goal and motivation of this study is to cover the gaps of the relationship

Since innovation is the creator and developer of new ideas and its consistency leads to the increasing success of the organization, entrepreneurship has increasingly become dependent on innovation in organizations in today's world. As the innovation creation process acts as a system, entrepreneurship depends on innovation, and innovation in turn, depends on knowledge and awareness; in other words, its input is knowledge and the correct understanding of the conditions and its process is able to achieve the proper result and output along with the scientific prioritization of the activities. Hence, knowledge and scientific prioritization are one of the important factors in the firms' innovation performance. In order to achieve entrepreneurship with innovative features, the present study firstly attempts to create knowledge base that is done through considering and identifying the main indices. Since the innovation creation and achieving proper performance is the basis for prioritization of activities and processes, the scientific prioritization of these indicators is included in the research procedure.

Entrepreneurship and innovation have been frequently used as two enabler dimensions in literature. Herbig et al. (1994) demonstrate the effects of organization's communicational structure on entrepreneurship and innovative success and identified the factors stimulating or moderating entrepreneurial activities.

Brown and Ulijn (2004) discussed the role of these relationships in shaping and changing the three elements of innovation, entrepreneurship and culture. Sarkar et al. (2006) discussed on the effect of innovative environment on the Exit of Entrepreneurial Firms. Examining the

affecting the organization strategic orientation in order to improve the innovation. Rezaei et al. (2013) attempted to measure entrepreneurship in companies emphasizing the entrepreneurial assessment criteria of the organization and utilizing the fuzzy analytic hierarchy process (FAHP). They used three main criteria if innovation, risk and proactiveness in their assessments.

Rostamzadeh et al. (2014) proposed a three-stage method combining three fuzzy AHP, VIKOR and TOPSIS decision-making methods to assess entrepreneurial strategies in small and medium enterprises.

Poledníková and Kashi (2014) assessed the regional innovation performance in the Czech Republic using the MCDM method.

Tseng et al. (2015) studied innovation improvement in service providing in the hotel industry. They proposed a combined method of fuzzy set theory, discrete multi-criteria method based on prospect theory and non-addictive Choquet integral in order to evaluate the service innovation. What distinguishes their research was to provide a hierarchical framework of useful and effective criteria for the industry.

Jafari-Moghadam et al. (2017) studied the entrepreneurship development policies in the tourism industry by combining DEMATEL and ANP methods. In addition, the role of small and medium enterprises has also been analyzed in their study.

Specific examination of entrepreneurship and innovation indicators to create international industrial companies is the contribution and distinction of this paper compared to the literature. In order to accomplish this purpose, two major new goals are pursued; 1) Identifying important and prioritized factors in the field of entrepreneurship and innovation according to the conditions of the region and the target society that motivate the entry of regional industries into international between entrepreneurship and innovation and achieving effective indicators for their assessment; most importantly, organizational facilities and resources are always limited and the ideal level of all these indicators cannot easily achieved simultaneously; so, these indices should enter the implementation process with an effective prioritization. The present paper seeks to fill these gaps. In this regard, a model was developed by: (1) Meta-synthesis method to create its knowledge base; (2) identifying the key elements of entrepreneurship and innovation to shaping it; (3) proposing a modern and new model of artificial neural networks for prioritizing entrepreneurial and innovative indicators in international companies.

The proposed model was then empirically tested in a survey of 10 experts in the field of entrepreneurship and innovation in universities and reputable companies in Iran. Our results have gained a better understanding of the role of indicators in developing entrepreneurship and innovation from a knowledge-based perspective and meta-synthesis approach and, the indicators were prioritized with the help of the new model. Identifying their related indicators is of particular importance along with the study of entrepreneurship and innovation. Also, the use of MCDM techniques to rank them is another important issue that has generally addressed to manage the organization's resources and time by prioritizing and differentiating the priority factors. The methods and approaches used in this regard are very diverse.

A fuzzy linear multi-objective model was developed by Kermani et al. (2010) for selecting entrepreneurs' suppliers based on their effective performance criteria. Lu et al. (2013) proposed a hybrid MCDM method by integrating the three methods of fuzzy DEMATEL, ANP and VIKOR to investigate the dimensions and criteria

qualitative research, and discover and create terms that show a more comprehensive representation of the phenomenon under study through examining the findings of other studies (Korhonen et al., 2013).
Accordingly, it was attempted to investigate the research literature based on meta-synthesis three steps. The assessments results showed the important indicators and criteria in the field of entrepreneurship and innovation, which were generally considered in lateral research, irrespective of the importance of the impact of these criteria on innovation and, consequently, on the creation of entrepreneurship, focusing only on their initial aspects. These criteria are categorized into three important dimensions of individual, organizational and cultural capabilities, and by completion of meta-synthesis steps, it was found that previous studies provided a valuable structure based on some of the capabilities.

Individual capabilities

Innovation is a prerequisite for the emergence of entrepreneurship and entrepreneurship is realized by human resources; meanwhile, individual capabilities are a fundamental category in human resources that value this resource in terms of efficiency. Many criteria have been introduced in literature to enhance this capability, some of which are common to most resources including:

Job motivation

Job motivation is an important issue in the field of individual capabilities that organizations always pay attention to, since it facilitates the achievement of the goal. The importance of the relationship between emotional intelligence and job motivation in staff is one of the topics discussed by Gorji et al. (2017) who found

markets leading to earn foreign currency and entrepreneurship. 2) Precise evaluation and prioritization of various factors for continuous improvement and creation of scientific monitoring and logical forecasts according to the world constantly changing technology using the powerful and modern tool of Artificial Neural Network (ANN) which has gained a special place in research science today because of accuracy in computing.
Accordingly, the main contribution of this paper can be stated in two general terms: 1) the application of the meta-synthesis methodology for the two categories of entrepreneurship and innovation to integrate the views raised in literature; 2) identify entrepreneurship and innovation indicators; 3) develop a new ANN model for indices prioritization.
The present study is structured as follows: Section 2 provides a literature review on the indicators and criteria affecting entrepreneurship and innovation. Section 3 is assigned to research methodology in detail. In Section 4, a hybrid multi-criteria decision-making algorithm is developed using DEMATEL and ANP methods for ranking indices and problem dimensions. In Section 5, the ANN model is designed and validated according to the results and findings of the research. Summarizing and future suggestions with the emphasis on the development of priority concepts in the innovation and entrepreneurship issues were provided in Section 6.

Meta-synthesis methodology and Assessment Criteria

The purpose of Meta-synthesis is to integrate multiple studies and create comprehensive and interpretive-adaptive findings (Walsh and Downe, 2005). Meta-synthesis requires that the researcher carry out a thorough and in-depth review, combine the findings of relevant

through enabling staff in case of availability, learning minimizes the possibility of error at any time.

1.1.2 Encouragement based on merit

Min et al. (2016) showed that the emergence of creativity and innovation is more possible if employees were given the opportunity to be aware of the performance of their organization and at the same time, have autonomy and then, be rewarded and encouraged according to their performance. Gong et al. (2017) proved that self-negative feedback is positively related to job performance and the transparency of its role in the job. In their book, Mone & London (2018) provide a practical guidance for managers to increase employee engagement.

So, it can be found that individual capabilities will not grow unless with job motivation (C1), and this will not occur unless considering the need for Learning and training capability (C2) according to time and space necessity, and these are realized in the light of the Competency-based encouragement system (C3) scientifically based on a researcher database (Jafari et al., 2013: Sha'ari et al., 2018).

1.2 Organizational capabilities

Organizational capabilities ensure the emergence and continuity of individual capabilities in supplying human resource requirements, and these requirements depends on the efficiency of organizational capabilities. The important criteria of these capabilities, presented in literature, are as follows:

1.2.1 Resource integration and reconfiguration capabilities

The integration and reconfiguring capability of resources is one of the most important indicators referred to in literature as the organization's growth the significance of this relationship and introduced it as an important factor in increasing job satisfaction. Huggins et al. (2016) evaluated this important issue that improving job incentives and sales performance can lead to significant positive changes in market share and profitability for most companies. The importance of Job motivation in the modern world is such that the impact of out of job categories such as home activities is examined on it. Nijp et al. (2015) demonstrated that work time control is a powerful tool for reducing the interference of activities at the workplace and home, and managing it will reduce fatigue and improve job motivation. It was also showed in Zahra et al. (2014) research that staff training will have a significant impact on employees' job motivation and commitment. Because many business organizations are very worried about training their employees throughout their professions to continue to be motivated and focused in today's competitive and rapidly changing world.

