# Integrating Balanced Scorecard and Fuzzy TOPSIS for Innovation Performance Evaluation

*Completed Research Paper*

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## Abstract

*Innovation performance measurement is challenging due to the complexity and multidimensionality of the innovation processes. In fact, it is difficult to recognize what and how it should be measured. A solution can be the use of Balanced Scorecard (BSC) method that is easily adaptable to the needs of the organization in any of its strategic areas. However, the comprehensive measurement of innovation performance is also associated with a high level of uncertainty. This is mainly due to the fact that measurement methods are very often based on respondents' opinions. Hence, fuzzy set-based approaches are appropriate for this evaluation. Fuzzy TOPSIS is reported to be a reliable method used for multi-criteria decision making, where reference is made to a preferred/non-preferred alternative. This method allows not only taking into account the uncertainty present in the evaluation of innovation performance, but it also allows comparison and ranking of companies both within and among the different branches of industry. Hence, we propose an approach for innovation performance evaluation that integrates BSC and fuzzy TOPSIS. Empirical experiments are carried out on a large data set of European companies and the results are verified by the division of companies into knowledge intensive and high-tech industries. Further, the results are compared with exploratory factor analysis, the traditional statistical method used to evaluate innovation performance.*

**Keywords:** Innovation, measurement, performance, Balanced Scorecard, fuzzy TOPSIS

## Introduction

Innovation management measurement as the key factor of development of companies' competitiveness and performance is a critical discipline for both academics and practitioners. Although the importance of innovation management measurement is recognized, in practise the measurement is undertaken infrequently, in an ad hoc fashion, and relies on dated, unbalanced or underspecified models of the innovation management (Adams, 2006). This fact is confirmed by a number of older as well as newer studies (Stivers et al., 1998; Kokkinaki and Ambler, 1999; James et al., 2008; Andrew at al., 2010; Dewangan and Godse, 2014). The main reason why it is still challenging for a number of enterprises is that innovations typically create much more intangible than tangible value, and intangible value cannot be measured using traditional financial/quantitative methods (Gama et al., 2007; Ivanov and Avasilcăi, 2014). In general, there is a little consensus about innovation measurement (Jensen and Webster, 2009) and rigorous model for measuring innovation performance has not been solved yet (Lazarotti et al., 2011).

It is well argued in literature that the Balanced Scorecard (BSC) is a management tool that a number of enterprises use to measure the performance of their business, integrate the strategic management, communicate to all organizational levels the innovative measures adopted, and to enhance the development of shared objectives and practices (Magalhães, 2004). The main advantage of BSC, compared to other measurement systems, lies in translation of strategic objectives and intangible results into operational measures that everyone in the organisation should follow in order to achieve an increase in their performance (Al-Ashaab et al., 2011).

Despite the fact that innovation has to be part of the BSC from the beginning, the traditional framework cannot properly measure the value added by innovation (Gama et al., 2007). In the context of measurement, innovation is particularly perceived as new products or services. But innovation may also allow changes in management, business model, organizational structure, processes, supply chain or strategic objective (Hamel, 2006). That means innovation must be reflected in all perspectives of BSC (Gama et al., 2007; Spanò et. al., 2016).

Furthermore, it is widely accepted that the concept of innovation performance involves uncertainty, imprecision and imperfect or vague information. The challenges faced then must be addressed by overrunning that level of uncertainty and providing useful tools in terms of administration models for the analysis and treatment of variables, taking into account endogenous and exogenous elements, qualitative and quantitative information, among other components (Garcia et al., 2015). Studies with a fuzzy-oriented standpoint have proven efficacy while dealing with complex phenomena. In fact, business performance measurement under fuzzy environment has attracted increased attention because it enables modelling of intrinsic uncertainty present in the expert evaluation of performance indicators. Therefore, traditional multi-criteria decision-making models have been extended to incorporate this quality of fuzzy sets, such as AHP (Analytic Hierarchy Process) or TOPSIS (Technique for Order Performance by Similarity to Ideal Solution) (Aydogan, 2011). Above all, TOPSIS has been applied in business performance evaluation models, including BSC (Bai et al., 2014), due to its capacity to evaluate the performance by using similarity to ideal solution. Specifically, the best performer should have the shortest distance from the positive ideal solution and the farthest one from the negative ideal solution.

Since literature is far from providing clear and definitive answers to the above-mentioned challenges, there is the need to further investigate, from both the theoretical and the practical point of view. This paper attempts to contribute to the body of knowledge of innovation measurement and management by integrating Balanced Scorecard and fuzzy TOPSIS approach. The remainder of this paper is organised as follows. The first section briefly reviews the literature on BSC with especial reference to the issues relating to innovation and fuzzy sets. The second section provides the characteristics of the dataset and the research methodology. The third section lists the experimental results and verifies them by the division of companies into knowledge intensive and high-tech industries. Further, the results are compared with the exploratory factor analysis, the traditional statistical method used to assess innovation performance. The last section discusses the results obtained and concludes the paper with suggestions for future research.

