Multicriteria decision choices for investment in innovative upper-middle income countries

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Abstract

Purpose – The purpose of this paper is to observe how to invest in upper-middle income countries via an innovation perspective following global innovation index (GII) by multicriteria decision aid (MCDA) approach, once MCDA was designed to support subjective decisions.

Design/methodology/approach – Pearson's correlation was the milestone for understanding innovation indicators at upper-middle income countries profiles. In a MCDA first step, the analytical hierarchy process (AHP) was applied to obtain the criteria weight. In this step, the judgments or evaluations inputted in AHP were collected from a sample composed by five experts in GII. After getting the criteria weights compose to GII, Borda and Preference Ranking Organization Method for Enrichment Evaluations (PROMÉTHÉE) methods were applied to obtain an MCDA-based GII. The inputs for this second step were: the weights come from AHP output; and the countries performance came from GII data.

Findings – As a result, it was found out the upper-middle countries' rank to invest and groups with countries acting like "hubs" or "bridges" for economic sectors in near countries; when they are grouped according to their maximum and minimum scores profiles, observing not only a particular region but also similar profiles at diverse world areas.

Originality/value – Pearson-AHP-PROMÉTHÉE works as a supportive decision tool for several and complex investment perspectives from criteria and alternatives analysis regarding innovation indicators for upper-middle income countries. This combination also demonstrates grouping possibilities, aligning profiles and not only ranking countries for investment and eliminating others but also grouping countries with similar profiles via innovation indicators MCDA combined application.

Keywords MCDA, AHP, Global innovation index, Pearson, World intellectual property organization, PROMÉTHÉE

Paper type Research paper

1. Introduction

The global innovation index (GII) is a yearly report where innovative countries are analyzed and ranked considering their innovative profile. It is adopted by the World Intellectual Property Organization (WIPO) for observing innovative tendencies regarding countries and their perspectives via seven innovation indicators, where five are innovation input

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indicators and the other two are innovation output indicators. WIPO is a United Nations' self-funding agency with 189 member states. It was established in 1967 as an institution in Stockholm for promoting intellectual property global protection and innovative tendency studies (Olwan, 2011).

On the one hand, GII is based on weighted sums and was not designed to work with subjective features. On the other hand, multicriteria decision aid (MCDA) methods were developed to work in situations where subjectivity is in the core of the problem. To fulfil this gap, this paper proposes the use of MCDA methods to review the GII calculation. Some of the research questions are: "Considering upper-middle income countries' scores in innovation indicators; which of them are better options for investment? Is it possible to invest in some particular groups? Is it possible to align Pearson's correlation to analytical hierarchy process (AHP) to create weights for results and analysis made in Preference Ranking Organization Method for Enrichment Evaluations (PROMÉTHÉE)?

Section 2 observes GII 2016 innovation indicators and multicriteria methods used. Section 3 describes the used multicriteria tools. Section 4 discusses results followed by final considerations.

2. Background

2.1 Global innovation indicators

As reported by Cornell University, INSEAD, and WIPO (2016), the GII (edition 2016) is composed of 82 indicators covering 16 composed indicators, 5 survey questions and 61 raw data dimensions of innovative skills of the countries. Such indicators are analyzed through the comparison among countries, consolidating their scores according to their pillars and sub-pillars (Cornell University, INSEAD and WIPO, 2015).

As observed in Silva, Gavião, Gomes, and Lima (2017), a MCDA ranking method (TOPSIS – Technique for Order of Preference by Similarity to Ideal Solution) was used for observing Latin America and Caribbean countries' innovative profiles in GII 2015. In our paper, the challenge is to observe GII 2016's upper-middle income innovative countries by using other MCDA tools to analyze investments opportunities in diverse world areas and upper-middle income countries. The results will be presented according to decision-makers' (DM) expectations taking into consideration the possibility of these countries to be part of a group of investment receivers according to their innovation indicators.

However, to analyze GII, it is important to be aligned with the six innovation policy principles defined by GII 2015, but still present in GII 2016 in its restructured indicators, as follows:

(1) *Principle 1*: Innovation policies should focus on maximizing innovation across all industries in all economic, correlated and supporting sectors so that the global production chain can develop technological innovation, being one of the pyramid's base principles.

(2) *Principle 2*: Innovation policies should support all types and innovation stages because one of the national innovation policies errors is to define innovation strategies on a microeconomic level, only focusing on the technological products production, whilst innovation should extend throughout the whole production chain to rethink the products mix that make up the production high value-added sectors, composing the pyramid's base as well.

(3) *Principle 3*: To empower creativity and creative destruction to pursue innovation; developing countries need to promote disruption in manufacturing to pursue innovation. Innovative entrepreneurships will enable new players to take part in new economic sectors, especially those who are well-positioned in terms of products and services. This is the last principle of the base of the pyramid.

(4) *Principle 4*: To keep the price of capital goods low – especially those related to information, communications and technology – because without the new incoming capital to invest in technology, the power to invest in innovation diminishes and productivity stagnates, causing a drop in the global strategic competitiveness. Monitoring quotas and tariffs, such as trade barriers, can therefore maintain the capital cost low.

(5) *Principle 5*: To support the creation of technology transfers related to support industries, where companies do not only need the access to innovation but also the access to inter- and intra-sectoral technology transfers. In addition, the digital infrastructure, skilled labor specialized in technological innovation and technological knowledge must be aligned with the changes in various economic sectors, starting with the fourth principle of the second layer of the pyramid.

(6) *Principle 6*: To develop a national innovation and production strategy with companies that support such strategies through the creation of agencies dedicated to fostering innovation, completing the innovation nationwide and reaching the top of the pyramid (Cornell University, INSEAD, & WIPO, 2015, 2016).

The identification of the indicators starts with the definition of sub-pillars and pillars of inputs and outputs. The first sub-pillar innovation input has five pillars, namely, institutions (indicator 1 – I1), human capital and research (indicator 2 – I2), infrastructure (indicator 3 – I3), market sophistication (indicator 4 – I4) and business sophistication (indicator 5 – I5). The sub-pillar input defines some aspects related to the favorable environment for innovation in the national economy. The second sub-pillar of the innovation output has two pillars, which is a result of innovative activities results within a national economic scenario. Even through there are only two pillars in this sub-pillar, they have the same weight in total. They are defined as knowledge and technology outputs (indicator 6 – I6) and creative outputs (indicator 7 – I7). Figure 1 demonstrates the seven innovation indicators and their input and output sub-pillars (Cornell University, INSEAD, & WIPO, 2016; Silva et al., 2017).

The scores of the GII countries are represented by their average scores and displayed from the bottom-up. It is important to observe how a hierarchical weighting can be perceived from the bottom-up; being more recommendable because participants' understanding of alternatives' impact ranges can be better in the bottom-up than in the top-down approach (Marttunen, Belton, & Lienert, 2018). That is the reason why the use of Pearson's correlation aligned with AHP-Borda and PROMETHÉE is important; the use of these statistical resources helps DMs to make better decisions in terms of investments in upper middle-income countries instead of only considering GII scores singly.