1.1.1 Learning and teaching

Many studies have discussed on staff learning and training, most of them focusing on learning feelings, learning styles, educational content, and technology, among which Navimipour & Zareie (2015) studied how to increase staff satisfaction through e-learning systems. They provided a model and framework for assessing the impact of e-learning on employee satisfaction, which improves learning and teaching results. However, employees' commitment is another indicator of learning and teaching achievements in developing the individual capabilities in an organization. Zareie & Navimipour (2016) investigated the impact of e-learning systems on employees' commitment and showed that in addition to having a positive impact in this regard,

(2017) showed that strategic agility is one of the key elements of the concepts raised in the business models. The role of information sharing has become increasingly important to achieve organizational agility, and all small and large companies need to be agile to achieve better performance and sustain this agility depends on information sharing (Salehzadeh et al., 2017).

1.2.3 Coordination capability (Inter-organizational coordination)

Inter-organizational co-operation and coordination is one of the most important organizational indicators that lead to inter-organizational desirable interactions (Wu, 2018). In the transportation sectors as one of the organizational units, integration and coordination between logistics service providers and shipping companies will have important consequences such as reducing harmful effects on the environment, improving the performance and coordination of the transportation system, speeding up service and reducing costs (Sallnäs, 2016). Resource co-operation is recognized as a coherent intra-organization framework as a management stabilizer factor (Kożuch & Sienkiewicz-Małyjurek, 2016). Therefore, according to the literature, it is necessary for the organization with enabling capabilities to have change management in order to correctly manage the resources so that its indicators include the Resource integration capability (C4), Resource reconfiguration capability (C5), Ability to respond to the rapidly changing environment (C6) which are changing rapidly, keep up-to-date the coordination capability (C7) with these changes (Tsai, 2002; Jansen et al., 2005; Huang and Jim Wu, 2010; Huang and L, 2017).

1.3 Cultural Capabilities

indicators, and it is referred to as the creator of phenomenological values in creating new applications (Vargo and Lusch, 2010). Sharma et al. (2014) also considers customers among the organization's resources and as a factor in better understanding of the organization's capabilities to respond to customers' requirements. Technology and its momentary growth have always been effective on the performance of the organization; hence, the study of organizational capabilities among technology-based companies is recognized in line with important corporate integration, and the coordination and integration of capabilities has a significant relationship with the long-term survival of companies (Löfsten, 2016). Today, considering the environmental issues is one aspect of innovation. Huang & Li (2017) have demonstrated the importance of coordinating and integration among the dynamic capabilities of an organization to reinforce the green innovation. The coordination and collaboration between individual and organizational capabilities is another new category studied for improving organizational performance that Karpen et al. (2017) investigated new interactive practices in this regard and designed an interactive model of three components of capability-practice-ability based on their findings.

1.2.2 Ability to respond to rapidly changing environment (Organizational agility)

Agility is one of the key characteristics in leading and entrepreneurial organizations, because agility is imperative in the rapidly changing world. Nowadays, the speed of reaction to the needs of the market and the environment of the organization implies the survival in the competitive cycle (Shuradze et al., 2018). In a logical argument in this regard, Battistella et al.

1.3.2 Likelihood to Share New Insights

Knowledge is a critical and fundamental feature to achieve business success in the organization. Hence, the presence of information technology has become more visible than before in the organization. Business Intelligence Systems (BIS) with the goal of gathering data and information from the organization's context, and then analyzing and transforming it into a new insight and sharing it at different levels of the organization are among these systems (Shollo and Galliers, 2016). Parte-Esteban & Alberca-Oliver (2015) know the success factors of companies as a function of new insights and awareness of this insight in the company's layers. Matthews et al. (2017) know that process improvement in the small and medium industries dependent on organizational learning.

Hence, cultural capabilities should be measured by criteria that will create a strong cultural context in the organization, and such context will increase the Likelihood to Share New Insights (C8) at the organizational levels and, consequently, among employees and as a result, interactions are formed in the organization which durability depends intensely on interdependent trust or Affect-based Trust (C9) and Cognition-based Trust (C10) (Chua and Morris, 2009; Zhang, 2018).

Three major personal, organizational and cultural dimensions were identified as essential categories in determining the criteria and indicators for entrepreneurship and innovation with the detailed studies and comparative literature review. A report in the form of a summary of triple steps was provided in Table 1, which is stated in their dimensions, criteria, and source. Also, some chained questions were also raised to achieve the main dimensions that are drawn briefly in Figure 1.

Culture is the common ground that enables the two sets of individual and organizational capabilities to exploit the maximum of their abilities. Therefore, cultural capabilities in an organization, with a meritocratic structure along with a strong culture, make it possible for an individual to implement his innovations in the context of organizational capabilities. Distinctive indicators in the field of cultural capabilities in the organization can be summarized in the following items:

1.3.1 Affect-based Trust and Cognition-Based Trust

It is management that defines the fields and orientation of innovation and the ideal interaction between management and employees depends on trust; however, trust has different types; it can be based on feelings (emotional) or based on the previous recognition. These two criteria direct the organizational behaviors (Newman et al., 2014). Entrepreneurship depends on knowledge and the sharing knowledge is related to the level of trust that exists in the organization. Hence, Yuan et al. (2016) assessed two types of trust indicators, namely the organizational features-based trust and interpersonal relationships-based trust. Similarly, Naeem et al. (2017) have examined the effect of cognition-based trust on the relationship between HRM practices and the behavior of colleges in sharing knowledge, and they found the significant role of mediating variables of emotional commitment and affect-based trust on this relationship. Studying affect-based and cognition-based trust was developed by Van Knippenberg's (2018). As mentioned above, there is a close relationship between the organization's leadership with the trust in the organization. The relationship between passive leadership, organizational justice and affect-based trust was investigated by Adeel et al. (2018).

in this constantly changing flow, improvement the ability to integrate resources from the economic dimensions' perspective, and achieving ability to resupply resources. Cultural capabilities will appear at the end of the chain in the next cycle, with the result that it creates the rationale for expectations for sharing new information and data, making the organization able to adapt to new insights, and finally implement a trust-based and cognition-based learning culture at various organizational levels. The relational structure between their dimensions and criteria was presented in Table 1, and each of them is introduced based on literature.

As can be seen from Figure 1, the level promotion cycle of innovation-based entrepreneurship depends on the creation and connection of a series of measures in the form of a chain. So that innovation should be improved to create entrepreneurship; also, motivation should be increased to create innovation. Educational goal should be determined to promote capabilities. The right resources supply can be done based on proper educational goals. Also, the resource ability to respond to the fast-changing environment is the most important loop in the organizational capabilities cycle that ensures the ability to coordinate resources