## Balanced Scorecard for Innovation Performance Evaluation

The innovative processes are characterized by the complexity, multidimensionality and uncertainty and therefore their measurement and management are questionable, because it is difficult to identify what should be measured and how the evaluation has to be carried out (Murray and Blackman, 2006). In such contexts, it is very challenging to establish performance measurement system capable to foster an effective R&D (Pearson et al., 2000) as well as develop a general framework that defines what concept to use if the measurement is missing (Kersens-van Drongelen and Cook, 1997; Adams, 2006).

As theory and practice is showing, BSC is the most important performance measurement tool. The fact that it can be adapted according to the needs of the organization in any of its areas makes BSC the most appropriate tool when it comes to measuring complex process like innovation (Li and Dalton, 2003; Ivanov and Avasilcăi, 2014). According to Neufeld et al. (2001), BSC offers the most promising approach to measure performance and achieve operational excellence. Several researchers have tried to develop a framework to measure innovation based on BSC.

One of the first study that suggested BSC as a way to systematize R&D performance measurement was done by Kersens-van Dronglene and Cook (1999). Based on the R&D performance measurement literature authors have given overviews of measurement system requirements and designed principles that can be helpful to the development process. Bremser and Barsky (2004) extended the work of Kersens-van Dronglene and Cook (1999) by integrating the Stage-Gate approach with the BSC to ensure enhanced customer and market focussed R&D efforts. Gama et al. (2007) proposed the Innovation Scorecard which is based on innovation metrics and the tradition BSC in order to measure the value added by innovation and also guarantee the alignment with the organization’s strategic objectives.

Saunila and Ukko (2011) created a conceptual framework with five perspectives for measuring the relationship between innovation capabilities and business performance. Their framework goes one step further than previous models by discussing both the cause-effects relationships and the innovation capability view and its effects on business performance. Lazzarotti et al. (2011) built a model on the theory of measurement in soft systems and BSC for the calculation of performance at two levels. In the first stage the comparative value of each indicator is computed using the previous indicator value, the target indicator value and the benchmark indicator value. In the second stage, the performance of R&D system as a whole is calculated. Ivanov and Avasilcăi (2014) presented a new model on the basis of a detailed analysis of the four most important performance measurement models (BSC, EFQM, Performance Prism and Malcolm Baldrige) that tries to emphasize the most important characteristics that have to be analysed when innovation performance is measured. Zizlavsky (2016) extended previous studies by integrating popular innovation management frameworks, the input-process-output-outcomes model and the Stage Gate approach, with the Balanced Scorecard. The limitations of these research studies are that they are based on one or few case studies and the results have not been verified on a large data set. Moreover, fuzzy environment of the innovation performance evaluation has not been considered in these studies.

Due to the complexity and lack of clarity in the assessment criteria for performance measure indicators, the fuzzy set approach is increasingly being integrated into the BSC model. Cebeci (2009) used fuzzy AHP and BSC to select an enterprise resource planning (ERP) system for the textile industry. Wu et al. (2009) applied fuzzy AHP to obtain the relative weights of BSC evaluation indexes. And the three multi-criteria decision-making analytical tools, including TOPSIS were then adopted to rank the banking performance. Chen et al. (2009) integrated fuzzy ANP (Analytic Network Process) and BSC for measuring knowledge management performance and Yüksel and Dagdeviren (2010) to measure the performance of a manufacturing firm in Turkey. Also, the results of Ghadim and Nobarzad (2012) and Kustiyahningsih et al. (2016) show that fuzzy multi-criteria decision-making methods can be successfully used by a structured methodology in designing BSC as performance measurement and management system.

## Research Methodology for Innovation Performance Evaluation

In this section, we first propose a BSC of innovation performance. This step requires the definition of variables and key performance indicators (KPIs) for each BSC perspective. Then, we propose a methodology for innovation performance evaluation, integrating the proposed BSC and fuzzy TOPSIS method.

Fig. 1 shows the four perspectives of the BSC of innovation performance. The individual variables (which are included in the individual perspectives, see Figure 1) have been carefully selected. The Learning and Growth perspective is represented by expenditures on innovation activities that companies need to strategically incorporate into their own business innovation processes, in-house educational activities and training, and an external way of acquiring the necessary knowledge. This perspective represents the potential for achieving the firm´s strategic goal. The Knowledge and

Growth perspective enters into Internal Business Process perspective where processes and organizational innovations are emerging together with innovation co-operation. All of this effort is reflected in Customer/Stakeholder perspective where marketing innovation and new products are emerging. All types of innovation are direct result of the firm´s growth and it´s continuous effort to achieve strategic goals. Without success in previous perspective, the firm could not be successful either in these two related perspectives. Finally, the financial perspective integrates the results and benefits of previous, successfully implemented perspectives. Based on the firm's turnover from innovative production or the turnover growth, it is possible to ascertain the extent to which corporate goals have been achieved.

