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Technology assessment with IF-TOPSIS: An application in the advanced underwater system sector

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ABSTRACT

Technologies are pivotal for firms' success, but also resource consuming. Therefore, managers have to assess and select technologies carefully in order to allocate resources on the most promising ones, grounding their decisions on adequate sets of criteria on which experienced people can express their opinion.

This work proposes an application of Multi Criteria Decision Aids to technology assessment, where Decision Support Systems offer an effective support for evaluating technology impact on firms' success, building on experts' judgments.

The method is based on a peer-based modification to Intuitionistic Fuzzy multi-criteria group decision making with TOPSIS method (peer IF-TOPSIS). A case study in which this methodology is applied to a company operating in the military sector (Advanced Underwater System) is also presented.

Besides the empirical proof of the method's suitability and value in assisting managers in their decision, the paper's contributions are both methodological and theoretical. Methodologically, while allowing a peer-based voting procedure, the method enhances the consensus in the firm and limits the possible biases that a supra-decision maker could introduce. Theoretically, the set of proposed criteria includes many facets of the assessment problem, and avoids being tailored to the investigated technological field, so enhancing its generalizability.

1. Introduction

Technologies play a key role for firms' success as they can positively contribute to create value and to stay ahead in the competitive arena. Nevertheless, technologies consume both resources and managers' attention (Aloini et al., 2011). Therefore, managers have to get most out of technologies, while properly allocating resources between the most promising ones, whatever their origin, either internal, external or co-developed with other partners.

Since the early '80s the scientific debate has proposed different approaches for evaluating and selecting technologies (Foster, 1981; Harris et al., 1981; Chien, 2002; Bitman and Sharif, 2008; Wang et al., 2008; Kester et al., 2009; Chiesa et al., 2008; Van Wyk, 2010). The result of this long debate is that, to date, the literature, on the one hand, has set forth interesting suggestions, but, on the other, has put forward models and methods that present some flaws (Jolly, 2012).

As regards this last point, some models are based on financial analysis (Raju et al., 1995; Chan et al., 2000), such as the net present value or the return on investments (Spradlin and Kutoloski, 1999; Kirchhoff et al., 2001), sometimes enriched with probability elements (Blau et al., 2004). The main limits of these methods dwell in the subjectivity, uncertainty and high variance of the financial judgments (particularly, as regards very far away cash flows), as well as in their inability to cope with non-financial elements, which are typically more challenging to measure and monetize, or they are not quantifiable at all. Another group of models builds on patents and bibliometric analyses in order to identify the potential areas of research interest (Yoon et al., 2002; Kelley and Rice, 2002; Levitas et al., 2006; Lee et al., 2009). The major flaw of this group of models consists of their narrow focus, in that decisions are based on a single indicator. Other models have been proposed in the literature, but usually they build on a very limited set of criteria (Jolly, 2012). For example, Jeong and Kim (1997) suggest that the most attractive technology is the one with a high technological causality or the shortest possible time lag between a seed technology and a goal technology. Therefore, it emerges the need of methods that, while going beyond the only financial or patent analysis, embrace multiple aspects to be measured by means of multiple criteria able to assess technologies developed non-only internally, but also by external partners.

However, as anticipated, the literature also offers interesting

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suggestions. For instance, it emphasizes that the evaluation process of technologies implies to take decisions in environments in which both imprecise and precise values, objective and subjective information coexist; therefore, methods should be able to cope with subjectivity, imprecision, and vagueness intrinsic in such environments (Byun and Lee, 2005). Technology assessment often requires the involvement of many persons (Torkkeli and Tuominen, 2002): a wide and comprehensive group of experts should participate in a company's technology selection process in order to base the decision on the best available knowledge. Besides, the necessity to rely on multiple experts brings about issues connected with the way the experts' judgments are combined. On this topic, very recent literature has pointed out that peer-based procedures, as opposed to hierarchical ones, bring in important advantages in terms of consensus achievement and avoidance of biases due to the personal impressions that a supra-decision maker may introduce (Aloini et al., 2014).