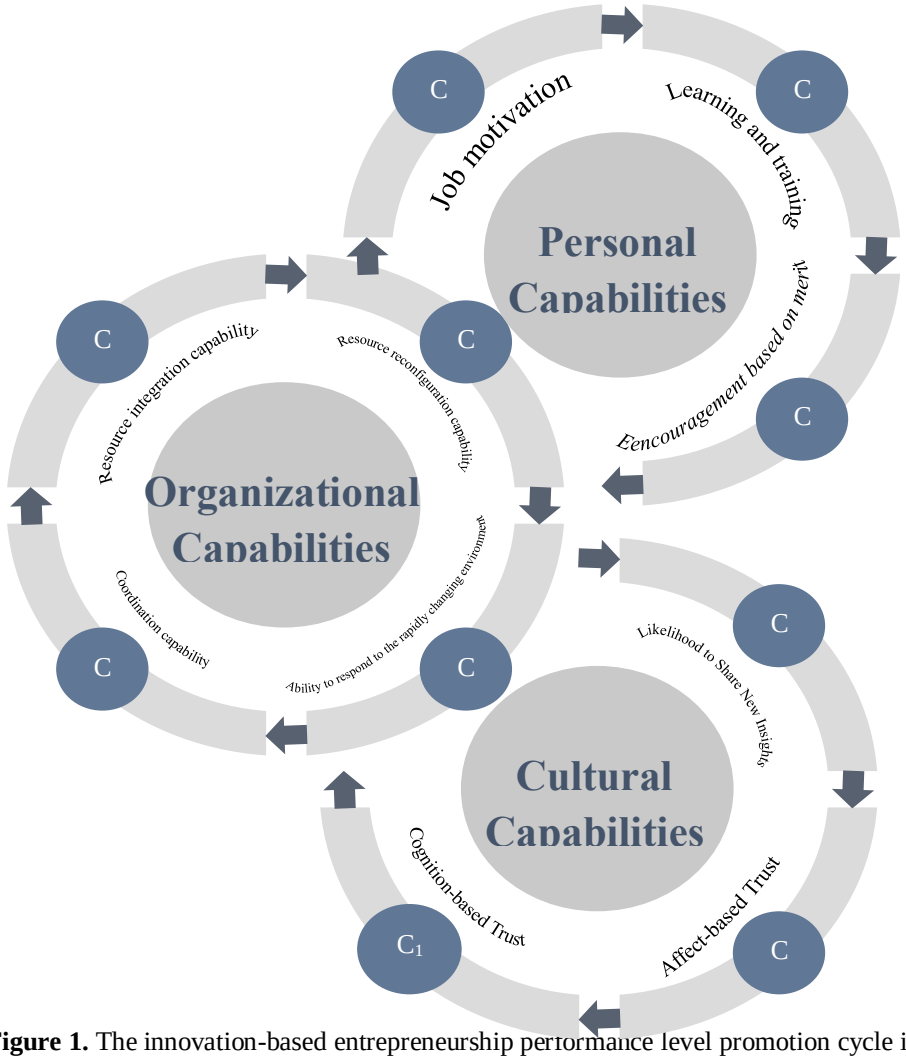

Figure 1. The innovation-based entrepreneurship performance level promotion cycle in terms of three dimensions of individual, organizational and cultural capabilities

entrepreneurship have enabled remarkable insights into the phenomenon, the added value has slowed down noticeably over the last decade (von Bloh et al., 2019). Hence, von Bloh et al.'s (2019) results showed mixed outcomes regarding the relationship between reporting of entrepreneurial events, i.e. media coverage, and entrepreneurial activity in German planning regions. Finally, their paper provided an entry point into Big Data usage in entrepreneurship research and they suggested a number of relevant research opportunities based on their results. The Human Capital, Innovation and Entrepreneurship in Micro and Small Businesses in Laos are assessed in Vixathep and Phonvisay's (2019) book. They are believed, that the small- and medium-sized enterprises (SME) constitute the core of the private sector, which has achieved rapid growth in the last three decades and noticeable contribution to job creation. This book attempts to address the relationship between entrepreneurial human capital, and successful entrepreneurship and innovation in Laos. The findings shed more light on the importance of human capital, and innovation and entrepreneurship promotion in economic development. It gives rise to the quality and appropriateness of education and training for entrepreneurs, if the target of the government policy is to foster successful innovation and entrepreneurship and to promote SME development as part of socio-economic development (Vixathep and Phonvisay, 2019).

However, the research is continuing in the world, hence, some new researches occurred in this scope, so, we discuss about that. Rexhepi et al. (2019) introduced a book, so that, inside the book, there are many analysis and research dealing with open innovation and entrepreneurship and give more proves of its importance in helping enterprises to develop faster. Paik et al. (2019) argued that political competition is a critical ingredient that explains whether cities accommodate or ban ridesharing platforms and that this relationship is moderated in more populous cities and in cities with higher unemployment rates. They study has important implications for nonmarket strategy, entrepreneurship and innovation, and public-private partnership literatures. A research presented with title of Entrepreneurship policy and the financing of young innovative companies in Italia by Giraudo et al. (2019), that it showed, young innovative companies need special attention by public policy. A historical perspective of innovation, intermediation, and the nature of entrepreneurship have been introduced by Toms et al. (2019). They considered two sources of innovation, technical and financial, and examine their separate and joint impacts, through the process of financial intermediation, on the nature of entrepreneurial opportunity. These impacts are time dependent and reflect the institutional context of entrepreneurship. They identified systematic underlying factors that can cause significant differences in the entrepreneurial opportunity set. Although conventional register and survey data on

Table 1. Assessment dimensions and criteria

Dimensions	Criteria	References
Personal Capabilities	Job motivation (C1)	Gorji et al. (2017), Huggins et al. (2016), Nijp et al. (2015), Zahra et al. (2014)
	Learning and teaching (C2)	Zareie & Navimipour (2016), Navimipour & Zareie (2015)

	Encouragement based on merit (C3)	Mone & London (2018), Gong et al. (2017), Min et al. (2016), Santandreu-Mascarell et al. (2013)
Organizational Capabilities	Resource integration capability (C4) Resource reconfiguration capability (C5)	Karpen et al. (2017), Huang & Li (2017), Löfsten (2016), Sharma et al (2014)
	Ability to respond to rapidly changing environment (Organizational agility) (C6)	Shuradze et al. (2018), Battistella et al. (2017), Salehzadeh et al. (2017)
	Coordination capability (Inter-organizational coordination) (C7)	Wu (2018), Kożuch & Sienkiewicz-Małyjurek (2016), Sallnäs (2016)
Cultural Capabilities	Likelihood to Share New Insights (C8)	Matthews et al. (2017), Shollo & Galliers (2016), Parte-Esteban & Alberca-Oliver (2015),
	Affect-based Trust (C9) Cognition-based Trust (C10)	Adeel et al. (2018), van Knippenberg, D. (2018), Naeem et al. (2017), Yuan et al. (2016), Newman et al. (2014),

2. Research method

Multiple assessment scales have been developed in this paper that is formed in a regular framework of the dimensions and criteria of each of them. This framework utilizes quantitative and qualitative assessment criteria simultaneously and includes 3 dimensions and 10 criteria, all of which are gathered and aggregated based on literature. The proposed framework allows experts in the field of entrepreneurship and innovation to identify priority options using Linguistic expressions and proposed prioritization, and efficiently and effectively ensure the reliability of programs to promote entrepreneurship and innovation and to address the progressive problems more than ever.

The research methodology is presented in terms of the research type, the implementation method, purpose, timeframe, the nature of the variables and the formation stages in the Figure 2 as follows:

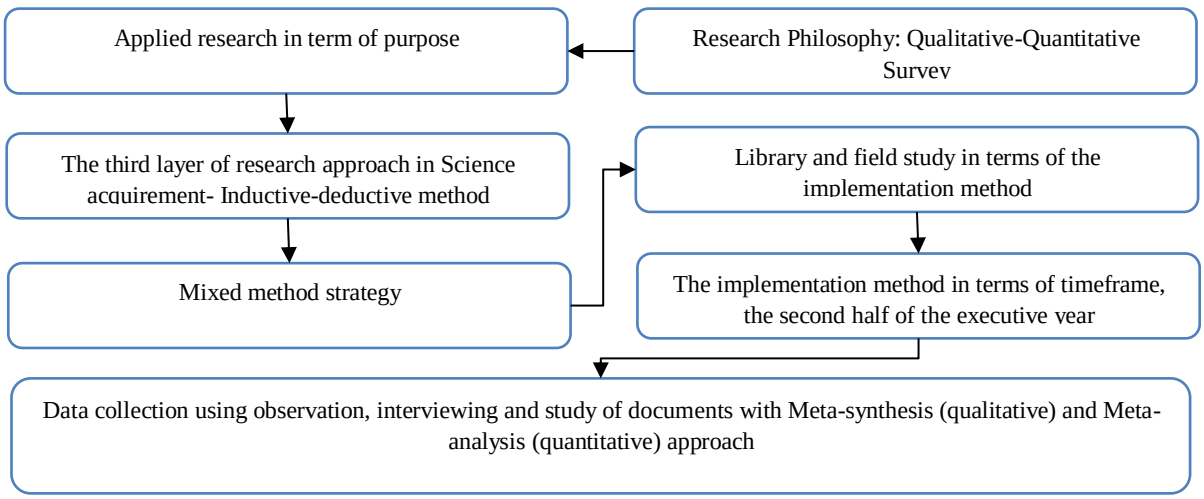

Figure 2. Research methodology during the various stages

The present study tries to develop an integrated approach to the ANP and DEMATEL combined method, and then, using ANN approach, develop the research literature in a new direction.