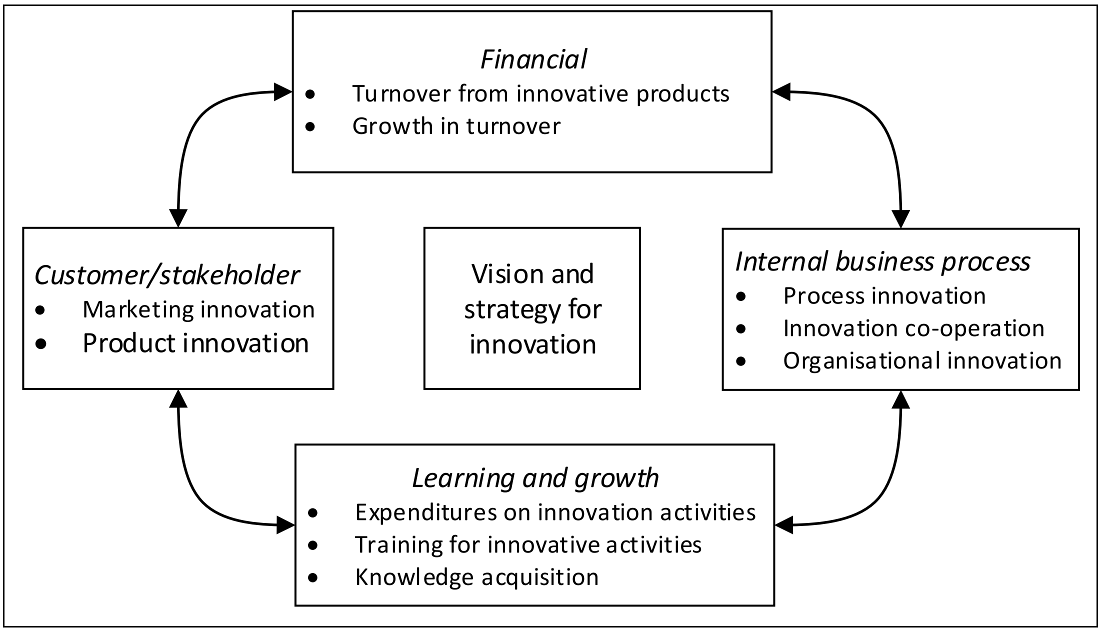


**Figure 1. Balanced Scorecard for Innovation Performance Evaluation**

In Table 1, we also present the detailed information on how each KPI can be measured using the harmonized questionnaire of the Community Innovation Survey (the detailed harmonized methodology is outlined in EU, 2014) and fuzzified to the interval of [0,1]. Several approaches had to be selected depending on the quantitative / qualitative character of the variables. The quantitative variables were rescaled to the interval of [0,1] where necessary. The labels of the qualitative variables were assigned with membership degrees to fuzzy sets based on the opinions of three experts in business innovation performance. Note that we attempted to keep the assignments as objective as possible, regularly distributing the membership degrees in the [0,1] interval.

In the first step of the methodology (Fig. 2), each BSC perspective is evaluated by using the fuzzified values of the KPIs presented in Table 1. These values represent the inputs to the fuzzy TOPSIS method. In this method, fuzzy decision matrix is first constructed for each perspective from the fuzzy values. Then, the weights of the KPIs are determined by an expert (or by a group of experts in case of group decision making). Thus, weighted fuzzy decision matrix can be calculated for each BSC perspective as the product of the fuzzy decision matrix and weight vector. Next, positive-ideal and negative-ideal solutions are identified in the weighted fuzzy decision matrixes. Using these solutions, separation measures and relative closeness coefficients can be calculated. In the final step, the relative closeness coefficients are combined to obtain the overall innovation performance score.

**Table 1 KPIs and their fuzzification for innovation performance BSC**

| Perspective | KPI | Description | Fuzzification |
|---|---|---|---|
| Learning and growth | Expenditure on innovation activities | Total expenditure on innovation activities | rescaled to [0,1] with $(x-x_{min})/(x_{max}-x_{min})$ |
| | Training for innovative activities | In-house/contracted out training for the personnel specifically for innovative activities | No – 0<br>Yes – 1 |
| | Knowledge acquisition | Importance of information sources – internal, market and education | No importance (0) – 0, Low (1) – 0.25, Medium (2) – 0.5, High (3) – 1<br>average from the three sources |
| Customer/stakeholder | Marketing innovation | Implementation of a new method for (1) design or packaging, (2) product promotion, (3) product placement, or (4) pricing | Three types of marketing innovation:<br>none of them – 0, 1 of them implemented – 0.25, 2 of them – 0.5, 3 of them – 0.75, all – 1 |
| | Product innovation | New good or service | No product innovation – 0, new to the firm innovation – 0.5, new to the market innovation – 1 |
| Internal business process | Process innovation | Implementation of (1) new production process, (2) distribution method or (3) supporting activities | Three types of process innovation:<br>none of them – 0, 1 of them implemented – 0.33, 2 of them – 0.67, all – 1 |
| | Innovation co-operation | Cooperation on innovation activities (1) within enterprise, (2) with supplier, (3) customer, (4) competitor, (5) consultant, (6) university, or (7) research institute | Breadth of cooperation partners:<br>1 partner – 0.14, 2 partners – 0.29, 3 – 0.43, 4 – 0.57, 5 – 0.71, 6 – 0.86, 7 – 1. |
| | Organizational innovation | New organizational method in (1) business practices, (2) decision-making, or (3) organizing external relations | Three types of organizational innovation:<br>none of them – 0, 1 of them implemented – 0.33, 2 of them – 0.67, all – 1 |
| Financial | Turnover from innovative products | The share of turnover from innovative products | scaled to [0,1], from no share to full share |
| | Growth in turnover | Growth in turnover between 2010 and 2012 | rescaled to [0,1] with $(x-x_{min})/(x_{max}-x_{min})$ |