2.2 Multicriteria

In the decision-making model, the following components are included criteria, weights and grades (classification) that are given for each alternative, in each criterion. Assuming the knowledge of the preferences of the DMs and the quality of the evaluation, it can be

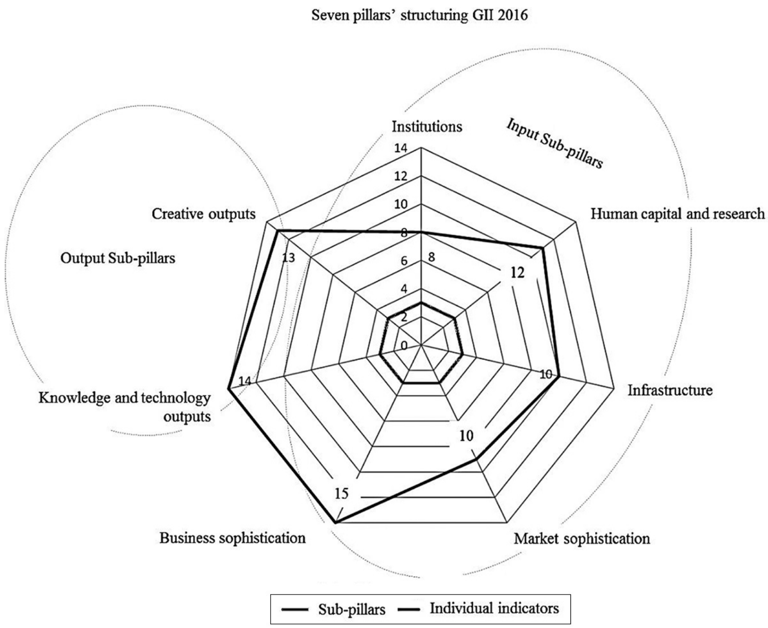


Figure 1.
Seven pillars that compose the GII 2016

Source: Adapted from Cornell University, INSEAD, and WIPO (2016)

admitted that one action is as good, better or worse than another, that is, to rank the alternatives (Cardoso, Xavier, Gomes, and Adissi, 2009).

The decision analysis process usually considers a variety of alternatives, which must be carefully evaluated so that the "best" decision can be made. The models based on multicriteria decisions are recommended for problems that present several evaluation criteria to consider (Dubois, 2003; Gomes, Costa, & Barros, 2017).

The DM has (Corrente, Figueira, Greco, & Słowiński, 2017; Fernández, Figueira, & Navarro, 2019):

- a set of alternatives $A = \{a_1, a_2, \ldots, a_n\}$, A be a finite and stable set of potential alternatives to be ranked;
- a set of criteria $C = \{c_1, c_2, ., c_j\}$, C be a set of criteria of performance with given ordinal measurement scale, thus we have a total pre-ordering of each attribute c. $c_j(a)$, $a \in A$, the best alternative on criterion c_j;
- a set of m decision-making agents ($D_1, D_2, \ldots, D_m$) expressing their opinion on the alternatives, through preference orderings;
- a set of criteria weights $W = \{w(c_1), w(c_2), \ldots, w(c_j)\}$, in which each W preference is an attribute weight vector satisfying $w(c) > 0$, for all $c \in C$.

The decision-making process largely consists of two phases (Dias, Antunes, Dantas, Castro, & de Zamboni, 2018; Petrović, Bojković, Stamenković, and Anić, 2018):

(1) construction of a decision-making problem and data preparation; and

(2) aggregation and exploitation.

Different aggregation methods are developed depending on which kind of data is prepared in the first phase. The ranking method can be placed into two basic categories such as cardinal and ordinal methods (Doumpos, & Figueira, 2018; Yu, Zhang, Liao, & Qi, 2018):

(1) cardinal methods require DMs to express their degree of preference for one alternative over another for each criterion; and

(2) ordinal methods require that only the rank order of the alternatives be known for each criterion.

As the modeling presented herein is based on two MCDA methods, namely, AHP (Saaty, 1980; De Borda, 1781) and PROMÉTHÉE (Brans, Mareschal, & Vincke, 1984), a short description about them is inserted as follows.

De Borda uses are usually for voting systems; however, it is an important multicriteria aid method for understanding the differences of ordering alternatives, especially when the criteria are weighted (Da Rocha, Da Silva, DE Barros, & Costa, 2016). On the other hand, PROMÉTHÉE observes preferences and computes them in the software; illustrations support the results to obtain a better perspective of all the preferences, for example, if a cluster is formed by the alternatives, etc.

AHP gives the opportunity for understanding indicators and their pairwise importance as criteria. This is a semi-qualitative method that involves a matrix-based pairwise comparison among the different factors (Mishra and Chatterjee, 2018). The wide applicability is because of its simplicity, easy of use and great flexibility. The AHP is a decision-making tool used to deal with multicriteria evaluation (Chaudhary, Chhetri, Joshi, Shrestha, & Kayastha, 2016; Dong, & Cooper, 2016).

Moreover, Pearson correlation shows strong and weak correlations among indicators, which can be used to encourage investments based on the innovation level of upper-middle income countries.

2.2.1 Analytical hierarchy process. AHP is based on the following principles:

- problem definition;
- structuring criteria in a tree or hierarchy composed of criteria and sub-criteria;
- pairwise judgments;
- prioritization based on the Eigen-value aggregation procedure; and
- consistency analysis.

Emrouznejad and Marra (2017) elaborated a literature review and demonstrated that most studies on AHP were published between 1979 and 2017, considering the large number of works in the field (8,441 published pieces). They show that AHP has attracted the attention of scholars in various fields because of its ability to provide support to different DMs, in areas ranging from medical issues to computer science and environmental studies. They identified that the limitation of the stand-alone AHP is the potential arbitrary judgment of the DM, which can lead to inconsistencies. It is interesting to notice that, in their paper, there is no identification of the multicriteria methodology, unlike we accomplished herein in Figure 2.

The pairwise comparison is conducted in a simple way, by asking experts some questions, such as how much a criterion is more important than another one. The collection of the answers is based on the Saaty' scale shown in Table 1.

AHP is mainly worthy because of its capacity of perceiving inconsistencies in judgments. Similarly, the judgments made by the experts calculate the coherence of the experts through the consistency index (CI). Saaty (1980) suggests that if the consistency ratio (CR) is greater than 0.1 (CR > 0.1), the judgments of the expert should be reviewed.

2.2.2 Borda. The Borda method was first proposed in De Borda (1781) as a procedure to deal with incoherence in ranking preferences in electoral processes.

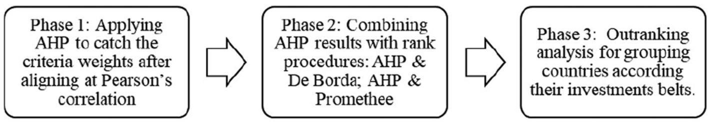
As reported in Costa (2014), the following steps are applied when De Borda method is adopted:

- Definition of DMs, judges and jury members.
- Definition of elements or alternatives to be ranked.
- Obtaining evaluations or established judgments by each DM for each alternative.
- Associating a rating score, order number to each alternative, considering individual judgments from each judge.
- Add order numbers obtaining a global number order for each alternative.
- Obtaining a final alternatives' score based on the global order numbers.