2.1 Determining the quantitative number

The criteria quantitative numbers (the data of the last three years, see Table 1) have different values that are not comparable. Thus, data was normalized to achieve valuable criteria that were without unit and comparable to all criteria. The normal value of the j[th] criterion related to the i[th] dimension is defined as W_{ij}^{k} by the k[th] assessor. Also, given that all criteria have the benefits role, the normal values are calculated by Equation 1, where $W_{ij}^{k} \in [0,1]$, $W_{ij}^{-} = Min\{W_{ij}^{1}, W_{ij}^{2}, ..., W_{ij}^{n}\}$ and $W_{ij}^{*} = Max\{W_{ij}^{1}, W_{ij}^{2}, ..., W_{ij}^{n}\}$ (Karsak, 2002; Tseng, 2011).

$$W_{ij} = \frac{W_{ij} - W_{j}^{-}}{W_{j}^{*} - W_{j}^{-}} \qquad (1)$$

2.2 DEMATEL Procedure

The DEMATEL procedure is efficient and useful in determining the complex structure of causal relationships between criteria and dimensions in the form of a matrix or graph (Gabus and Fontela, 1976; Tseng, 2011).

The matrices represent a context relationship between the elements of the decision-making system. Their content numbers represent the power of influence. The DEMATEL method can transform the relationship between the causes and effects of the criteria into an understandable structural model of the system (Tseng, 2011). Hence, this method can be successful in the analysis of the complex relationships and can be applied in different fields (Hori and Shimizu, 1999; Ravi Sankar and Prabhu, 2001; Seyed-Hosseini et al., 2006; Tseng, 1998; 2011). Before describing the steps of DEMATEL, I first consider a decision-making system including n criteria as the set $C = \{C_1, C_2, ..., C_n\}$, and specific paired relationships are determined between these two criteria for modeling based on a mathematical relationship. Based on these two steps, achieving answer is defined in the following steps:

1. In the first step, the initial data is obtained through a direct relation matrix, defined as an n × n matrix called A. a_{ij} arrays of this matrix indicates the effect of the i^{th} criterion on the j^{th} criterion.
2. Normalization of the direct relations matrix A in the form of the normalized matrix X by formulas (2) and (3) is performed at this stage.

$$X = k.A \qquad (2)$$

$$k = \frac{1}{\max\limits_{1 \le i \le n} \sum_{j=1}^{n} a_{ij}} \qquad (3)$$

3. In the third step, the total relations matrix T is determined by formula (4), in which "I" is an identity matrix.

$$T = X(I - X)^{-1} \quad (4)$$

4. Generating a cause and effect chart occurs at this stage. In this regard, the sum of rows and columns are calculated separately in equations (5) - (7), respectively, in the vectors D and R.

$$T = [t_{ij}]_{n\times n} \quad (5)$$

$$D = [\sum_{j=1}^{n} t_{ij}]_{n\times 1} = [t_i]_{n\times 1} \quad (6)$$

$$R = [\sum_{i=1}^{n} t_{ij}]_{1\times n} = [t_j]_{n\times 1} \quad (7)$$

So, the above equations of vector D and vector R estimate the sum of the rows and columns respectively, in the total relations matrix $T = [t_{ij}]_{n\times n}$.

5. The internal dependence matrix is obtained at the last stage. To do this, the sum of each column is equal to one in the total relations matrix by the Normalization method, and now we can obtain the internal dependency matrix. Also, based on the sum symmetry, the D + R column was standardized with the $\frac{(D+R)_i}{\sum_{i=1}^{n}(D+R)_i}$ standard and presented as the weight of each indicator.

The proposed framework is a hierarchical structure between dimensions and criteria and the interdependence between levels forced us to use the ANP[2] method. Therefore, the way of implementing this method is presented in the next section.

2.3 ANP Procedure

The ANP method, as a multi-criteria decision-making technique, improves the analytical hierarchy process by replacing the "network" rather than the "hierarchy". In fact, the ANP is a mathematical theory that systematically applied on dependency and feedback between levels simultaneously in a successful manner in a variety of contexts. Therefore, the Analytical Network Process or the same ANP can be called the most complete multi-criteria decision-making method (Niemira & Saaty., 2004).

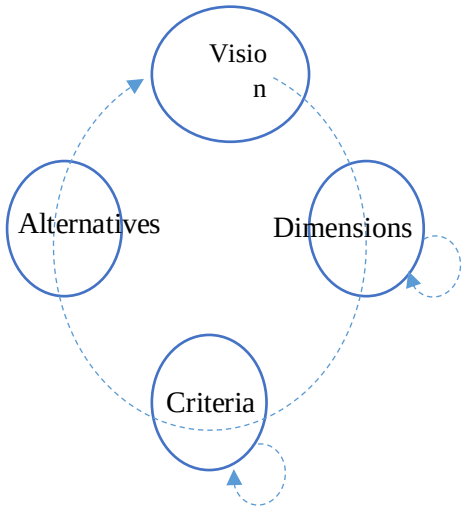

Figure 3. The closed-loop structure of the hierarchical framework of interrelationships between dimensions and metrics

[2] Analytic network process

The ANP provides a deeper approach for decision making, without assumptions on the independence of the higher level from lower level elements or from the similar level elements, assuming the dependence between the analysis levels. Hence, many researchers used this method and confirmed its effectiveness (Hallikainen et al., 2009; Chen and Chen, 2010; Shih et al., 2013).

The two-way arrow between the different levels shows the dependence of the criteria in the ANP model. Interdependencies at each level are shown with a "circular arc". Figure 1 depicts the hierarchical structure by observing how the proposed framework is interconnected. If there is "n" criteria entitled $(C_1, C_2, ..., C_n)$ and with a Pairwise comparison matrix A, so that A=(a_{ij}), where a_{ij} is the relative importance of the criterion C_i on the criterion C_j, the ANP method steps are as follows.

1. The Wi weight related to criterion C_i is calculated by Eq. (8) in this step, which is the same normalized average row vector (Saaty, 1996);

$$W_i = \frac{\sum_{j=1}^{n} \left(a_{ij} / \sum_{i=1}^{n} a_{ij} \right)}{n}, \quad \forall i, j \in \{1, ..., n\} \qquad (8)$$

2. In the second step, the ANP compliance test is designed to ensure decision-makers' judgment during the decision-making process. When there are contradictions in the partial comparison matrix A, it can be proved that for a Consistent reciprocal matrix, the λ_{max} value is equal to the number of comparisons, or $\lambda_{max} = n$ (Saaty, 2222). Hence, the Consistency Index (CI), as the degree of deviation or compatibility, is defined using formula (9):

$$CI = \frac{\lambda_{max} - n}{n - 1} \qquad (9)$$

3. Consistency Ratio (CR) is defined as CR for the average Random Consistency Ratio, and its value must be less than 0.1 and calculated by the ratio of equation (10). The CR ratio should be less than 0.1; this indicates that the consistency level of the pair comparison matrix is acceptable. CR larger than 0.1 indicates that the results of the decision-making process is not consistent and proposed repetition of the process by the decision maker.

$$CR = \frac{CI}{RI} \qquad (10)$$

4. Determining the weighted super-matrix is performed at this stage to determine the criteria weights. The ANP uses a super matrix to consider feedback and interdependence between criteria, by which, if there are no interrelations between the criteria, the paired comparison value is zero. Otherwise, if there is an interrelation and feedback among the criteria, then the pair

comparison value will not be zero and the super matrix M will be obtained without weight. If the matrix is not consistent with the original random column, the decision maker can enter the weights in a super-matrix to adjust it to the original random pillar and convert it into a weighted super-matrix M.