Minimum function is used in order to achieve a balanced performance measure. Indeed, the four BSC perspectives are not only considered equally important in the literature but, in addition, they are strongly causally interconnected (Kaplan and Norton, 2004). Thus, a poor performance in one perspective will deteriorate the performance in the remaining perspectives. Let $A = \{A_1, A_2, \ldots, A_i, \ldots, A_n\}$ be a set of firms and $C = \{C_1, C_2, \ldots, C_j, \ldots, C_m\}$ be a set of KPIs in the $k$-th BSC perspective, $k = 1, 2, 3$ and 4. The proposed methodology can be defined in the following steps:

*Step 1*. Fuzzify the values of the KPIs for the $i$-th BSC perspective as presented in Table 1.

*Step 2*. Construct a fuzzy decision matrix from the fuzzified values.

*Step 3*. Determine the weights of the KPIs. Either use expert opinion or assign equal weights to the KPIs.

*Step 4*. Calculate the weighted fuzzy decision matrix by using a multiplication operator (weighted average) between the fuzzy decision matrix and KPIs' weights.

*Step 5*. Obtain fuzzy positive-ideal solution $A^+$ and fuzzy negative-ideal solution $A^-$ from the weighted fuzzy decision matrix. The fuzzy positive-ideal solution is calculated as the set of $m$ maximum fuzzy values from all $n$ firms, while the fuzzy negative-ideal solution is represented by the minima of these fuzzy values.

*Step 6*. Calculate the separation measures $S_i^+$ and $S_i^-$ using the Euclidean distance between the $i$-th firm and $A^+$ and $A^-$, respectively.

*Step 7*. Calculate the relative closeness coefficient of the $i$-th firm to the fuzzy positive-ideal solution $A$+ as $C_{ik} = S_i^- / (S_i^+ + S_i^-)$, where $k = 1$.

*Step 8*. Perform steps 1 to 7 for the remaining BSC perspectives, $k = 2, 3$ and 4.

*Step 9*. Obtain the overall innovation performance score by using minimum function as follows:
$P_i = \mathrm{MIN}(C_{i1}, C_{i2}, C_{i3}, C_{i4})$.