In order to fill the above gap, while concurrently considering the useful suggestions, this work proposes a Multi Criteria Decision Aids (MCDA) approach to the appraisal of technology assessment, which could take into account the strategic nature of some key advantages of technologies. In fact, MCDA methods are a valuable solution able to include both quantitative and qualitative evaluation factors and to deal with the vagueness and imprecision inherent with technology assessment problem. More specifically, this paper builds on a modified version of Boran et al. (2009) an intuitionistic fuzzy multi-criteria decision making approach based on TOPSIS method which is inspired by a peer-based view of judgments (Aloini et al., 2014). Hence, a peer voting procedure among Decision Makers (DMs) supported by Intuitionistic Fuzzy Weighted Averaging (IFWA) operator (Xu, 2007) is used to obtain the group opinion on the relevance of the single decision maker.

The paper is structured as follows: theoretical background on the evolution of MCDA methods and particularly on MCDA applications in technology assessment is reported in Section 2, then Section 3 presents the methodology and (for sake of brevity and in order to avoid redundancy) its concurrent application to the case study, finally discussion and conclusion are given in Section 4.

2. Literature background

Multi Criteria Decision Aid and Technology Assessment are two huge, established, yet still very active research topics in the literature. Specifically, MCDA methods have received much attention from both researchers and practitioners for evaluating, assessing and ranking alternatives across diverse problems and industries. This also applies to technology assessment domain where MCDAs are adopted at different decision levels - global, national, sectorial, firm or specific R & D projects. As a matter of fact, most of the technology assessment related decisions can be conceptualized as a multi-objective, multi-criterion problem wherein subjective judgments and uncertainty play a key role.

In this context, the value of MCDA methods is well recognized for its capacity to deal with the complexity of decisions under conditions of uncertainty as it happens for example for technology management problems. Evidence from the literature clearly shows the high dynamism of the field. See for example the review papers by Mardani et al. (2015a, 2015b, 2015c) which exhaustively present the state-of-the-art about MCDA techniques since the '90 in different application areas, including service (Aloini et al., 2010). Accordingly, for sake of brevity it is hard here to make a thorough and comprehensive state-of-the-art analysis. We will just report an overview from the healthcare and energy domain where most recent and interesting developments were manifested.

As far as healthcare, MCDA methods are considered as a suitable way to overcome the limits of traditional technology evaluations, mostly based on a single indicator such as the Incremental Cost-Effectiveness Ratio (ICER), or the Incremental Cost per Quality-Adjusted Life-Year (QALY) (Thokala and Duenas, 2012). Recently, Ivlev et al. (2014) reviewed more than twenty contributions specifically addressing MCDA for to the assessment and management of medical technologies. In Ivlev et al. (2015), authors also suggest innovative approaches using a combination of health technology assessment (HTA) and MCDA methods.

MCDA has also become particularly popular for energy technology planning and management where complexity and uncertainty are mostly due to the involvement of multiple benchmarks and a high number of conflicting objectives and constraints like technical, social, economic and environmental issues. In this field, early MCDA approaches enriched single criteria approaches (Pohekar and Ramachandran, 2004), whose aim was only the sheer minimization of costs, with environmental and social considerations. Kumar et al. (2017) have recently provided an interesting and extensive MCDA review in the sphere of sustainable energy systems.

From a methodological perspective, researchers have continuously suggested modifications and hybridizations of traditional methods in order to overcome most relevant limitations – e.g. to deal with subjectivity of the experts' judgment and unavailability of exact data on technologies. Linstone et al. (1979) and Tran and Daim (2008) present a taxonomic review of methods and tools applied in technology assessment since 1970, ranging from analytic techniques up to integrated impact-analysis approaches to decision analysis. We report here some relevant contributions in order to draw a brief historical map of the methodology developments.

Evidence shows AHP, one of the most known and adopted MCDA techniques, being among the first methods to be interested to the adaptations (Winebrake and Creswick, 2003). The combination of the Delphi method and AHP was first suggested by Prasad and Somasekhara (1990) for the technology assessment in Indian Telecommunication industry. After them, Khouja (1995) combined DEA and MCDA for supporting technology selection of robotic machines. Later on, Fuzzy Set Theory – in some cases jointly with other techniques such as AHP and TOPSIS – was introduced in support of the technology assessment decision process in order to deal with uncertainty and related concepts like risk and ambiguity, which are prominent in the literature on decision making and the natural representation of the judgment. As an example, Jeong and Kim (1997) adopted linguistic variables for supporting a qualitative analysis of the impact exerted by technologies. After them, Chan et al. (2000) and Prabhu and Vizayakumar (2001) suggested an application of the fuzzy sets to hierarchical structural analysis for quantifying both tangible and intangible benefits in technology selection processes. More recently, Dereli and Altun (2013) developed a Fuzzy Inference System to evaluate and prioritize technologies with respect to their innovation potentials. Finally, Tavana et al. (2013) adopted a hybrid fuzzy/group decision support framework (Fuzzy-ANP and Fuzzy-TOPSIS) to address the need for a transparent, structured and analytical method for assessing and prioritizing the advanced-technology projects at the Kennedy Space Center.