2.2.3 Preference Ranking Organization Method for Enrichment Evaluations. The PROMÉTHÉE was first proposed by Brans et al. (1984) as method for ranking a finite set of alternatives (Bouyssou, 1992; Bouyssou, Marchant, Pirlot, Perny, Tsoukiàs, & Vincke, 2000). The PROMÉTHÉE method is important because it involves concepts and parameters that have some physical or economical interpretation that is easy for most DMs to understand (Sarrazin, & De Smet, 2015).

It ranks the alternatives based on their "net flow," i.e. the difference between how much an alternative "a" is better than alternative "b" and how much an alternative "b" is better than alternative "a" (Bogdanovic, Nikolic, & Ilic, 2012).

It is necessary to specify to each defined criteria a generalized preference function (P_j) (Silva, & De Almeida-Filho, 2018), such as:



Source: Own Elaboration

Figure 2. Illustrating the methodological stepsSource: Own elaboration.

Verbal judgment	Numerical rating
Equally preferred	1
Moderately preferred	3
Very strongly preferred	5
Strongly preferred	7
Extremely preferred	9
2, 4, 6 and 8 are intermediate values	

Source: Saaty (1980)

Table 1. Pairwise comparison scale for AHP preference

$$P_j : \ A \text{ x } A \ \rightarrow [0,1] \tag{1}$$

Comparing alternatives a_1 e a_2 belonging to A-*set*; it has: $P_j(a_1,\ a_2) = P(x) = P\left[f(a_1) - f(a_2)\right]$, representing the preference level of a_1 over a_2 following criterion j; as:

- P(x) = 0, a_1 is not preferable regarding a_2;
- P(x) $\cong$ 0, a_1 is less preferable regarding a_2;
- P(x) $\cong$ 1, a_1 is strongly preferable regarding a_2;
- P(x) = 1, a_1 is entirely preferable regarding a_2.

When the criterion can be optimized, it is used x $= f(a_1) - f(a_2)$ for defining the preference function. When the criterion is minimized, the preference function is x $= f(a_2) - f(a_1)$.

The next step is to compute the aggregated preference indices $\pi(a_1, a_2)$. It is computed to each pair of alternatives, indicating that the percentage of the preference over alternative a_1 regarding alternative a_2 is considered by attributing weights to each defined criteria:

$$\pi(a_1, a_2) = \sum_{j=1}^{n} \alpha_j P_j(a_1, a_2) \tag{2}$$

where:

$$\sum_{j=1}^{n} \alpha_j = 1 \tag{3}$$

$$0 \ \leq \pi(a_1, a_2) \ \leq 1 \ \forall \ a_1, \ \ a_2 \in A \tag{4}$$

The next step is the definition of the positive and the negative outranking flows. The positive flow indicates how an alternative a_1 is outranking all the others belonging to the A-set:

$$\Phi^{+}(a_1) = \frac{1}{n-1} \cdot \sum_{x \in A}^{n} \pi(a_1, x) \tag{5}$$

Thus, the higher the positive outflow of a_1 ($\Phi^{+}(a_1)$), the better the alternative.

The negative outranking flow indicates how an alternative a_1 is outranked by all the others:

$$\Phi^{-}(a_1) = \frac{1}{n-1} \cdot \sum_{x \in A}^{n} \pi(x, a_1) \tag{6}$$

The lower the negative flow of a_1 ($\Phi^{-}(a_1)$), the better the alternative.

The last step is to define the importance of the net outranking flow, after defining positive and negative outranking flows. The objective is to define importance levels to each alternative and structure following a decreasing order. The net outranking flow is the balance between the positive and the negative outranking flows, as follows:

$$\Phi(a_1) = \Phi^{+}(a_1) - \Phi^{-}(a_1) \quad (7)$$

- where a_1 is preferable over a_2 (a_1Pa_2) *whether* : $\Phi(a_1) > \Phi(a_2)$;
- where a_1 is indifferent regarding a_2 (a_1Ia_2) *whether* : $\Phi(a_1) = \Phi(a_2)$; and
- $\begin{cases} a_1Pa_2 & \Phi(a_1) > \Phi(a_2) \\ a_1Ia_2 & \Phi(a_1) = \Phi(a_2) \end{cases}$.

2.3 Pearson's correlation

The Pearson's correlation coefficient (r) measures the linear association between two quantitative variables. In the analysis of innovation indicators, the correlation coefficient measures the pairwise association among indicators, considering the values of the set of indicators' values among themselves, as the variables analyzed. The value of r varies between −1 and 1, so it can be positive or negative. A positive correlation between two innovation indicators indicates the same tendency of either growth or decrease of these innovation indicators. Subsequently, a negative correlation between two indicators indicates opposite tendencies of growth and decrease of innovation values; in other words, as one of them tends to be a better reference in terms of innovation indicator, the others tend to be less representative to be considered as innovation indicators. These results depend on each country profile (Grácio & Oliveira, 2015).

Regardless of the direction of the correlation (positive or negative), the correlations can also vary in terms of strength: from absence (equal to zero) to a very strong or even perfect correlation (r value equal to −1 or 1). Considering x_i the frequency of values of one indicator X in relation to other indicators and y_i the frequency of i values of one indicator Y with the other innovation indicators, for i varying from 1 to n, with n equal to the number of indicators in the GII 2016, the Pearson's correlation coefficient (r) between X and Y is defined by equation (1) (Galarça, Lima, Silveira, & Rufato, 2010; Grácio & Oliveira, 2015):

$$\mathrm{r} = \frac{\sum x_i.\ y_i - \frac{\sum x_i.\sum y_i}{n}}{\sqrt{\left(\sum x_i^2 - \frac{(\sum x_i)^2}{n}\right).\left(\sum y_i^2 - \frac{(\sum y_i^2)}{n}\right)}} \quad (1)$$

The Pearson's correlation coefficient results from the WIPO's GII Audit 2016, which demonstrated such as the GII 2015 Report the three highest Pearson's correlation sub-pillars that enabled their allocation in the seven innovation pillars. After other multivariate statistical analysis procedures, the audit team adds the conceptual framework of quantitative data and analysis to corroborate to the next GII Report to be published, formulating an innovation ranking with innovation indicators along with their pillars and sub-pillars (Cornell University, INSEAD and WIPO, 2015, 2016).

3. Methodology

As it can see in Figure 2, the methodology is structured in three phases, namely,

(1) using AHP to define criteria weights;
(2) ranking the alternatives;
(3) comparing the results.

3.1 Using analytical hierarchy process to define criteria weights

The AHP was used to obtain the weight of each one of the criteria of GII 2016, after aligning it with Pearson's correlation. The alignment was made by the global average of Pearson's correlation innovation indicators used by WIPO compared to the AHP standard scale. According to Macharis, Springael, De Brucker, and Verbeke (2004), this procedure provides an opportunity to apply AHP-Borda as a weight to PROMÉTHÉE.

The judgments were made during meetings by experts in economic development, innovation (based on the understanding of GII reports published by WIPO), operational research, applied mathematics and computer science.

3.2 Ranking the alternatives

This phase is divided into two. In the first, the De Borda method is applied to rank the countries, having as input the weights from AHP and the countries' evaluations under GII criteria. In the second one, the PROMÉTHÉE is adopted to obtain the ranking of the countries. The inputs of this step are the weights from AHP and the countries' performance according to the GII. As one can notice, in this phase the weights generated through AHP were used as an input to be used in the MCDA method – as first proposed by Da Rocha, Da Silva, DE Barros, & Costa, 2016.