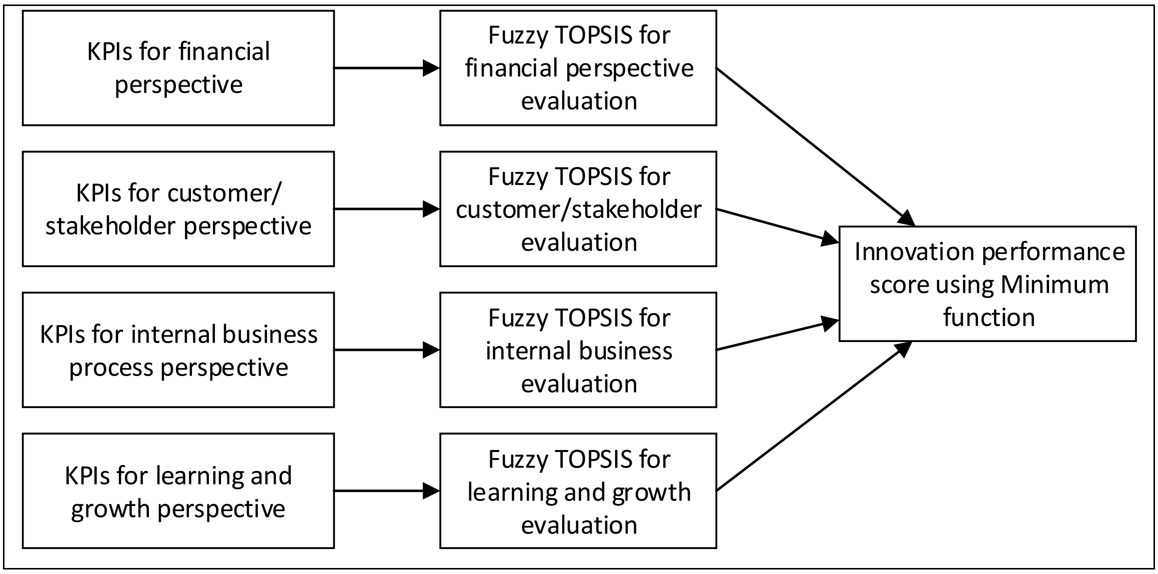


**Figure 2. Research Methodology for Innovation Performance Evaluation**

## Dataset

The data for the BSC were collected from the Eurostat, Community Innovation Survey (CIS) 2010-2012. This is the latest data currently available at the Eurostat. Details on the sampling methodology can be found here http://ec.europa.eu/eurostat/web/microdata/community-innovation-survey. The survey is limited to firms with at least 10 employees. We collected the data for those countries where KPIs were available, this is Bulgaria (2,409 firms), Croatia (944 firms), Cyprus (388 firms), Estonia (771 firms), Germany (5,777 firms), Hungary (1,182 firms), Lithuania (653 firms), Portugal (3,341 firms), Romania (829 firms), Slovenia (733 firms), and Slovakia (560 firms). A harmonized questionnaire was used for all these countries. The CIS 2012 Survey Questionnaire can be downloaded at the Eurostat web pages, http://ec.europa.eu/eurostat/documents/. Note that not all firms in the sample answered all questions. Therefore, missing data had to be treated. We used a common procedure for this task, replacing the missing values with median values of the respective country and industry (Zhang, 2016).

The basic descriptive statistics of the dataset are presented in Table 2. Regarding the size of the firms in the dataset, most firms were small and medium enterprises, with less than 50 employees. Only less than half firms conducted training for innovative activities. Table 2 also shows that knowledge acquisition from internal sources was the most important source of information for innovative activities, whereas education sources were the least important. From the four types of innovations, product innovations were the most common ones, with almost half of the innovative firms. Note that all these innovations were new to the firm, but only about two-thirds of them were also new to the market innovation. This is also why these percentages do not give the total of 100 %. Marketing innovation were mostly oriented on product promotion, while process innovation on new production process methods and organizational innovation on new decision-making methods, respectively. Considering the type of cooperation partner, suppliers were engaged most frequently. The firms in the dataset also experienced a period of turnover growth with 13.6 % on average. Innovative products accounted for more than one-fifth of the turnover.

**Table 2 Descriptive statistics of the dataset**

| KPI | Mean value / frequency |
|---|---|
| Expenditure on innovation activities | 26,580 EUR |
| Training for innovative activities | yes (46.0 %) |
| Knowledge acquisition | importance of internal (1.93), market (1.16) and education sources (0.57) |
| Marketing innovation | design or packaging (25.5 %), product promotion (27.9 %), product placement (23.1 %), pricing (23.3 %) |
| Product innovation | no (54.7%), new to the firm (45.3 %), new to the market innovation (31.8 %) |
| Process innovation | production process (38.6 %), distribution method (20.5 %) and supporting activities (35.8 %) |
| Innovation co-operation | within enterprise (27.5 %), supplier (39.0 %), customer (34.3 %), competitor (22.1 %), consultant (25.5 %), university (33.6 %), research institute (23.2 %) |
| Organizational innovation | business practices (36.6 %), decision-making (39.2 %), organizing external relations (22.3 %) |
| Turnover from innovative products | 21.5 % |
| Growth in turnover | 13.6 % |

## Empirical Results

The proposed methodology was empirically tested on the set of 17,586 firms characterized in the previous section. For the sake of objectivity, we assigned equal weights to the KPIs of all the BSC perspectives in Step 3 of the methodology. Thus, the fuzzy decision matrix from Step 2 was equal to the weighted fuzzy decision matrix in Step 4. This was also because we aimed to evaluate an extensive number of firms from various countries and industries. In fact, these weights can be easily adjusted for each company, country or industry. Fuzzy positive-ideal solution $A^+$ and fuzzy negative-ideal solution $A^{-}$ for each BSC perspective were as follows: $A^{+}$=(1,1,1) and $A^{-}$=(0,0,0) for the Learning and growth perspective, $A^{+}$=(1,1) and $A^{-}$=(0,0) for the Customer/Stakeholder perspective, $A^{+}$=(1,1,1) and $A^{-}$=(0,0,0) for the Internal business process perspective, and $A^{+}$=(1,1) and $A^{-}$=(0,0) for the Financial perspective. In other words, there were firms with both maximum and minimum fuzzy values in the dataset. This can be mainly attributed to the large number of firms in the dataset. The results of the relative closeness coefficients for each BSC perspective are presented in Table 3. As the results cannot be showed for all the firms, we only present mean and standard deviation values here. Obviously, the best performance was achieved for the financial perspective on average, whereas the firms performed poor in the learning and growth perspective of the BSC. In addition, Table 3 also shows the average overall innovation performance score.