In this context, last research directions seem to propose Intuitionistic Fuzzy Set (IFS) theory (Atanassov, 1986) as a valuable tool to better cope with the presence of vagueness and hesitancy originating from imprecise knowledge or information. However, while potentially promising, applications of the IFS related methods are to our best knowledge still neglected in the technology assessment.

3. Methodology and application

We adopt a peer-based modification to intuitionistic fuzzy (IF) multi-criteria group decision making with TOPSIS method (peer IF-TOPSIS). Drawing on IF-TOPSIS method by Boran et al. (2009), it seems suitable in order to face with subjectivity, imprecision, and vagueness in group decision making problem under multiple criteria. Also coherently with Aloini et al. (2014), the IFWA operator is here modified accordingly to a peer approach in order to skip a centralized assignment of DMs' weights and any possible related bias.

The method considers that the group involves multiple DMs, each with different skills, experience and knowledge relating to different aspects (criteria) of the problem so that the authors used IFWA operator to aggregate individual opinions of DMs for rating the importance of criteria and alternatives.

The suitability of the method is shown through an application to the case of a Business Division of a company operating in the Advanced Underwater System sector, which needs a tool to support its choices in terms of technologies to be developed in house, outside, or in co-development and to be embedded in products or systems.

The research has gone through the following phases:

1. *Analysis of the Decision Making Context*. The first step in good decision making involves defining what problem is being addressed and why, identifying scope and bounds for the decision, and clarifying the roles and responsibilities of the decision team. Decision makers' preference elicitation and modelling as the kind of input information are other important issues (Guitouni and Martel, 1998).
2. *Identification of the criteria for technology assessment*. A wide set of available criteria to be used in the technology assessment was identified by an in-depth literature review. The set of criteria was then reduced accordingly to the specific requirements coming from the step 1. Section 3.2 gives details of this step.
3. *Data collection and IF-TOPSIS implementation*. Collected data refer to a specific technological area of the investigated Business Division. Decision makers were asked to express their opinion on the importance of the evaluation criteria and of the other DMs, as well on the impact of the different technologies on the provided criteria.
   As regards the implementation of the method, we followed the well-known eight steps of the procedure as reported in Boran et al. (2009) and Aloini et al. (2014). Section 3.3 shows the mathematical details and the numerical exemplification about this phase. Briefly, they are reported below:
   – **Step 1:** Construct the aggregated importance IF decision matrix. Each decision maker votes the importance of each of the others on the basis of an intuitionistic fuzzy scale and all the opinions are fused into a group opinion.
   – **Step 2:** Determine the weights of the Decision Makers. Since all decision makers may not be assumed to be equally important and in order to obtain a set of grades of importance of each decision maker, the individual opinions need to be fused into a whole judgment.
   – **Step 3:** Construct the “aggregated IF decision matrix” based on the opinions of DMs. Each decision maker gives evaluations about each alternative according to the selected criteria, then all the opinions are aggregated into a decision matrix.
   – **Step 4:** Determine the weights of criteria. Since not all criteria may be assumed to be equally important, in order to obtain a set of grades of importance of each criterion, the individual decision maker opinions need to be fused into a whole judgment.
   – **Step 5:** Construct the “aggregated weighted IF decision matrix”. After the weights of criteria and the aggregated intuitionistic fuzzy decision matrix are determined, the aggregated weighted intuitionistic fuzzy decision matrix is obtained.
   – **Step 6:** Obtain IF positive-ideal solution and IF negative-ideal solution. The chosen criteria can be grouped in two different set, one including all the benefit criteria, and the other including the cost ones. Than for each alternative both the intuitionistic fuzzy positive-ideal and the intuitionistic fuzzy negative-ideal solution are obtained.
   – **Step 7:** Calculate the separation measures and closeness coefficient. The separation measures of each alternative from intuitionistic fuzzy positive and negative ideal solutions are calculated according to the normalized Euclidean distance and the relative closeness coefficient to the ideal solution is obtained.
   – **Step 8**: Rank the alternatives. The different alternatives are ranked according to the descending order of the relative closeness coefficient.