3.3 Comparing the results

From Pearson's correlation initial analysis, it is possible to understand the importance of the innovation indicators for upper-middle income countries (i.e. understanding their pertinence for these peculiar countries). After aligning Pearson's ranges to AHP Saaty' scale, AHP was computed and combined with De Borda ranking system. Such AHP combinations made the Operational Research team execute quantitative procedures by using PROMÉTHÉE, observing an outranking of results that indicated potential investments groups of countries presenting a "hub" profile.

This paper aims to discover if these innovation indicators can be considered good parameters for understanding the profile of upper-middle income countries. Pearson's correlation was the basis for understanding how upper-middle income countries act, considering the innovation indicators of these countries' profiles.

Pearson's correlation was identified as the milestone for this paper because it was necessary to understand how innovation indicators were representative for upper-middle income countries. After carrying out Pearson's correlation analysis in these indicators aligned with the calculated and validated AHP and considering the representativeness of the indicators according to the DMs of the operational research team, it was necessary to provide a brief understanding on MCDA; more specifically, how Borda was applied in the AHP results.

Hence, after achieving weights via AHP, these weights were used in an ordering-ranking with Borda for a pilot project to make investors understand the MCDA concepts and how AHP weights were used in PROMÉTHÉE; whose results were computed via GAIA software. The use of the software GAIA was necessary herein because it is PROMÉTHÉE's seminal software. The use of GAIA provides the original perspective of the decision-making process. Thus, the exploratory nature might show relevant variables necessary to understand innovation indicators in the environment of national and international strategy and competitiveness (Martins, Lima, & Costa, 2015). In this paper, inspired by Da Rocha et al. (2016), the De Borda method combined with AHP was used as the sum of the alternatives; the AHP results were used as weights that resulted in the global net flow.

PROMÉTHÉE II results provide a ranking that can be used to solve the decision-making problem according to the alternatives considered herein. The software GAIA was used to compute all the data. From these last multicriteria applications, the decision for investment was explored jointly with investors.

3.4 Multicriteria decision aid computing procedures

This paper observes via MCDA tools if innovation indicators might be considered by investors for investment possibilities in upper-middle income countries according to the GII 2016 data. Pearson's correlation was the basis for starting an AHP application regarding innovation indicators.

Pearson's correlation practiced by GII 2016 had innovation indicators audited with the same system from 2015: all the sub-pillars with the highest Pearson correlation coefficients were bracketed inside the innovation indicators; thus, all 21 sub-pillars were defined in each of one 7 innovation indicators, as shown in Table 2 (Cornell University, INSEAD, & WIPO, 2016).

Initially, Pearson's correlation shows a concentration between 0.4 and 0.7. If this concentration has not been observed, the calculations of the MCDA stages would not have been pertinent in terms of undertaking investments. Pearson's correlation shows a statistical correlation regarding the strength of each pair of variables observed whilst AHP observes the importance. Some analysts understand the strength brought by Pearson's correlation as an opportunity for aligning a statistical data from GII 2016 to a MCDA tool such as AHP, whose importance serves as several other multicriteria analyses when used with other multicriteria aid tools.

Saaty's scale was used for analysts who observed usual concentration of odd numbers in the scale, which could not indicate a good alignment between Pearson's correlation and AHP scale; contrary to a fairly common practice among multicriteria aid tools when AHP is applied with odd numbers (Franek, & Kresta, 2014). The use with Saaty's scale of importance was tested with 8 and 9; however, such importance numbers showed incoherence when applied to Pearson's correlation because no indicators have an absolute dominance over their pairs; the dominance indicated is the most adequate high scale level for aligning Pearson's correlation organized in ranges according to Table 3.

From this perspective, analysts decided to range Pearson's correlation for observing the behavior of indicators inside these ranges when they were aligned with AHP's consistency considering the matrix size. Intervals from 0 to 0.99 were used, being the first interval from 0 to 0.39 because such interval did not appear at GII 2016 Pearson's correlation, turning Saaty's comparison scale into an important resource, represented by the number 1. The following ranges were established in 0.09 ranges by each interval and were equalized to each AHP scale within the comparison scale shown in Table 3.

This alignment allows to start AHP computations according to Table 4, where the AHP scale was inserted aligned with the range from the coefficient average of Pearson's correlation.

Table 5 shows AHP results with each innovation indicators and their weight.

In the third stage, after observing both importance and strength among GII 2016 indicators, it was necessary to show DMs a perspective for investment in upper-middle income countries, defined by analysts as a pilot project for the decision-making process considering multicriteria investments perspectives. With such innovation indicators representative percentage calculated after alignment, the next stage was the better understanding for sorting middle-income countries according to these innovation indicators

Table 2. Pearson correlation coefficient results for each sub-pillar inside innovation indicators

Sub-pillar	Indicator 1 – institutions	Indicator 2 – human capital and research	Indicator 3 – infrastructure	Indicator 4 – market sophistication	Indicator 5 – business sophistication	Indicator 6 – knowledge and technology outputs	Indicator 7 – creative outputs
Input							
Political environment	0.94	0.77	0.84	0.7	0.74	0.69	0.8
Regulatory environment	0.92	0.63	0.67	0.58	0.65	0.6	0.67
Business environment	0.9	0.71	0.75	0.68	0.62	0.68	0.71
Education	0.52	0.75	0.54	0.4	0.48	0.51	0.52
Tertiary education	0.65	0.79	0.75	0.57	0.46	0.52	0.57
Research and development (R&D)	0.69	0.89	0.77	0.78	0.81	0.84	0.74
Information and communication technologies (ICTs)	0.77	0.83	0.94	0.7	0.64	0.69	0.76
General infrastructure	0.62	0.62	0.74	0.55	0.58	0.56	0.54
Ecological sustainability	0.62	0.6	0.74	0.52	0.51	0.52	0.63
Credit	0.65	0.6	0.58	0.85	0.59	0.52	0.57
Investment	0.48	0.5	0.42	0.76	0.52	0.49	0.4
Trade, competition and market scale	0.51	0.66	0.71	0.71	0.5	0.64	0.6
Knowledge workers	0.63	0.8	0.68	0.67	0.85	0.73	0.67
Innovation linkages	0.53	0.4	0.42	0.43	0.72	0.49	0.49
Knowledge absorption	0.6	0.56	0.56	0.54	0.82	0.71	0.59
Output							
Knowledge creation	0.63	0.79	0.63	0.66	0.75	0.88	0.77
Knowledge impact	0.51	0.51	0.56	0.44	0.5	0.73	0.59
Knowledge diffusion	0.52	0.54	0.51	0.52	0.64	0.73	0.5
Intangible assets	0.62	0.61	0.67	0.54	0.56	0.65	0.89
Creative goods and services	0.67	0.63	0.64	0.54	0.61	0.69	0.84
Online creativity	0.81	0.78	0.77	0.67	0.76	0.77	0.88

Source: Cornell University, INSEAD and WIPO (2016) using other MCDA information. To identify the level of comprehension, the AHP-Borda method was used.