In fact, the super-matrix columns are composed of several Eigen vectors, each of which is equal to one. Therefore, it is possible that the sum of each column of primary super-matrix is more than one (corresponding to the Eigen vector exist in each column). Each column of the matrix is standardized to fit the column elements proportional to their relative weight, and the column summation becomes equal. As a result, a new matrix is obtained that the sum of each of its columns is equal to one. This is similar to the Markov chain in which the probable sum of all positions equals one. The new matrix is called the weighted matrix.

The weighted super-matrix is powered by the limit to converge matrix elements and its row values become equal. According to the obtained matrix, the general weight vector is determined which is the matrix that is obtained as the result of powering the weight matrix, a limit matrix which the sum of each row is equal to other rows. If the super-matrix has a chain effect, there may be two or more super-matrices that are converges as the weight super-matrix, that the way of powering super matrix is displayed in Equation (11), which ultimately, the dependence weight of criteria can be calculated after this step:

2.4 Hybrid method of ANP-DEMATEL

The following research method is proposed to combine the proposed methods of DEMATEL and ANP:

1. Collecting appropriate information according to the research direction to assess the benefits and disadvantages and monitor the results to ensure the accuracy of achieving the goal. This action has an important place in the formation of a specialized committee for the acquisition of collective knowledge; this is because the formation of a specialized group is necessary to achieve goals.
2. Developing the assessment criteria and audit tools is critical for creating a set of criteria and attributes for assessment. Although it should be noted that the criteria, have complex relationships in the form of a cluster of criteria in essence. So, in order to achieve a better practical application of the two ANP and DEMATEL methods, a structural model should be designed that divides the assessment criteria into cause and effect groups (Wu and Lee, 2007; Tseng, 2009; Tseng, 2011). In order to ensure the consideration of relationships among the assessment criteria, it is necessary that the expert group confirm the reliability of the information obtained from the criteria effects and directions.
3. In order to achieve the criteria value that provides the ability to compare between all the criteria, the quantitative data value must be normalized, which is calculated by equation (1).
4. The decision-making objectives are examined by the proposed method

$$M^{*} = \lim_{i \to \infty} M^{i} \qquad (11)$$

and the internal dependency matrix is obtained by the DEMATEL method and equations (2) to (7).

5. Utilizing the equations (8) to (10), the internal dependency matrix and the unweighted supermatrix are created by the combination of a super matrix (Tsang, 2011). The final result is achieved using equation (11) for convergence of results and achievement of overall priority weights.
6. Achieving higher accuracy and speed in calculations with estimation and prediction by ANN model. In this phase, the weights and priorities are estimated with the help of ANN applying quantitative data as inputs and prioritizing results of the ANP-DEMATEL combined method as an output in artificial neural networks and during the process.

2.5 ANN

There are usually complexities in the process of solving various problems. Researchers have been trying to overcome various problems by creating new ways to address this complexity in the real world. One of these methods is the artificial neural network (ANN), which is more useful than most models, because of its speed and precision (Leśniak and Juszczyk, 2018).

Hence, because of the complex process of solving different problems, researchers are trying to overcome these complexities by developing new approaches. As one of these methods, ANN outperforms most of the models in terms of speed and accuracy (Leśniak and Juszczyk, 2018). On the one hand, the complexity and time-consuming process of achieving weights and priorities in multi-criteria decision-making techniques are among the problems that implicitly increase the error probability in the computations (Emamgholizadeh et al., 2015; Jafari-Moghadam et al., 2017). Therefore, the ANN method is used in this paper for modeling the criteria prioritization and prediction process using the past experiences in different fields.

The prediction of the amount of sesame seed production was one of the research applications of ANN in which ANN models and multiple regression model (MLRs) were utilized that the ANN outperform MLR and realized the goals at the desired level (Emamgholizadeh et al., 2015). By analyzing networks with different structures in this study, it is found that the ANN model is the most suitable model (Heidari et al., 2016). Operational parameters of the counter-rotating wind turbine were estimated in the clean energy generation sector by the ANN for rotary counter-rotating wind turbines, and the process of optimizing the dual-rotor turbine parameters (Romański et al., 2017). ANN models were also used in Road construction industry to optimize the process of mixing asphalt (Sebaaly et al, 2018). ANN was frequently used in literature; however, there is clearly a gap of considering MCDM problems. Therefore, it is tried to use ANN in the ANP-DEMATEL hybrid method in the present paper.

3. Computational results for the hybrid method

This section aimed to describe the methodology of evaluating and prioritizing entrepreneurial and innovative criteria in smart international companies. As mentioned, the main reason for this measure is to create a template for classifying and arranging payments to effective measures in the continuous direction of development and improvement, so that companies smartly choose according to their resources. The expert team used for analyses in this section consists of three university professors, a high-level executive of the government in the executive branch, and

six specialists with experience in consulting and implementing entrepreneurship and innovation development projects.

3.1 Case study

The analyses were conducted in this research at the lowest level of its hierarchy on the three international companies Keison, Sabir International and Mapna as alternatives. The international companies of Mapna, Keison and Sabir International will be hereafter displayed with the abbreviations A1, A2 and A3, respectively. According to three available alternatives, the team of experts has sought to identify innovative dimensions of entrepreneurship that is expected to be effective in the development and improvement of performance and even the formation of smart international companies; because international companies are consistently evaluated as one of the key problems for management (Tseng, 2011).

So, the expert group conducted their assessments based on the common view at the senior management level, however ultimately founded the basis of the willingness to conduct an assessment based on a logical and convincing policy. Finally, the management team of ten experts has also used executives' opinion to find useful and applicable recommendations.

3.2 Multi-criteria decision-making procedure

It is tried in this section to use the hybrid approach of DEMATEL and ANP to assess the three dimensions and ten criteria in the field of entrepreneurship and innovation. Identifying the capabilities and abilities of the DEMATEL and ANP hybrid method to determine the degree of significance of the research dimensions and criteria is one of the objectives of this research. The process of implementing this hybrid approach has been accomplished through an interactive relationship with the expert group in five phases. Focusing on the direction of the research was always considered in the process of gathering information. Hence, a specialized committee was formed to create group knowledge and help us to achieve the goals of the study.

The expert group designed a checklist of dimensions and criteria based on the three dimensions and ten criteria described in Table 1, by which the target community of academics and academics was questioned. It is tried to select experts with at least 5 years of experience in the field of entrepreneurship and innovation. Respondents were requested to complete their checklist by their mental judgments on the importance of each criterion based on the assessment criteria and hierarchical structure of the company (as in Figure 3). Given the quantitative and qualitative data collected, which are different in terms of the measurement unit type, we normalized the data for their comparability to allow comparison between all the criteria. The normalized value of the data was calculated by equation (1). The proposed method considered the study decision making objectives for the purpose of analysis. The unweighted super-matrix is formed by normalized data. The inner dependence matrix is obtained after applying the different steps of the DEMATEL method using Equations (2) to (7) and is presented in Table 2 below.