3.1. The decision making context

The Business Division belongs to a company operating in the Advanced Underwater System sector. It designs, develops and produces systems like artillery, weapons and torpedoes. The continuous technological evolution that the company has consistently applied to these systems over the years, allows offering a highly innovative, technologically advanced portfolio of products and systems able to respond effectively to the new operational land, naval and underwater warfare scenarios. Nevertheless, the possibility to offer such an array of complex systems and products requires the Division to manage many technological areas, each of which is composed of different technologies that are developed not only internally, but also together with other partners, or even thoroughly externally, because of the impossibility for the Division to completely rely only on internal technologies.

Whatever the origin of the technology – development, co-development or acquisition – resources are needed and budget constraints obviously apply to the company. This means that not all the internal (or co-developed) technologies can actually be advanced within each technological area, and not all the external technologies can be licensed-in or acquired.

In this context, the problem concerns with a “strategic” technology assessment in a business domain where the evaluation deals with the selection and acquisition of specific technologies to embed in new products (technologies that enhance the properties, features or qualities of a product to create a commercially relevant advantage such as cost, convenience, performance or safety). More exactly, we address a choice problem whose goal is to select the single best option or reduce the group of options to a subset of equivalent options. Situations of preference, weak-preference or indifference are possible. Instead, we exclude incomparability that might, for instance, be associated with missing information at the time of the assessment.

In the following we take as a reference (for sake of brevity) a specific technological area out of the three we investigated – that of *Guidance, Navigation and Control* – which is composed of nine technologies connected with aspects like the mission planning and the obstacle avoidance of vehicles in the underwater environment. Because of confidentiality reasons, their names will not be revealed in the paper.

As technology selection can significantly influence the whole company, the assessment of the nine technologies included in the selected technological area has been assigned to three decision experts with different educational backgrounds and knowledge (Torkkeli and Tuominen, 2002). Specifically, the choice of relying on three DMs rather than a single expert or a multiplicity of experts endowed with similar perspectives is rooted not only on the assumption that the collective error is less than the average individual error (Linstone, 2010), but also, and most importantly, on the fact that the three of them have T-shaped competences (Iansiti, 1993). Indeed, the selected DMs are, in the firm, the main specialists in the areas of guidance, navigation and control technologies, respectively (T's vertical stroke), and at the same time have an overall view of all the nine technologies included in the investigated technological area and therefore are acquainted with the interactions between technologies (the T's horizontal top stroke). Given these premises, the involvement of additional people in the technology assessment was considered non-efficient: it would have implied greater managerial attention, without any advantages in terms of incremental information.

To this aim, a Group Decision Support Method able to aggregate individual opinions of decision makers for rating the importance of criteria and alternatives was necessary. Given their competence, the technical opinions of each DM have been judged to have the same value. Therefore, a peer procedure for determining the weights of DMs opinions was employed: each decision maker has been asked to autonomously express the weights of the other DMs. This avoided the presence of a supra-decision maker with authority for determining the voting powers of the group members on the different criteria. Besides, each decision maker has also autonomously evaluated the relevance (weights) of the adopted criteria as well on the impact of the different technologies on the provided criteria.

Since both the importance of the criteria and the impact of different technological alternatives on criteria provided by decision makers are difficult to express by crisp data, we adopted linguistic variables (in both cases on the basis of a five-level scale: Very Important, Important, Medium, Unimportant, Very Unimportant). These evaluations, expressed in literary form, were transformed into fuzzy variables (Atanassov, 1986), through the definition of a fuzzy value on the three components (degree of membership, degree of non-membership and degree of hesitation), so limiting the uncertainty and ambiguity related to linguistic expressions.

3.2. Identification of criteria

As previously stated, the set of criteria come out with an in-depth literature review. We analysed 31 articles selected from the top 50 most-cited technology and innovation management journals (Linton and Thongpapanl, 2004) and published between 2001 and 2015 on Scopus and ISI Web of Knowledge. Specifically, 27 criteria were identified among that used in extant literature.