The analysts decided to show the pilot project using the AHP-Borda to support innovation investment tendencies, for considering this tool simple for being understood by anyone not involved in MCDA analysis. Analysts made two different procedures using Borda: a simple Borda demonstration using the row sum from the seven innovation indicators of upper-middle income countries and also the AHP results used as weights for calculating Borda via weights. The different results are shown in Table 6, where it is possible to observe that only three positions (positions: 7, 24 and 32) in the rank do not change using these two different ways of calculating Borda.

After achieving weights via AHP, these weights were used in an ordering-ranking with Borda in a pilot project to make investors understand the MCDA concepts. After understanding the analysis, AHP weights were used in PROMÉTHÉE, whose results were computed via GAIA software. Thus, exploratory nature analyses might show relevant variables to understand innovation indicators in the environment of national and international strategy and competitiveness (Martins et al., 2015).

When analysts explain the method for choosing innovative upper-middle income countries to invest in, it was possible to understand tendencies and outranking changings using weights or not. As the qualitative data, according to GII 2016, was aligned with the quantitative result of the pilot project, analysts keep on calculating the MCDA using AHP-PROMÉTHÉE at GAIA software. With DMs understanding the supportive tools, considering the global and complete analysis with the upper-middle income countries, we used AHP-PROMÉTHÉE II to conclude the analysis in which some GII 2016 countries show possibilities for investment to promote the development of innovation.

4. Results and discussion

After analysts explained the method for choosing innovative upper-middle income countries to invest in, it was possible to understand the tendencies and rankings using weights or not. As the qualitative data, according to GII 2016, was aligned with the quantitative result of the pilot project, analysts keep on calculating the MCDA using AHP-PROMÉTHÉE and GAIA.

The AHP results were used as weights in PROMÉTHÉE II. The GAIA software computation revealed a different investment scenario for upper-middle income countries from the GII 2016 ranking: Malaysia becomes the first country to be chosen for investment, followed by Montenegro, Bulgaria, Romania and China.

Figure 3 show an adaptation from the GAIA software illustration of net flow (Phi) result, the positive preference flow result (Phi+) and the negative preference flow result (Phi−).

Pearson's range organized from GII's audit	AHP scale compared to Pearson's correlation	Saaty's comparison scale	Saaty's scale of importance
[0, 0.39]	1	Equal importance	1
[0.40, 0.49]	2	Weak dominance	3
[0.50, 0.59]	3	Strong dominance	5
[0.60, 0.69]	4	Demonstrated dominance	7
[0.70, 0.79]	5	Absolute dominance	9
[0.80, 0.89]	6	(Intermediate values)	(2, 4, 6, 8)
[0.90, 0.99]	7		

Source: The authors

Table 3. Aligning Pearson's range to AHP

Description	Indicator 1 – institutions	Indicator 2 – human capital and research	Indicator 3 – infrastructure	Indicator 4 – market sophistication	Indicator 5 – business sophistication	Indicator 6 – knowledge and technology outputs	Indicator 7 – creative outputs
Indicator 1 – institutions	1	5	5	4	4	4	5
Indicator 2 – human capital and research	0.2	1	4	3	3	4	4
Indicator 3 – infrastructure	0.2	0.25	1	4	3	4	4
Indicator 4 – market sophistication	0.25	0.333333	0.25	1	3	3	3
Indicator 5 – business sophistication	0.25	0.333333	0.33333333	0.33333333	1	4	3
Indicator 6 – knowledge and technology outputs	0.33333333	0.25	0.25	0.33333333	0.25	1	4
Indicator 7 – creative outputs	0.33333333	0.25	0.25	0.33333333	0.33333333	0.25	1

Source: The authors

Table 4.
AHP initial computations

Malaysia shows the distance from the other upper-middle income countries having 0.8737 in preference for investments considering the innovative profile of innovation indicators weights used in PROMÉTHÉE II calculus.

Figure 4 shows an adaptation from a GAIA image with a net flow graph result. It is possible to observe clusters being formed as a sequence of investments in the same region; for example, it is possible to start an investment in Montenegro, followed by Bulgaria and Romania, with the same potential investment because they are developing industries in their region as a cluster. Observing the results presented by the graph, it is possible to understand the investment cycle in upper-middle income countries because there is an investment tendency rebounding in these economies and inside the integrated chain from each region where these countries belong to.

Figure 5 has an interesting perspective of strong and weak innovation indicators for each selected country. Despite being an individual perspective stemming from PROMÉTHÉE I in each innovation indicator, it is interesting to analyze it because it indicates deeply in which investment scenarios it is possible to invest in to obtain profits in the short-term, considering the economic sectors involved in each countries and investments that only provide financial returns in the long-term.

The use of all these MCDA tools was important to encourage DMs to invest in countries not only taking into consideration the GII 2016 ranking of the most innovative countries by area, region or economic profile. These MCDA tools combined showed how the qualitative data available at GII 2016 is important to be analyzed from a quantitative perspective for multicriteria decision supportive tools because there are possibilities to see beyond the ranking report, the global innovation tendency and how countries will project their economies using their strong and weak innovation indicators.

It is possible to observe investment opportunities organizing the countries in subsets according to the following analysis results from AHP-BORDA and AHP- PROMÉTHÉE. Table 7 shows the GII's 2016 upper-middle income countries' ranking organized in the initial analysis. The three first subsets present a bold minimum number and the fourth subset presents a bold maximum number to highlight borderline numbers

Table 8 compares ranking results of Borda row sum, AHP-Borda and AHP-PROMÉTHÉE II where only Paraguay at position 32 presents the same result for all the three MCDAs adopted.

Considering the information presented in Table 8, the results of the Pearson's correlation and AHP-Borda result in a Borda's row sum of 0.87. The results of the Pearson's correlation that stem from AHP-Borda and AHP-PROMÉTHÉE II was 0.98. The result of the Pearson's correlation and Borda's row sum with AHP-PROMÉTHÉE II was 0.88. These correlations demonstrate a strong consistency of results.

Item description	Weight (%)
Indicator 1 – institutions	35.75
Indicator 2 – human capital and research	19.63
Indicator 3 – infrastructure	15.42
Indicator 4 – market sophistication	10.30
Indicator 5 – business sophistication	8.42
Indicator 6 – knowledge and technology outputs	6.36
Indicator 7 – creative outputs	4.12