Table 2. Dependency matrix of DEMATEL results

	C1	***C2***	***C3***	***C4***	***C5***	***C6***	***C7***	***C8***	***C9***	***C10***
C1	0	0.033	0.03	0.017	0.018	0.031	0.035	0.037	0.038	0.042
C2	0.032	0	0.02	0.027	0.028	0.034	0.031	0.036	0.038	0.042

C3	0.03	0.024	0	0.004	0.01	0.011	0.012	0.018	0.024	0.014
C4	0.008	0.003	0	0	0.013	0.003	0.003	0.002	0.010	0.01
C5	0.003	0.004	0	0.015	0	0.017	0.026	0.015	0.021	0.021
C6	0.028	0.009	0.02	0.004	0.004	0	0.03	0.028	0.025	0.024
C7	0.029	0.009	0.01	0.024	0.019	0.021	0	0.022	0.037	0.033
C8	0.009	0.008	0	0.002	0.008	0.002	0.002	0	0.018	0.015
C9	0.007	0.006	0	0.002	0.002	0.015	0.004	0.004	0	0.027
C10	0.009	0.008	0.01	0.002	0.002	0.002	0.007	0.007	0.024	0

Furthermore, based on the superiority and relational axis in Table 3, the causal diagram is shown in terms of criteria in Figure 4. By observing Figure 4, which shows the data pair graph (D + R, DR), it can be clearly seen that the cause group consists of criteria C1, C2, C3, C5, C6 and C7, while the effect group is consisted of C4, C8, C9, and C10 criteria. Another important note is the weight of each criterion calculated by $\frac{(D+R)_i}{\sum_{i=1}^{n}(D+R)_i}$ and reported in Table 3. Hence, the vector $W_1=(C_1,C_2,C_3,C_4,C_5,C_6,C_7,C_8,C_9,C_{10})$ represents the weight of each of the indicators relative to the purpose of the research, which the weights values can be represented as rounded $W_1=(0.15,0.13,0.09,0.05,0.08,0.11,0.12,0.08,0.1,0.1)$.

Table 3. Summary of the DEMATEL results based on the superiority and relational axes of the cause and effect group of criteria

Criteria	D	R	D-R	D+R	Wight	Rounded Wight
C1	0.282	0.155	0.126	0.437	0.1471612	0.15
C2	0.291	0.104	0.186	0.395	0.1328637	0.13
C3	0.148	0.109	0.038	0.257	0.0865332	0.09
C4	0.055	0.096	-0.04	0.151	0.0509806	0.05
C5	0.125	0.104	0.021	0.229	0.0772014	0.08
C6	0.178	0.136	0.041	0.314	0.1057522	0.11
C7	0.204	0.15	0.054	0.353	0.1189640	0.12
C8	0.066	0.169	-0.1	0.234	0.0788435	0.08
C9	0.069	0.234	-0.17	0.303	0.1019640	0.10
C10	0.069	0.227	-0.16	0.296	0.0997361	0.10

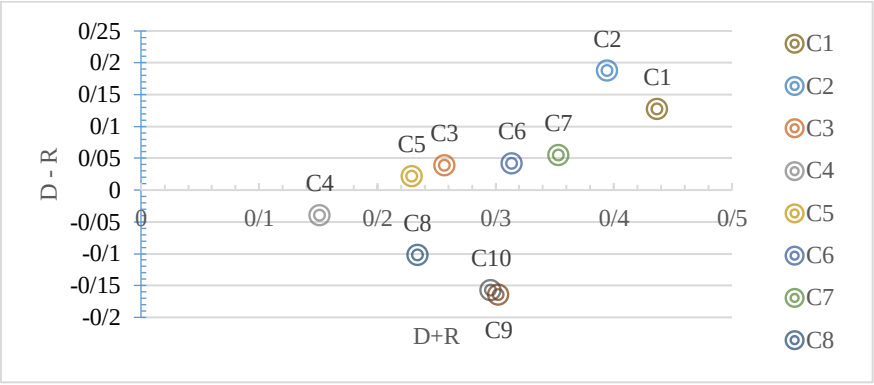

Figure 4. The causal diagram of the DEMATEL results

The paired comparisons, internal dependency and unweighted super-matrix matrices were provided in the form of a multiple super-matrix using the equations (8) to (10) in Table 4. Finally, the final result is the same normalized weighted super-matrix or limited super-matrix, which is estimated by Eq. (11) and is

presented in Table 5 for the calculation of global prioritization weights. The final results calculated the weights of each level of the hierarchy, namely, the research purpose, dimensions, criteria and alternatives (companies), respectively including:

$W_{\text{Goal}} = (\text{G}) = (0.324)$,

$W_{\text{criteria}} = (\text{D}_1, \text{D}_2, \text{D}_3) = (0.238095, 0428571, 0333333)$,

$W_{\text{criteria}} = (\text{C}_1, \text{C}_2, \text{C}_3, \text{C}_4, \text{C}_5, \text{C}_6, \text{C}_7, \text{C}_8, \text{C}_9, \text{C}_{10}) = (0.15, 0.13, 0.09, 0.05, 0.08, 0.11, 0.12, 0.08, 0.1, 0.1)$,

$W_{\text{criteria}} = (\text{A}_1, \text{A}_2, \text{A}_3) = (0.385144, 0315453, 0297782)$.

Table 4. The unweighted super-matrix

	G	*D1*	*D2*	*D3*	*C1*	*C2*	*C3*	*C4*	*C5*	*C6*	*C7*	*C8*	*C9*	*C10*	*A1*	*A2*	*A3*
G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
D1	0.24	0.08	0.07	0.11	0	0	0	0	0	0	0	0	0	0	0	0	0
D2	0.43	0.33	0.23	0.31	0	0	0	0	0	0	0	0	0	0	0	0	0
D3	0.33	0.59	0.70	0.58	0	0	0	0	0	0	0	0	0	0	0	0	0
C1	0	0.10	0.10	0.10	0.30	0.31	0.30	0.27	0.28	0.32	0.30	0.32	0.33	0.33	0	0	0
C2	0	0.09	0.10	0.10	0.20	0.20	0.20	0.20	0.21	0.18	0.21	0.20	0.18	0.21	0	0	0
C3	0	0.10	0.09	0.08	0.13	0.12	0.14	0.14	0.12	0.13	0.12	0.12	0.13	0.12	0	0	0
C4	0	0.10	0.09	0.12	0.12	0.11	0.10	0.12	0.12	0.09	0.12	0.11	0.10	0.09	0	0	0
C5	0	0.10	0.08	0.08	0.07	0.07	0.06	0.07	0.09	0.09	0.06	0.06	0.05	0.06	0	0	0
C6	0	0.10	0.11	0.09	0.05	0.06	0.07	0.06	0.06	0.06	0.06	0.06	0.07	0.07	0	0	0
C7	0	0.09	0.10	0.10	0.04	0.06	0.05	0.05	0.05	0.04	0.04	0.04	0.06	0.04	0	0	0
C8	0	0.10	0.10	0.12	0.04	0.04	0.04	0.04	0.03	0.04	0.04	0.04	0.04	0.04	0	0	0
C9	0	0.09	0.11	0.11	0.03	0.02	0.03	0.03	0.02	0.02	0.03	0.03	0.03	0.02	0	0	0
C10	0	0.09	0.10	0.12	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0	0	0
A1	0	0	0	0	0.38	0.37	0.39	0.36	0.40	0.38	0.40	0.41	0.42	0.35	0	0	0
A2	0	0	0	0	0.32	0.33	0.30	0.35	0.30	0.32	0.31	0.28	0.32	0.34	0	0	0
A3	0	0	0	0	0.29	0.30	0.32	0.30	0.30	0.29	0.29	0.32	0.26	0.31	0	0	0

Table 5. The limited weighted super-matrix

	G	*D1*	*D2*	*D3*	*C1*	*C2*	*C3*	*C4*	*C5*	*C6*	*C7*	*C8*	*C9*	*C10*	*A1*	*A2*	*A3*
D1	0.00	0.04	0.04	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.00	0.00	0.00
D2	0.02	0.37	0.37	0.37	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.02	0.02	0.02
D3	0.23	0.85	0.85	0.85	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.23	0.23	0.23
C1	0.36	1.03	1.03	1.03	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
C2	0.12	0.34	0.34	0.34	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
C3	0.04	0.10	0.10	0.10	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
C4	0.04	0.09	0.09	0.09	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
C5	0.01	0.03	0.03	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C6	0.01	0.02	0.02	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C7	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C8	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C9	0.00	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
A1	0.45	1.51	1.51	1.51	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
A2	0.26	0.87	0.87	0.87	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
A3	0.21	0.72	0.72	0.72	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03

Then, the most important criteria were C1 and C2 respectively, with C1 being the highest-rated job incentive with a weight of 0.3578, followed by C2, or training and learning within the individual skill level weighing 0.1240 in the next rank. Also, the most important alternative, which can be determine as a target and template, is assigned to A1 or MAPNA Holding, which has the highest priority position with a weight of 0.4498 in top priority, followed by A2 and A3 respectively with weights of 0.2579 And 0.2132 in the second and third places.