**Table 3 Innovation performance in BSC perspectives and overall innovation performance score**

| BSC perspective | Mean±St.Dev. |
|---|---|
| Learning and growth | 0.297±0.179 |
| Customer/stakeholder | 0.346±0.281 |
| Internal business process | 0.318±0.209 |
| Financial | 0.410±0.141 |
| Overall innovation performance score | 0.171±0.149 |

To verify these results, we adopted two approaches used in related literature on firm innovation activity, namely the divisions of the firms into: (1) knowledge intensive and non-intensive industries (An et al., 2011; Chen et al., 2016), and (2) low-tech and high-tech industries (Mendonça, 2009; Som and Kirner, 2016). To identify the knowledge intensive industries, we adopted the Eurostat methodology. According to this definition, the knowledge intensive industries include those industries for which persons with tertiary education employed represent account for more than 33% of the total employment. This division was used because the knowledge-intensive industries represent a major source of innovation and an important driver of economic growth (Domenech et al., 2016). The latter division is based on the technology intensity of manufacturing industries. Again, the sectoral approach developed by Eurostat was used to divide the firms into the two technological intensity categories. The technological intensity of the industry is measured as R&D expenditure divided by value added. Generally, the firms in high-tech industries are considered as the fundamental drivers of productivity and the source of high value-added. Regarding individual industries, "Manufacture of chemicals and chemical products" and "Manufacture of basic pharmaceutical products and pharmaceutical preparations" performed best in terms of average innovation performance, while "Employment activities" and "Security and investigation activities" had the poorest performance.

The results in Table 4 and Table 5 provide support to our methodology because the innovation performance was significantly higher for both knowledge intensive and high-tech firms than their non-intensive and low-tech counterparts. Student's paired *t*-test was used for the statistical comparison of the mean values. The results confirm that our methodology provide significantly higher evaluation in all BSC perspectives to knowledge and technological intensive firms.

**Table 4 Average innovation performance in knowledge intensive and non-intensive industries**

| BSC perspective | Knowledge intensive | Knowledge non-intensive | *p*-value |
|---|---|---|---|
| Learning and growth | 0.333 | 0.281 | 0.000 |
| Customer/stakeholder | 0.393 | 0.325 | 0.000 |
| Internal business process | 0.338 | 0.310 | 0.000 |
| Financial | 0.416 | 0.408 | 0.000 |
| Overall innovation performance score | 0.197 | 0.159 | 0.000 |

**Table 5 Average innovation performances in high and low technology industries**

| BSC perspective | High-tech | Low-tech | *p*-value |
|---|---|---|---|
| Learning and growth | 0.369 | 0.274 | 0.000 |
| Customer/stakeholder | 0.396 | 0.360 | 0.000 |
| Internal business process | 0.333 | 0.300 | 0.000 |
| Financial | 0.429 | 0.414 | 0.000 |
| Overall innovation performance score | 0.208 | 0.162 | 0.000 |

In further experiments, the results were compared with exploratory factor analysis, the traditional statistical method used to assess firms' innovation performance (Dobni, 2008; Yam et al., 2011; Dekolou et al., 2017). We performed the exploratory factor analysis with maximum likelihood estimates in IBM SPSS Statistics 19. To obtain one indicator for each BSC perspective, one factor was extracted for each set of the KPIs. For the overall innovation performance, we extracted one factor from the whole set of the KPIs. Table 6 presents the variance explained by each exploratory factor analysis model. In addition, Cronbach's alpha was calculated to measure the internal consistency of these models. In all cases, the Eigenvalues of the first factors were larger than one, suggesting that the analysis can be effective in detecting research constructs. However, as showed in Table 6, the acceptable values of Cronbach's alpha (usually > 0.60) was achieved only in cases of the internal business process perspective and for the overall innovation performance. This indicates a poor internal consistency of the remaining models. When comparing the internally consistent overall innovation performance score obtained by the exploratory factor analysis with that of the proposed methodology, we used Pearson correlation coefficient $r$. This comparison showed $r = 0.829$ with significant correlations at $p < 0.01$. In other words, $r^2 = 0.687$ indicates that the exploratory factor analysis could explain only about 70 % of the total variation of the overall innovation performance score. Thus, a substantial proportion of information contained in this score remained unexplained.

**Table 6 Results of exploratory factor analysis**

| BSC perspective | Variance explained [%] | Cronbach's alpha |
|---|---|---|
| Learning and growth | 47.49 | 0.400 |
| Customer/stakeholder | 64.55 | 0.434 |
| Internal business process | 56.63 | 0.604 |
| Financial | 56.77 | 0.227 |
| Overall innovation performance score | 31.18 | 0.723 |

## Conclusion

In summary, our study proposes a novel methodology for firm innovation performance evaluation. The contribution of this methodology is the integration of two approaches, BSC and fuzzy TOPSIS. To develop a BSC for innovation performance evaluation, we also propose a set of KPIs for each BSC perspective. To integrate this BSC model with the fuzzy TOPSIS approach, we propose the fuzzification process for each KPI. The integrated model was tested on a large real-world dataset. To verify the results, we also showed that knowledge and technology intensive firms performed well in terms of the proposed innovation performance score. In addition, we demonstrated that traditional statistical approaches may suffer poor consistency in measuring firm innovation performance. Taken together, the results suggest that the proposed methodology can be effectively applied to measure firm innovation performance in all the four perspectives of the BSC.