Source: The authors

Table 5. Innovation indicators' AHP results

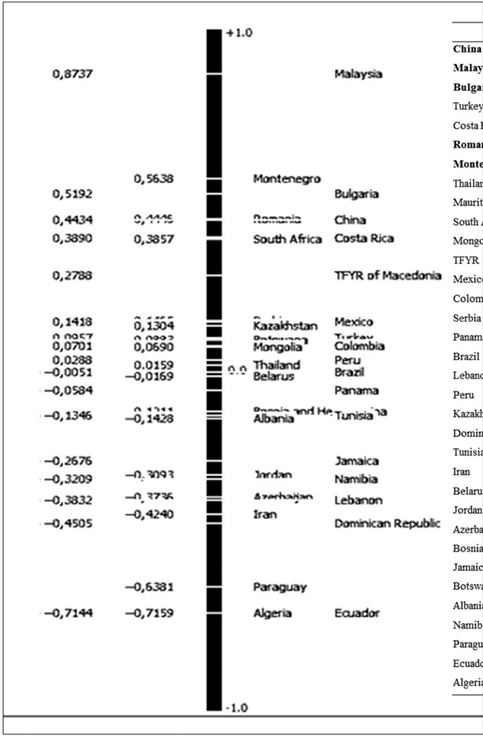
UM countries	Global order number (row sum)	Global order number (AHP weights)	Final rank by row sum	Final rank by AHP weights
China	361.7	52.7027	1	2
Malaysia	329.5	54.2216	2	1
Bulgaria	301.6	49.1042	3	5
Turkey	283.8	44.7568	6	15
Costa Rica	288.5	48.0115	4	8
Romania	283.7	48.3001	7	7
Montenegro	287.8	49.2535	5	4
Thailand	275	43.5735	10	19
Mauritius	280.6	51.2203	9	3
South Africa	281.7	48.3881	8	6
Mongolia	267.6	44.8256	13	12
TFYR of Macedonia	268.5	47.0867	11	9
Mexico	265.7	44.7746	14	13
Colombia	267.9	44.5585	12	16
Serbia	257.8	45.3774	17	11
Panama	255	42.5575	18	22
Brazil	260.9	43.1900	15	20
Lebanon	244.2	39.6076	21	29
Peru	259.4	44.0146	16	17
Kazakhstan	251.3	45.4998	19	10
Dominican Republic	235.7	38.6272	25	30
Tunisia	236.6	42.0417	24	24
Iran, Islamic Rep.	229.2	37.5875	29	31
Belarus	247.6	43.7283	20	18
Jordan	228.1	40.8777	30	26
Azerbaijan	233.6	40.0873	27	28
Bosnia and Herzegovina	240	42.7529	22	21
Jamaica	229.7	41.4919	28	25
Botswana	238.5	44.7571	23	14
Albania	235.1	42.4701	26	23
Namibia	222.9	40.5823	31	27
Paraguay	217	35.6831	32	32
Ecuador	210.2	34.3115	33	34
Algeria	196.3	34.3877	34	33

Source: The authors

Table 6.
Borda results using row sum and AHP

Although China, according to GII 2016, is the first upper-middle income country, the infrastructure innovation indicator presents a weak profile in the short-term qualitative and quantitative data analysis because the increase in steel inventory from 2016 to 2017 shows that the processing industries perspective for developing new production chain links become less preferable for investing than ICT sectors, which can be observed in other innovative indicators in recent years.

Similarly, Malaysia presents an ICT economic sector stronger than other countries geographically and by economic profile according to the GII 2016 selection of upper-middle income countries. As part of the Asian tigers as a country with a strong electronic processing industry, Malaysia's innovation indicators presented three stronger scores than other upper-middle income countries and the strongest innovation indicators scores in comparison to other Asian countries. Regarding the ICT economic sector profile, with a cyclical demand and offer movement for new production process and new adjustments in



	Phi+	Phi-	Phi	Global Rank
China	**0.6902**	**0.2469**	**0.4434**	**5**
Malaysia	**0.9134**	**0.0397**	**0.8737**	**1**
Bulgaria	**0.6898**	**0.1705**	**0.5192**	**3**
Turkey	0.4906	0.3949	0.0957	13
Costa Rica	0.6289	0.24	0.389	7
Romania	**0.6626**	**0.218**	**0.4446**	**4**
Montenegro	**0.7244**	**0.1606**	**0.5638**	**2**
Thailand	0.437	0.4211	0.0159	18
Mauritius	0.6428	0.2512	0.3916	6
South Africa	0.6166	0.2309	0.3857	8
Mongolia	0.4664	0.3973	0.069	16
TFYR of Macedonia	0.5871	0.3082	0.2788	9
Mexico	0.5031	0.3613	0.1418	11
Colombia	0.4841	0.414	0.0701	15
Serbia	0.4931	0.3466	0.1465	10
Panama	0.4014	0.4598	-0.0584	21
Brazil	0.4149	0.4201	-0.0051	19
Lebanon	0.2514	0.6347	-0.3832	29
Peru	0.4583	0.4294	0.0288	17
Kazakhstan	0.4938	0.3634	0.1304	12
Dominican Republic	0.2265	0.677	-0.4505	31
Tunisia	0.3946	0.5292	-0.1346	23
Iran	0.2437	0.6677	-0.424	30
Belarus	0.4315	0.4484	-0.0169	20
Jordan	0.3012	0.6105	-0.3093	26
Azerbaijan	0.2642	0.6378	-0.3736	28
Bosnia and Herzegovina	0.3892	0.5103	-0.1211	22
Jamaica	0.3148	0.5824	-0.2676	25
Botswana	0.4571	0.3688	0.0883	14
Albania	0.3705	0.5133	-0.1428	24
Namibia	0.2858	0.6068	-0.3209	27
Paraguay	0.1491	0.7872	-0.6381	32
Ecuador	0.0993	0.8136	-0.7144	33
Algeria	0.094	0.8098	-0.7159	34

Figure 3.
Adaptation from GAIA with net flow results

Source: Brans & Mareschal (1990) - Visual PROMÉTHÉE Academic

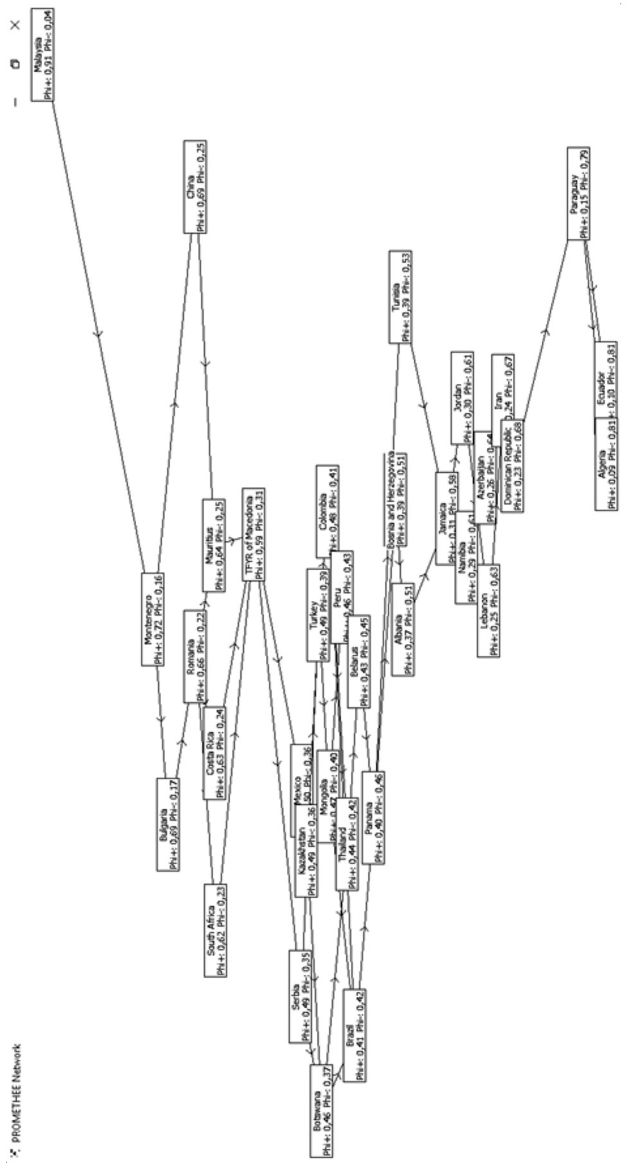
the production chain for competitiveness, Malaysia becomes the first destination of investments when observing the countries selected.