Despite the criteria for technology selection are often settled by the researchers, without any empirical validation as concerning their appropriateness, in the specific case they were discussed and validated by a team of experts from the company. A final set of 17 criteria was hence selected. Table 1 shows the two macro-issues considered in the evaluation, respectively attractiveness and technological competitiveness. Attractiveness is analysed according to five main issues, which bring to the identification of 13 out of the 17 evaluation criteria (see Table A.1 in the Appendix A for more details about the descriptions and references of the criteria).

3.3. IF-TOPSIS implementation

Here in the following, for sake of brevity and in order to avoid redundancy in the presentation, we report theoretical details about the peer IF-TOPSIS method and numerical results coming from the implementation.

Let $Q = \{A, B, \dots, I\}$ be the set of the selected technological alternatives and $X = \{X_1, X_2, \dots, X_{17}\}$ be the set of the selected criteria, the procedure that we propose is as follows:

Step 1: Construct the aggregated Importance IF decision matrix.

The "Opinion" of each decision maker (DM) (l is the number of decision makers involved into the decision process, here $l = 3$) is considered to have the same value. The value of the opinion is represented by the coefficient ϕ in Eq. (1):

$$\phi_1 = \phi_2 = \dots = \phi_l = \frac{1}{l} \tag{1}$$

Hence, the group decision making process requires that all the individual opinions are fused into a group opinion. In so doing, we decided to use the IFWA operator as shown here:

$$D_k = \phi_1 i_1^{(1)} \oplus \phi_2 i_2^{(2)} \oplus \dots \oplus \phi_l i_l^{(l)} =$$
$$= [1 - \prod_{k=1}^{l} (1 - \mu_k)^{\phi}, \prod_{k=1}^{l} (\nu_k)^{\phi}, \prod_{k=1}^{l} (1 - \mu_k)^{\phi} - \prod_{k=1}^{l} (\nu_k)^{\phi} \ ]$$

Where:

- ϕ_l value of the opinion of each of the l decision makers;
- $i_l^{(l)}$ the intuitionistic fuzzy number associated with the importance of each of the l decision makers according to Table 2.
- $\mathrm{DM_i}$ decision maker
- D_k $[\mu_k, \nu_k, \ \pi_k]$ is the IFN which represents the aggregate importance of the decision maker k-th.

In addition, μ, ν, and π are *the membership degree*, the *non-membership degree* and the *hesitancy degree*, respectively. The sum of such values for each Intuitionistic Fuzzy Number (IFN) is equal to one.

Linguistic terms used for the ratings of the DMs and criteria are given in Table 2.

Each of the three chosen decision maker voted the importance of each of the other decision makers as shown in Table 3. Linguistic evaluations were then transformed into IFN accordingly to Table 2.

Table 4 shows the group opinions resulting from the implementation of the IFWA operator:

Table 1
Criteria adopted for the evaluation of technologies.

Macro-issues	Issues	Criteria
ATTRACTIVENESS The capacity of the technology to create value	MARKET POTENTIAL Commercial reward obtained by means of the technology	Market volume opened by the technology Range of applications opened by the technology Number of new products opened by the technology Potential improvement of the performance of the existing products
	COST REDUCTION Contribution given by the technology to the reduction of costs	Reduction of recurring costs Reduction of non-recurring costs Reduction of life-cycle-cost
	TECHNOLOGICAL IMPLEMENTATION Complexities and risks in the development of the technology	Implementation risks Complexity
	TECHNICAL CHARACTERISTICS Technical aspects which can potentially influence value	Innovative degree Technology maturity: internal Technology Readiness Level – TRL Technology maturity: external Technology Readiness Level – TRL
	POLITICAL ASPECTS Political impact on attractiveness	Public support to development
TECHNOLOGICAL COMPETITIVENESS The impact exerted by the technology on the competitive position of the firm with respect to competitors		Difference between external and internal TRL Number of owned patents (and in general of IPPMs) Competitive intensity Barriers to imitation

Table 2
Linguistic terms for rating the importance of the DMs and criteria.

Linguistic terms	Intuitionistic fuzzy numbers (IFN) μ	ν	π
Very important (VI)	0,9	0,05	0,05
Important (I)	0,65	0,25	0,1
Medium (M)	0,5	0,4	0,1
Unimportant (U)	0,35	0,55	0,1
Very unimportant (VU)	0,15	0,8	0,05

Table 3
The rating of the DMs.

	DM 1	DM 2	DM 3
DM 1	Important	Important	Medium
DM 2	Important	Very Important	Medium
DM 3	Medium	Very Important	Important

Table 4
The aggregate importance of the decision maker D_k.