4. 3 Managerial implications

It can be seen, according to the causal diagram in Figure 4, that the highest amount (D + R) is related to C2 and C1

criteria, that are respectively learning and training capability and job motivation as the subcategories of individual abilities. The next criteria at a lower level are C7 and C6, both of which are related to organizational capabilities. Therefore, it can be clearly understood that firstly, these are the individual abilities that provide the starting point for an action set for creating innovation and entrepreneurship, and consequently, the organization provide the appropriate space and facilities to make these two important items realized.

Although some criteria like C9 and C10 have high values of (D + R), but their (D-R) values are close to zero or negative. Such conditions mean that these criteria have a great impact on the innovation and entrepreneurship of companies; however, they are also influenced by other criteria. Hence, they are specific receivers and should be placed at a lower level in management prioritization.

The experts group ranked individual abilities and capabilities at first place stating that individual capabilities with motivation create the field for better and faster learning and, it is organizational capability that provides the context for individual capabilities to be activated given the time and place necessity. Meanwhile, the ability to respond to the rapidly changing environment and personnel coordination capability will have a constructive and fundamental role in fulfilling the vision of entrepreneurship and innovation of international companies given the constantly changing world. Finally, it should be noted that although numerous valid studies have been conducted on developing an entrepreneurial and innovation model and it successful implementation, however there are few studied that have provided a coherent framework for systematic assessment of these two. The wide scope and considering the complex interactions of goals, dimensions, criteria and alternatives at different levels is another highlighted feature that is rarely seen.

Broadly speaking, the framework proposed in this study can be used as an analytical and monitoring tool for developing and establishing an international assessment model for international companies at the organizational macro level. The results obtained from this framework can help senior managers to identify and understand the effective dimensions and criteria in the field of entrepreneurship and innovation to adequately meet cognitive expectations. In other words, managers will be able to have a fairly comprehensive picture in their minds from the interactions and effects of innovation and entrepreneurship elements by these outputs, and use them in the decision-making process. Another important point is to consider the application of this framework and the assessment approach to the relative performance assessment of the companies' executive, developmental, credit, and operational components.

5. ANN Model for innovation and Entrepreneurship indices evaluation

A Method of information processing system is used to forecast and determine the weight and rank of agents and indices of innovation and entrepreneurship. This system consists of significant number of super-integrated processing elements which are known as neuron. These neurons coordinately work together to solve a problem. They are transferred by synopsis (Electromagnetic communication). In the literature and neural biology, this system is called artificial neural network (ANN). The main idea of ANN is inspired by the structure of human brain activity (Haykin, 1999). Nowadays, several methods have been developed to efficiently solve different problems. ANN is one of these

methods. The feature that distinguishes this method from the other methods is its definability in a mathematical system. In this system neuron is referred to processing unit. Moreover, network architecture is created by organization of neurons. Different types of architecture are designed in the literature; the most popular of them are the multi-layer perceptron (MLP) networks which are feed-forward neural networks. On the other hand, these networks have input, hidden, and output layers in their topologies. Layers provide a platform for establishment of neurons and activation function. Each neuron is connected to the neurons of next layer; this connection has a specific weight (Hayati et al., 2014; Khoshroo et al., 2018).

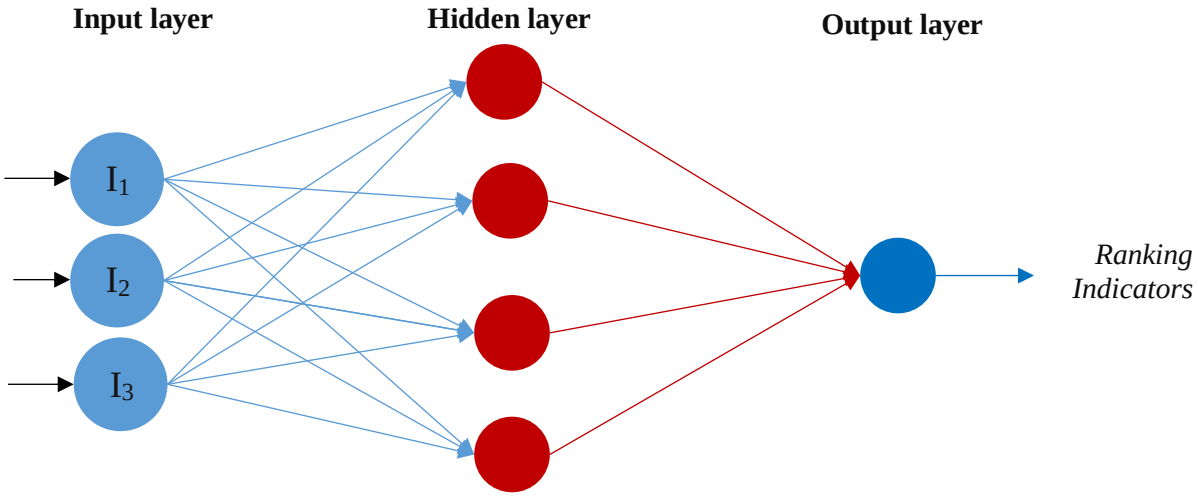

Figure 5. The proposed MLP model architecture

The various layers of the MLP have different weights which must be corrected. To perform this correction, the network is trained by an error back-propagation algorithm (BPA). The main network complexities are the number of layers and neurons of each layer. Hence, accurate selection of these two parameters has a great impact on obtaining the best solution in the shortest possible time. Therefore, a suitable topology should be designed. Here, according to the literature on ANN, the sensitivity analysis of neural network is conducted based on different numbers of hidden layers, the number of neurons, activation functions, and etc. Sensitivity analysis is done in order to determine the best topology for designing the model of innovation and entrepreneurship indices evaluation. The output of this sensitivity analysis is the proposed MLP model structure which has three inputs, four hidden layer and one output, as it is shown in figure 5. Inputs include paired comparison table of criteria and criteria (I_1), paired comparison table of options and criteria (I_2), paired comparison table of dimensions and criteria (I_3). The criteria are provided by passing the inputs from the output hidden layers; this procedure is also called ranking.

Input data is collected of problem parameters (i.e. I_1, I_3 and I_2) and the outcomes of the DEMATEL-ANP method selected as output data for training for the ANN model. The Levenberg–Marquardt (LM) algorithm used for the training rule of network. These data were divided into two sets: training set (80 % of data) and

test set (20% of data). The ANN model has been trained by the MATLAB R2013a 8.1.0.604 software. The Figure 6 shows The implementing phases of the ANN model with back-propagation algorithm. The planned ANN model specifications have been presented in Table 6.