Table 9 presents a proposal for investors, considering the integration between production chain and transnationality involving economic sectors in different countries and continents. Considering the profiles of the countries, the basic competitive industrial structure and the supply flows in several production chains, it is possible to observe four groups in which countries present a similar behavior, whose integrated investment development of different regions and areas promote competitiveness according to the innovation indicators observed in these countries. It is interesting to analyze these groups as an opportunity for technological frontiers.

Table 10 shows the minimum score's validation for each country obtained in each indicator by subset. By analyzing these scores, it was possible to observe, for instance, that Thailand – despite having a Group 1 profile – is allocated in Group 2; the same way, even though Paraguay presents a Group 3 profile, it was allocated in Group 4.

In the light of the above-mentioned information, groups where re-organized according to Table 11 observing the new subsets for investments of upper-middle economies.

After the profile identification, it is possible to notice that Group 1 has four countries showing a peripheral industry behavior in their regions; Group 2 has opportunities for investments in countries with integrated production chain in extractive



Source: Brans & Mareschal (1990) - Visual PROMÉTHÉE Academic

Figure 4.
Adaptation from
GAIA screen graphs

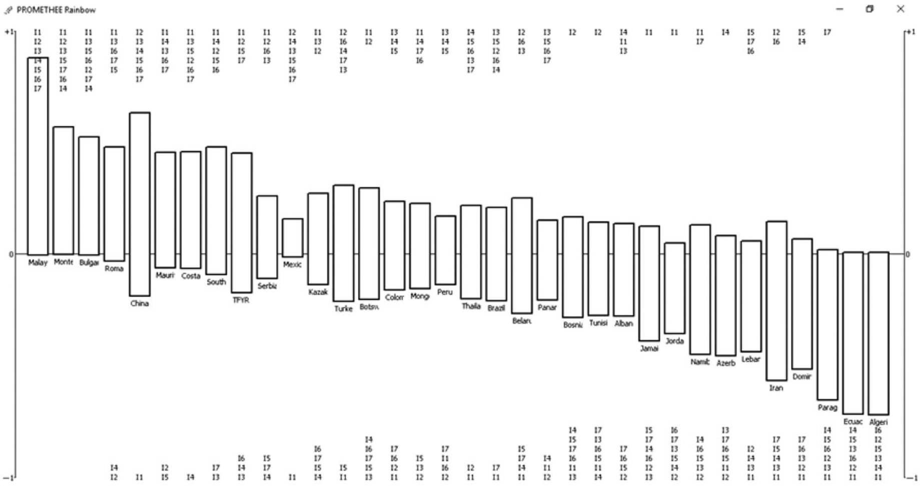


Figure 5.
Walking weights

Source: Brans & Mareschal (1990) - Visual PROMÉTHÉE Academic

industries (Oil & Gas) and manufacturing industry belonging to a hub in their regions for supplying added value industries. Group 3 presents opportunities for investing in these countries where they have production sectors or economic sectors where the investment leverages also other integrated sectors.

Regarding the quantitative perspective, using Borda's row sum, AHP-Borda and AHP-PROMÉTHÉE II shown in Table 8, it is also interesting for investors to observe that despite the use of three different MCDA applications, it was possible to envision investments in these countries, i.e. four groups with similar country behaviors. When changes in the ranking results become concentrated in some countries creating an "investment belt," it indicates another opportunity for DMs to define their investments preferences more accurately.

Therefore, achieving a threshold from the minimum score at each of the three first groups and the maximum for the last group becomes an opportunity for raising upper-middle countries' investment standard; it means that for each country there is a growth goal according to the minimum innovation indicator belonging to the next group level. Table 10 indicates such thresholds moving within the groups.

5. Conclusion and final considerations

The question proposed by this paper was answered with the combined tools MCDA, AHP-PROMÉTHÉE II giving opportunity for investing in upper-middle income countries. These countries were analyzed for their innovation indicators; being corroborated by short- and long-term economic prospects.

After meeting the purpose of this research, it was possible to identify minimum values for scoring countries in subsets, whose values may become goals for reaching by the countries raising their economic development sectors.

The result brought up by the hierarchical model used in the two models of MCDA considered the methodology and adoption of criteria and sub criteria that presented some technological potential. These methodological concepts were determinant for proposing technological arrangements compatible with AHP and PROMÉTHÉE II multicriteria decision support aid models. The results obtained are compatible with the authors' proposal

Table 7. GII's 2016 WIPO's rank for upper-middle income economies

Upper-middle countries	Indicator 1 institutions	Indicator 2 human capital and research	Indicator 3 infrastructure	Indicator 4 market sophistication	Indicator 5 business sophistication	Indicator 6 knowledge and technology outputs	Indicator 7 creative outputs
Montenegro	69.2	35.8	45.8	43.8	36	*23.4*	33.8
South Africa	69.1	33.1	37.4	58.7	32.2	24.7	26.5
Costa Rica	66.7	32.1	47.4	38.1	40.4	26.8	37
Turkey	54.6	39.2	43.6	47.7	27.6	29.1	42
Romania	69	30.2	48.9	41.8	30.2	31	32.6
Bulgaria	67.8	32.1	46.7	43.7	36.2	32.1	43
Malaysia	70.9	43.3	49.2	55	41.8	33.4	35.9
China	55.2	48.1	52	56.6	53.8	53.3	42.7
Belarus	56	42.6	43.6	39.1	28.7	28.1	*9.5*
Kazakhstan	66.5	31.4	46.8	38.6	25.4	21.2	21.4
Brazil	55.3	32.5	44.9	43.9	37	23.7	23.6
Serbia	65.7	32.8	43.7	34.3	28.1	27.7	25.5
Peru	60.4	27.5	45	50	32.9	16.4	27.2
Colombia	58.2	27.9	52.5	49.4	30.8	21.2	27.9
Mauritius	80.5	30	43.1	49.5	25.6	22.9	29
Panama	59.6	22	47	42.3	30.7	24.2	29.2
Mexico	60.5	33.7	42.8	45.7	29.8	23.3	29.9
Thailand	54.7	30.7	42.8	51.4	35.3	29	31.1
TFYR of Macedonia	71.4	33.4	34.5	40.7	31.5	21.9	35.1
Mongolia	64.8	26.9	38.3	49.9	27.8	23.4	36.5
Namibia	64.7	21	36.2	40	21.3	*8.8*	30.9
Jamaica	65.3	24.2	31.2	40.3	28.8	16.3	23.6
Albania	62.3	23.6	43.6	51.2	21.9	17.2	15.3
Azerbaijan	56.4	22.9	40.8	52.1	19.7	17.6	24.1
Bosnia and Herzegovina	58.7	41	33	42.8	27.1	17.8	19.6
Botswana	68.3	32.6	37	42.8	23.9	18.6	15.3
Dominican Republic	53.6	19	38.9	45.5	32.1	19.1	27.5
Tunisia	58.3	38	41.6	29	23.7	19.9	26.1
Jordan	62.6	25.4	38.5	32	21.5	21.7	26.4

(*continued*)

Table 7.