	D_k μ	ν	π
DM 1	0.606	0.292	0.102
DM 2	0.848	0.085	0.066
DM 3	0.556	0.342	0.102

Step 2: Determine the weight of the decision makers.

The weight λ_k of the k-th decision maker is obtained as (Boran et al., 2009):

$$\lambda_k = \frac{\left(\mu_k + \pi_k \cdot \left(\frac{\mu_k}{\mu_k + \nu_k}\right)\right)}{\sum_{k=1}^{l}\left(\mu_k + \pi_k \cdot \left(\frac{\mu_k}{\mu_k + \nu_k}\right)\right)} \tag{2}$$

and

$$\sum_{k=1}^{l} \lambda_k = 1.$$

Table 5 shows the weights of the three decision makers:

Step 3: Construct the aggregated IF decision matrix based on the opinions of DMs.

The aggregated IF decision matrix R based on aggregation of DMs' opinion has been constructed according to the following procedure.

Let $R^{(k)} = (r_{ij}^{(k)})_{mxn}$ be an Intuitionistic fuzzy decision matrix of each k-th decision maker when we have to select m alternatives on the base of n criteria.

$\lambda = \{\lambda_1, \lambda_2, \ldots, \lambda_l\}$ is the weight of each decision maker. Again, we aggregated all the individual decision opinions into a group opinion by IFWA operator

$$R = (r_{ij})_{mxn},$$

where

Table 5
Decision makers' weights.

DM	DM_1	DM_2	DM_3
Weights	0.306	0.413	0.281

$$r_{ij} = IFWA_\lambda(r_{ij}^{(1)}, r_{ij}^{(2)}, \ldots, r_{ij}^{(l)}) = \lambda_1 r_{ij}^{(1)} \oplus \lambda_2 r_{ij}^{(2)} \oplus \ldots \oplus \lambda_l r_{ij}^{(l)} = \left[1 - \prod_{k=1}^{l}(1-\mu_{ij}^{(k)})^{\lambda_k}, \prod_{k=1}^{l}(\nu_{ij}^{(k)})^{\lambda_k}, \prod_{k=1}^{l}(1-\mu_{ij}^{(k)})^{\lambda_k} - \prod_{k=1}^{l}(\nu_{ij}^{(k)})^{\lambda_k}\right]$$

and:

$$r_{ij} = (\mu_{A_i}(x_j), \nu_{A_i}(x_j), \pi_{A_i}(x_j)) \quad (i = 1, 2, \ldots, m; j = 1, 2, \ldots, n)$$

The aggregated IF decision matrix can be defined as follows:

$$R = \begin{bmatrix} \mu_{A_1}(x_1), \nu_{A_1}(x_1), \pi_{A_1}(x_1)) & \mu_{A_1}(x_2), \nu_{A_1}(x_2), \pi_{A_1}(x_2)) \cdots & \mu_{A_1}(x_n), \nu_{A_1}(x_n), \pi_{A_1}(x_n)) \\ \mu_{A_2}(x_1), \nu_{A_2}(x_1), \pi_{A_2}(x_1)) \vdots & \mu_{A_2}(x_2), \nu_{A_2}(x_2), \pi_{A_2}(x_2)) \ddots & \mu_{A_2}(x_n), \nu_{A_2}(x_n), \pi_{A_2}(x_n)) \vdots \\ \mu_{A_m}(x_1), \nu_{A_m}(x_1), \pi_{A_m}(x_1)) & \mu_{A_m}(x_2), \nu_{A_m}(x_2), \pi_{A_m}(x_2)) \cdots & \mu_{A_m}(x_n), \nu_{A_m}(x_n), \pi_{A_m}(x_n)) \end{bmatrix}$$

$$R = \begin{bmatrix} r_{11} & r_{12} \cdots & r_{1m} \\ r_{21} \vdots & r_{22} \ddots & r_{2m} \vdots \\ r_{n1} & r_{n2} \cdots & r_{nm} \end{bmatrix}$$

The linguistic terms for rating the alternatives were shown in Table 2. Outcome is shown in Appendix A (Tables A.2a, A.2b).

Step 4. Determine the weights of criteria.

Criteria are not assumed equally significant; let W represents a set of grades of importance. In order to obtain W, the individual decision maker opinions related to the importance of each criteria need to be fused into a whole judgment as follows.