Table 6. The planned ANN model features

Neural network	Part	MLP
No. neurons	input layer	3
No. neurons	hidden layer	4
No. neurons	output layer	1
No. neurons		1000
Activation function		Tansig

We use tangent sigmoid transfer function Tansig function as activation function in MLP models. This function has been used by Hayati et al. (2014), Sarve et al. (2015), Stamopoulos et al. (2018) and other researchers. The Tansig formulation defines by equation (12) as follow:

$$Tansig(x) = \frac{2}{1+\exp-2(x)} - 1 \quad (12)$$

The got outcomes for the proposed ANN model for Problem shows in the Table 7. So that, the equations (13), (14) and (15) are used to calculating the mean relative error percentage (MRE %), the mean absolute error percentage (MAE %) and the root means square error (RMSE) of the network, respectively. The symbols and indexes are used in these equations, define as follow:

N: the number of data

x(exp): stand for real ANN values

x(pred): stand for predicted ANN values.

$$MRE\% = 100 \times \frac{1}{N} \sum_{i=1}^{N} \left| \frac{x_i(\exp) - x_i(pred)}{x_i(\exp)} \right| \quad (13)$$

$$MAE\% = 100 \times \frac{1}{N} \sum_{i=1}^{N} \left| x_i(\exp) - x_i(pred) \right| \quad (14)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (x_i(\exp) - x_i(pred))^2}{N}} \quad (15)$$

Table 7. The training and testing errors results of the proposed ANN model

Error	Train	Test
MRE%	1.5471	2.2348
RMSE	0.0028	0.0039
MAE%	0.1989	0.2467

Several numbers of neurons have been applied for the proposed ANN architectures, which best structure is choose. The applied networks outcomes with the different neurons number in the hidden layer are illustrated in Figure 6. This figure shows the MAE errors of the networks versus different number of

neurons in the hidden layer. Each point in this figure represent the network with best MAE results during 100 times. These MAE errors are reported according to the normalized data.

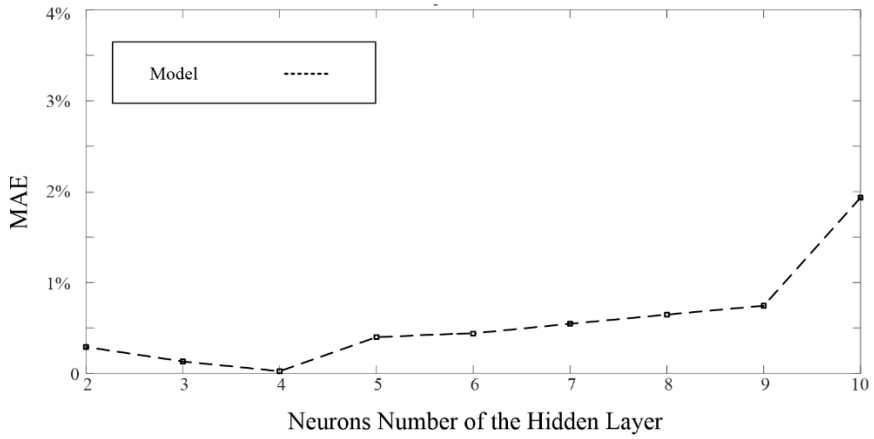

Figure 6. MAE errors of the networks versus different number of neurons in the hidden layer

According to Figure 6, the number of 4 neurons, which have the best MAE error value. In the proposed networks, 80 % of data is used for training, while 20 % of the data set is used for testing process of the presented model. So, we suggested ANN model, then train and test. The Output (Ranking Indicators) actual and predicted values comparison, using the proposed MLP model is illustrated in Figures 8 and 9. The Output actual and predicted data for training and testing process are listed in Tables 8 and 9, respectively.

Table 8. Model results for train data.

	Input			Output	
	I_1	I_2	I_3	Actual	Predicted
C1	1.034776	0.065412	0.067872	0.147	0.137
C2	0.341537	0.026967	0.026515	0.133	0.143
C3	0.103395	0.010253	0.009481	0.087	0.090
C5	0.025393	0.003932	0.003546	0.077	0.071
C6	0.022001	0.004316	0.004058	0.106	0.112
C7	0.014489	0.00324	0.003213	0.119	0.110
C8	0.011734	0.00317	0.003402	0.079	0.088
C10	0.003256	0.001544	0.001828	0.100	0.090

Table 9. Model results for test data.

	Input			Output	
	I_1	I_2	I_3	Actual	Predicted
C4	0.086879	0.010212	0.010171	0.051	0.048
C9	0.006236	0.0023	0.002374	0.102	0.112

As can be seen from Figures 8 and 9 and Tables 8 and 9, the test and train data are predicted precisely and the predicted values of the rank output for the Entrepreneurship and Innovation Indicators by ANN model is the instances

of near to the DEMATEL-ANP actual results, undoubtedly. The outcomes endorse the accuracy and applicability of estimation of ANN as a hybrid MADM model to predict the proposed MLPs output Indicators ranking from I_1, I_2 and I_3.

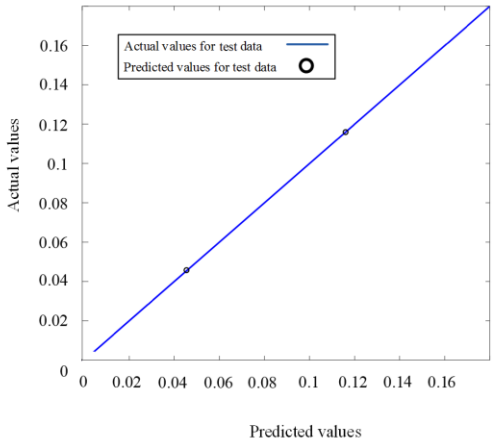

Figure 8. Actual and predicted values comparison of test using the proposed MLP model

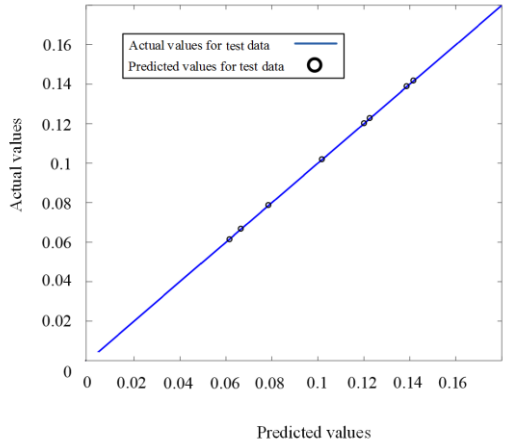

Figure 9. Actual and predicted values comparison of train data, using the proposed MLP model

6. Conclusions

In this paper the research gap between two fields of innovation and entrepreneurship is identified by literature evaluation. Moreover, a new model is proposed for evaluation and analysis of innovation and entrepreneurship indices of international companies. The evaluation is simultaneously focused on three major dimensions of individual, cultural and organizational characteristics. The proposed model could identify the relationship between dimensions, criteria and options in the field of innovation and entrepreneurship indices by using Meta-synthesis method. Then, the prioritization of criteria and indices are obtained by using Meta-analysis and DEMATEL-ANP combined method. Then, ANN method is developed for the proposed model in order to accelerate and facilitate the ranking procedure. To achieve this purpose, the obtained data of DEMATEL-ANP combined method are converted to the model by using Multilayer perceptron (MLP) neural network; the result of model implementation verified the output accuracy. Hence, in this paper a

feedforward method is proposed to estimate the ranking of innovation and entrepreneurship criteria. Results of this method are compared by forecasted data with 20-80 ratios; the comparison proved the model validation. Therefore, the proposed ANN model accelerated and facilitated the estimation procedure of ranking and it could replace multi-criteria decision-making methods. The results obtained in the individual capabilities section of this research are in line with Gorji et al. (2017) that the relationship between employees' emotional intelligence and job motivation is significant and emotional intelligence is an important factor in enhancing job satisfaction. Also, based on other research findings, the impact of educational and learning systems on employee commitment is significant, which is consistent with Zarei and Navimipour (2016) research and demonstrates that learning can minimize the probability of error through the mediating role of staff empowerment. The results of the competency-based incentive system indicate that clarity in the job position, along with meritocracy, provide effective encouragement for the role the individual plays in improving the organization, which is consistent with Gong et al. (2017). The three components of capability-practice-ability obtained as components of individual capabilities are the basis of organizational capabilities which are also important to focus according to Karpen et al. (2017). The importance of paying attention to the above-mentioned items through sharing information has also been emphasized by Salehzadeh et al. (2017). Finally, the results of cultural capabilities can be obtained by creating a strong organizational culture, that Chua and Morris (2009), Parte-Esteban & Alberca-Oliver (2015) and Zhang (2018) also mentioned " an appropriate platform for sharing new information at the organization level, scientifically managing organizational mutual relationships, creating a mutual-trust climate based on desire and sufficient understanding", as some solutions in this regard.

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