Upper-middle countries	Indicator 1 institutions	Indicator 2 human capital and research	Indicator 3 infrastructure	Indicator 4 market sophistication	Indicator 5 business sophistication	Indicator 6 knowledge and technology outputs	Indicator 7 creative outputs
Lebanon	52.1	29.8	37.5	37.9	31.7	22.4	32.8
Iran, Islamic Republic	45.9	36.9	36.7	36.2	22.8	24	26.7
Paraguay	*47.9*	24.4	34.1	42.3	25	11.8	31.5
Algeria	45.7	28.2	37.2	31.7	21.2	17.7	14.6
Ecuador	44.6	21.4	38.7	40.7	24.2	13.2	27.4

Source: Adapted from Cornell University, INSEAD and WIPO (2016)

UM countries	Borda row sum	AHP-Borda	AHP-PROMETHEE II
China	1	2	5
Malaysia	2	1	1
Bulgaria	3	5	3
Turkey	6	15	13
Costa Rica	4	8	7
Romania	7	7	4
Montenegro	5	4	2
Thailand	10	19	18
Mauritius	9	3	6
South Africa	8	6	8
Mongolia	13	12	16
TFYR of Macedonia	11	9	9
Mexico	14	13	11
Colombia	12	16	15
Serbia	17	11	10
Panama	18	22	21
Brazil	15	20	19
Lebanon	21	29	29
Peru	16	17	17
Kazakhstan	19	10	12
Dominican Republic	25	30	31
Tunisia	24	24	23
Iran, Islamic Republic	29	31	30
Belarus	20	18	20
Jordan	30	26	26
Azerbaijan	27	28	28
Bosnia and Herzegovina	22	21	22
Jamaica	28	25	25
Botswana	23	14	14
Albania	26	23	24
Namibia	31	27	27
Paraguay	*32*	*32*	*32*
Ecuador	33	34	33
Algeria	34	33	34

Source: The authors

Table 8. Rankings comparison with different MCDAs combination

of offering to DMs a complete ranking of alternatives for contributing with the decision-making process improvement in terms of choices related to technological investments alternatives.

This paper presents quantitative observations based on which upper-middle income country DMs can invest considering strong and weak innovation indicators according to their perspectives, supported by the qualitative observation obtained from GII 2016.

When first analyzing the ranking of innovation indicators, the MCDA provided a better support to investment decision-making because all the innovation indicators were considered in the results in a deep way when Pearson's correlation coefficient was the highest one in the sub-pillars of each innovation indicator and PROMÉTHÉE II completes the ranking. AHP weights are used in PROMÉTHÉE II computations justifying the rank according to the weights. A pilot project for investors proposed the MCDA using AHP-Borda.

Borda row sum	AHP-Borda	AHP- PROMÉTHÉE II	Groups
China	Malaysia	Malaysia	Group 1: China, Malaysia, Bulgaria, Costa Rica, Montenegro, Romania and South Africa
Malaysia	China	Montenegro	
Bulgaria	Mauritius	Bulgaria	
Costa Rica	Montenegro	Romania	
Montenegro	Bulgaria	China	
Turkey	South Africa	Mauritius	
Romania	Romania	Costa Rica	
South Africa	Costa Rica	South Africa	
Mauritius	TFYR of Macedonia	TFYR of Macedonia	Group 2: Mauritius, Thailand, Macedonia, Colombia, Mongolia, Mexico, Brazil, Peru, Serbia, Kazakhstan and Belarus
Thailand	Kazakhstan	Serbia	
TFYR of Macedonia	Serbia	Mexico	
Colombia	Mongolia	Kazakhstan	
Mongolia	Mexico	Turkey	
Mexico	Botswana	Botswana	
Brazil	Turkey	Colombia	
Peru	Colombia	Mongolia	
Serbia	Peru	Peru	
Panama	Belarus	Thailand	
Kazakhstan	Thailand	Brazil	
Belarus	Brazil	Belarus	
Lebanon	Bosnia and Herzegovina	Panama	Group 3: Lebanon, Bosnia and Herzegovina, Botswana, Tunisia, Dominican Republic, Albania, Azerbaijan, Jamaica, Iran Islamic Rep., Jordan and Namibia
Bosnia and Herzegovina	Panama	Bosnia and Herzegovina	
Botswana	Albania	Tunisia	
Tunisia	Tunisia	Albania	
Dominican Republic	Jamaica	Jamaica	
Albania	Jordan	Jordan	
Azerbaijan	Namibia	Namibia	
Jamaica	Azerbaijan	Azerbaijan	
Iran, Islamic Republic.	Lebanon	Lebanon	
Jordan	Dominican Republic	Iran, Islamic Rep.	
Namibia	Iran, Islamic Rep.	Dominican Republic	
Paraguay	Paraguay	Paraguay	Group 4: Paraguay, Ecuador and Algeria
Ecuador	Algeria	Ecuador	
Algeria	Ecuador	Algeria	

Source: The authors

Table 9.
Groups of countries for investing according to their similar profiles

It is important to demonstrate herein that when investing in one single economic sector of a country, there is a subsequent investment in another country, which boosts transnational economy and investment. The three MCDA tools used herein provide the possibility of investing according to investors' preference in four different countries groups correlated due to their integrated supply chain in some economic sectors.

All these MCDA methods used in this paper are important to observe how the investment decision can change when criteria are deeply computed and associated with weights from other multicriteria tools, increasing the investment understanding and the country profile, the cluster association among neighboring partners inserted or not in the alternatives analyzed.

Table 10. Scores' validation analysis

UM countries	Indicator 1 – institutions	Indicator 2 – Human capital and research	Indicator 3 – infrastructure	Indicator 4 – market sophistication	Indicator 5 – business sophistication	Indicator 6 – knowledge and technology outputs	Indicator 7 – creative outputs
Group 1 – minimum	54.6	30.2	37.4	38.1	27.6	23.4	26.5
Group 2 – minimum	54.7	22	34.5	34.3	25.4	16.4	9.5
Group 3 – minimum	45.9	19	31.2	29	19.7	8.8	9.5

Source: Adapted from Cornell University, INSEAD, & WIPO (2016)

Table 11.
Re-organized subset of countries for investments

Group	Countries' subset
Group 1	China, Malaysia, Bulgaria, Costa Rica, Montenegro, Romania, South Africa and Thailand
Group 2	Mauritius, Macedonia, Colombia, Mongolia, Mexico, Brazil, Peru, Serbia, Kazakhstan and Belarus
Group 3	Lebanon, Bosnia and Herzegovina, Botswana, Tunisia, Dominican Republic, Albania, Azerbaijan, Jamaica, Iran Islamic Rep., Jordan, Namibia and Paraguay
Group 4	Ecuador and Algeria

Source: The authors

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Appendix

Abbreviation	Description
AHP	Analytical hierarchy process
CI	Consistency index
CR	Consistency ratio
DM	Decision-makers
GII	Global innovation index
ICT	Information and communication technologies
MCDA	Multicriteria decision aid
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluation
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
UM	Upper-middle income countries
WIPO	World Intellectual Property Organization

Source: The authors

Table A1. List of abbreviations

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