Let $w_j^{(k)} = [\mu_j^{(k)}, \nu_j^{(k)}, \pi_j^{(k)}]$ be an IFN assigned to criterion X_j by the k-th decision maker.

Then, the weights of the criteria are calculated by using the IFWA operator:

$$w_j = IFWA_\lambda(w_j^{(1)}, w_j^{(2)}, \ldots, w_j^{(l)}) = \lambda_1 w_j^{(1)} \oplus \lambda_2 w_j^{(2)} \oplus \ldots \oplus \lambda_l w_j^{(l)} = \left[1 - \prod_{k=1}^{l}(1-\mu_j^{(k)})^{\lambda_k}, \prod_{k=1}^{l}(\nu_j^{(k)})^{\lambda_k}, \prod_{k=1}^{l}(1-\mu_j^{(k)})^{\lambda_k} - \prod_{k=1}^{l}(\nu_j^{(k)})^{\lambda_k}\right]$$

$$W = [w_1, w_2, \ldots, w_j]$$

Here:

$$w_j = (\mu_j, \nu_j, \pi_j) \quad (j = 1, 2, \ldots, n)$$

Referring to the case study, the importance of the criteria represented as linguistic terms are aggregated in W (Table 6) to determine the weight of each criterion.

Step 5. Construct the aggregated weighted IF decision matrix.

The aggregated weighted IF decision matrix is constructed according to the following definition (Atanassov, 1986):

$$R \otimes W = \{x, \mu_{Ai}(x) \cdot \mu_W(x), \ \nu_{Ai}(x) + \nu_W(x) - \ \nu_{Ai}(x) + \nu_W(x) | x \in X\}$$

and

$$\pi_{Ai \cdot W}(x) = 1 - \ \nu_{Ai}(x) - \ \nu_W(x) - \ \mu_{Ai}(x) \cdot \mu_W(x) + \ \nu_{Ai}(x) + \nu_W(x)$$

Then, the aggregated weighted IF decision matrix R' can be defined as follows:

$$R' = \begin{bmatrix} \mu_{A_1W}(x_1), \nu_{A_1W}(x_1), \pi_{A_1W}(x_1)) & \mu_{A_1W}(x_2), \nu_{A_1W}(x_2), \pi_{A_1W}(x_2)) \cdots & \mu_{A_1W}(x_n), \nu_{A_1W}(x_n), \pi_{A_1W}(x_n)) \\ \mu_{A_2W}(x_1), \nu_{A_2W}(x_1), \pi_{A_2W}(x_1)) \vdots & \mu_{A_2W}(x_2), \nu_{A_2W}(x_2), \pi_{A_2W}(x_2)) \ddots & \mu_{A_2W}(x_n), \nu_{A_2W}(x_n), \pi_{A_2W}(x_n)) \vdots \\ \mu_{A_mW}(x_1), \nu_{A_mW}(x_1), \pi_{A_mW}(x_1)) & \mu_{A_mW}(x_2), \nu_{A_mW}(x_2), \pi_{A_mW}(x_2)) \cdots & \mu_{A_mW}(x_n), \nu_{A_mW}(x_n), \pi_{A_mW}(x_n)) \end{bmatrix}$$

Table 6
The vector of aggregated weights for the j criteria (W).

Criteria	W		
	μ	ν	π
Potential improvement of the performance of the existing products	0.610	0.289	0.102
Recurring costs reduction	0.752	0.161	0.088
Non-recurring costs reduction	0.551	0.347	0.102
Life cycle cost reduction	0.843	0.090	0.067
External TRL	0.594	0.304	0.102
Internal TRL	0.594	0.304	0.102
Competitive intensity	0.594	0.304	0.102
Range of applications opened by the technology	0.761	0.153	0.086
Number of new products opened by the technology	0.716	0.191	0.093
Patents number	0.420	0.486	0.094
Difference between external and internal TRL	0.552	0.346	0.102
Market volume opened by the technology	0.791	0.129	0.080
Implementation risks	0.500	0.400	0.100
Complexity	0.500	0.400	0.100
Innovative degree	0.682	0.223	0.095
Public support to development	0.548	0.351	0.102
Barriers to imitation	0.462	0.437	0.101

$$R' = \begin{bmatrix} r'_{11} & r'_{12}\cdots & r'_{1j} \\ r'_{21}\vdots & r'_{22}\ddots & r'_{2j}\vdots \\ r'_{i1} & r'_{i2}\cdots & r'_{ij} \end{bmatrix}$$

where:

$r'_{ij} = (\mu_{ij}', \nu_{ij}', \pi_{ij}') = (\mu_{A_i}W(x_j), \nu_{A_i}W(x_j), \pi_{A_i}W(x_j))$ is an element of the aggregated weighted IF decision matrix.