It is recommended that further research should be undertaken in the following areas. First, the design of the KPIs can be extended to meet the specific needs of each firm or industry. Second, the fuzzification process was strongly affected by the underlying data used in this study. Although a large dataset was used here, alternative fuzzification approaches are recommended to ensure robust performance. Finally, the results of the fuzzy TOPSIS should be compared with other multi-criteria decision-making methods under fuzzy environment in future.

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## References

Adams, R., Bessant, J., and Phelps, R. 2006. "Innovation Management Measurement: A Review," *International Journal of Management Reviews* (8:1), pp. 21-47.

Al-Ashaab, A., Flores, M., Doultsinou, A., and Magyar, A. 2011. "A Balanced Scorecard for Measuring the Impact of Industry–University Collaboration," *Production Planning & Control (22:*5-6), pp. 554-570.

An, Y., Davey, H., and Eggleton, I. R. 2011. "The Effects of Industry Type, Company Size and Performance on Chinese Companies' IC Disclosure: A Research Note," *Australasian Accounting Business & Finance Journal*, (5:3), pp. 107-116.

Andrew, J. P., Manget, J., Michael D. C., Taylor, A., and Zablit, H. 2010. *Innovation 2010: A Return to Prominence – and the Emergence of a New World Order*, The Boston Consulting Group.

Aydogan, E. K., 2011. "Performance Measurement model for Turkish Aviation Firms using the Rough-AHP and TOPSIS Methods under Fuzzy Environment," *Expert Systems with Applications* (38:4), pp. 3992-3998.

Bai, C., Dhavale, D., and Sarkis, J. 2014. "Integrating Fuzzy C-Means and TOPSIS for Performance Evaluation: An Application and Comparative Analysis," *Expert Systems with Applications* (41:9), pp. 4186-4196.

Bremser, W.G., and Barsky, N.P. 2004. "Utilizing the Balanced Scorecard for R&D Performance Measurement," *R&D Management* (34:3), pp. 229-238.

Cebeci, U. 2009. "Fuzzy AHP-based Decision Support System for Selecting ERP Systems in Textile Industry by using Balanced Scorecard," *Expert Systems with Applications* (36), pp. 8900-8909.

Chen, M.Y., Huang, M.J., and Cheng, Y.C. 2009. "Measuring Knowledge Management Performance using a Competitive Perspective: An Empirical Study," *Expert Systems with Applications* (36:4), pp. 8449-8459.

Chen, W., Niebel, T., and Saam, M. 2016. "Are Intangibles More Productive in ICT-intensive Industries? Evidence from EU Countries," *Telecommunications Policy*, (40:5), pp. 471-484.

Dekoulou, P., Dekoulou, P., Trivellas, P., and Trivellas, P. 2017. "Organizational structure, innovation performance and customer relationship value in the Greek advertising and media industry," *Journal of Business & Industrial Marketing* (32:3), pp. 385-397.

Dewangan, V., and Godse, M. 2014. "Towards a Holistic Enterprise Innovation Performance Measurement System," *Technovation* (34:9), pp. 536-545.

Dobni, C. B. 2008. "Measuring Innovation Culture in Organizations: The Development of a Generalized Innovation Culture Construct using Exploratory Factor Analysis," *European Journal of Innovation Management* (11:4), pp. 539-559.

Domenech, J., Escamilla, R., and Roig-Tierno, N. 2016. "Explaining Knowledge-Intensive Activities from a Regional Perspective," *Journal of Business Research* (69:4), pp. 1301-1306.

EU. 2014. *The Community Innovation Survey 2014 - Methodological Recommendations*, available at: https://circabc.europa.eu/sd/a/daec8c5b-5570-4712-bf6d-ea7a51710a51/CIS%202014%20Methodological%20recommendations.pdf

Gama N., Silva M. M., and Ataíde J. 2007. "Innovation Scorecard: A Balanced Scorecard for Measuring the Value Added by Innovation," in *Digital Enterprise Technology*, Cunha P. F., Maropoulos P. G. (eds.). Boston, MA: Springer-Verlag, pp. 417-424.

Garcia, V.G.A., Gil-Lafuente, A.M., and Calderón, G.G.A. 2015. "Fuzzy Logic Approach towards Innovation Measurement," *Global Journal of Business Research* (9:3), pp. 53-71.

Ghadim, M. R. K., and Nobarzad, Y. E. 2012. "Performance Evaluation of Supply Chain by Using Balanced Scorecard and Fuzzy TOPSIS Technique (Case Study- Pars Renault Company)," *Journal of Supply Chain Management Systems* (1:4), pp. 13-22.

Hamel, G. 2006. "The Why, What, and How of Management Innovation," *Harvard Business Review* (84:2), pp. 72-84.

Ivanov, C. I., and Avasilcăi, S. 2014. "Performance Measurement Models: An Analysis for Measuring Innovation Processes Performance," *Procedia - Social and Behavioural Sciences* (124), pp. 397-404.

James, P. A., Knut, H., David, C. M., Harold, L. S., and Andrew, T. 2008. *A BCG Senior Management Survey - Measuring Innovation 2008: Squandered Opportunities*, retrieved from https://www.bcg.com/documents/file15302.pdf

Jensen, P.H., and Webster, E. 2009. "Another Look at the Relationship between Innovation Proxies," *Australian Economic Papers* (48:3), pp. 252-269.

Kaplan, R., and Norton, D. P. 2004. *Strategy Maps – Converting Intangible Assest into Tangible Outcomes*. Boston: Harvard Business School Press.

Kerssen-van Drongelen, I. C., and Cook, A. 1997. "Design Principles for the Development of Measurement Systems for Research and Development Processes," *R&D Management* (27:4), pp. 345-357.

Kokkinaki, F., and Amber, T. 1999. *Marketing Performance Assessment: An Exploratory Investigation into Current Practice and the Role of Firm Orientation*, Cambridge: Marketing Science Institute.

Kustiyahningsih, Y., Rahmanita, E., and Purnama, J. 2016. "Integration Balanced Scorecard and Fuzzy Analytic Network Process (FANP) For Measuring Performance of Small Medium Enterprise (SME)," *Journal of Theoretical and Applied Information Technology* (94:2), pp. 343-352.

Lazzarotti, V., Manzini, R., and Mari, L. 2011. "A Model for R&D Performance Measurement," *International Journal of Production Economics* (134:1), pp. 212-223.

Li G., and Dalton, D. 2003. "Balanced Scorecard for I + D," *Pharmaceutical Executive* (23:10), pp. 84-90.

Magalhães, R. 2004. *Organizational Knowledge and Technology: An Action-oriented Perspective on Organization and Information Systems*, Northampton: Edward Elgar Publishing Limited.

Mendonça, S. 2009. "Brave old world: Accounting for 'high-tech'knowledge in 'low-tech'industries," *Research Policy*, (38:3), pp. 470-482.

Murray, P., and Blackman, D. 2006. "Managing Innovation through Social Architecture, Learning, and Competencies: A New Conceptual Approach," *Knowledge and Process Management* (13:3), pp. 132-143.

Neufeld, G. A., Semeoni, P. A., and Taylor, M. A. 2001. "High Performance Research Organization," *Reserach Technology Management* (44:6), pp. 42-52.

Pearson, A. W., Nixon, W. A., and Kerssen-van Drongelen, I. C. 2000. "R&D as a Business - What are the Implications for Performance Measurement?," *R&D Management* (30:4), 355-366.

Saunila, M., and Ukko, J. 2012. "A conceptual framework for the measurement of innovation capability and its effects," *Baltic Journal of Management*, *7*(4), 355-375.

Som, O., and Kirner, E. 2016. "*Low-tech Innovation*," Singapore: Springer International Pu.

Spanò, R., Sarto, F., Caldarelli, A., and Vigano. R. 2016. "Innovation & Performance Measurement: An Adapted Balanced Scorecard," *International Journal of Business and Management* (11:6), pp. 194-204.

Stivers, B. P., Covin, T. J., Hall, N. G., and Smalt, S. W. 1998. "How Nonfinancial Performance Measures are Used," *Management Accounting* (79:8), pp. 44-49.

Wu, H. Y., Tzeng, G. H., and Chen, Y. H. 2009. "A Fuzzy MCDM Approach for Evaluating Banking Performance based on Balanced Scorecard," *Expert Systems with Applications* (36:6), pp. 10135-10147.

Yam, R. C., Lo, W., Tang, E. P., and Lau, A. K. 2011. "Analysis of Sources of Innovation, Technological Innovation Capabilities, and Performance: An Empirical Study of Hong Kong Manufacturing Industries," *Research Policy* (40:3), pp. 391-402.

Yüksel, I., and Dagdeviren, M. 2010. "Using the Fuzzy Analytic Network Process (ANP) for Balanced Scorecard (BSC): A Case Study for a Manufacturing Firm," *Expert Systems with Applications* (37:2), pp. 1270-1278.

Zhang, Z., 2016. "Missing Data Imputation: Focusing on Single Imputation," *Annals of Translational Medicine* (4:1), pp. 1-8.

Zizlavsky, O. 2016. "Innovation Scorecard: Conceptual Framework of Innovation Management Control System," *Journal of Global Business and Technology* (12:2), pp. 10-27.