As regards the case study, the aggregated weighted IF decision matrix is computed and shown in Tables A.3a and A.3b of Appendix A.

Step 6. Obtain Intuitionistic fuzzy positive-ideal solution and Intuitionistic fuzzy negative-ideal solution.

Let J_1 and J_2 be benefit criteria and cost criteria (as partitions of X, the overall set of the selected criteria), which respectively include:

$$J_1 = \left\{ \begin{array}{l} \textit{Potential improvement of the performance of the existing produ} \\ \textit{External TRL},\quad \textit{Internal TRL},\quad \textit{Recurring costs reduction}, \\ \textit{Range of applications opened by the technology}, \\ \textit{Life cycle cost reduction}, \textit{Non} - \textit{recurring costs reduction}, \\ \textit{Innovative degree}, \\ \textit{Public support to development}, \\ \textit{Number of new products opened by the technology}, \\ \textit{Patents number}, \textit{Market volume opened by the technology}, \end{array} \right\}$$

$$J_2 = \left\{ \begin{array}{l} \textit{Competitive intensity}, \textit{Difference between external and internal TRL}, \\ \textit{Implementation risks}, \\ \textit{Complexity},\quad \textit{Barriers to imitation} \end{array} \right\}$$

A^+ is intuitionistic fuzzy positive ideal solution and A^- is intuitionistic fuzzy negative ideal solution. Both solutions are vectors of IFN elements, and are obtained as follows (Table 7):

$$A^+ = (\mu_{A^+W}(x_j), \nu_{A^+W}(x_j)) \text{ and } A^- = (\mu_{A^-W}(x_j), \nu_{A^-W}(x_j))$$

where:

$$\mu_{A^+W}(x_j) = ((max_i\, \mu_{A_iW}(x_j) \mid j \in J_1), (min_i\, \mu_{A_iW}(x_j) \mid j \in J_2)$$

$$\nu_{A^+W}(x_j) = ((min_i\, \nu_{A_iW}(x_j) \mid j \in J_1), (max_i\, \nu_{A_iW}(x_j) \mid j \in J_2)$$

$$\mu_{A^-W}(x_j) = ((min_i\, \mu_{A_iW}(x_j) \mid j \in J_1), (max_i\, \mu_{A_iW}(x_j) \mid j \in J_2)$$

$$\nu_{A^-W}(x_j) = ((max_i\, \nu_{A_iW}(x_j) \mid j \in J_1), (min_i\, \nu_{A_iW}(x_j) \mid j \in J_2)$$

The numerical results of A^+ and A^- are shown in Table 6.

Step 7. Calculate the separation measures and closeness coefficient.

A number of alternative distance measures is available in order to calculate the separation between alternatives on Intuitionistic Fuzzy Set, see Atanassov (1999), Szmidt and Kacprzyk (2001), Grzegorzewski (2004). These also include the generalization of Hamming distance, Euclidean distance and their normalized distance measures.

Hence, the separation measures, S_{i^+} and S_{i^-}, of each alternative from intuitionistic fuzzy positive ideal and negative ideal solutions are calculated to evaluate the choice.

In this paper we use normalized Euclidean distance (Szmidt and Kacprzyk, 2000):

$$S^+ = \sqrt{\frac{1}{2n}\sum_{j=1}^{n} [(\mu_{A_iW}(x_j) - \mu_{A^+W}(x_j))^2 + (\nu_{A_iW}(x_j) - \nu_{A^+W}(x_j))^2 + (\pi_{A_iW}(x_j) - \pi_{A^+W}(x_j))^2]}$$

$$S^- = \sqrt{\frac{1}{2n}\sum_{j=1}^{n} [(\mu_{A_iW}(x_j) - \mu_{A^-W}(x_j))^2 + (\nu_{A_iW}(x_j) - \nu_{A^-W}(x_j))^2 + (\pi_{A_iW}(x_j) - \pi_{A^-W}(x_j))^2]}$$

The relative closeness coefficient to the ideal solution is:

$$C_i = \frac{S_{i^-}}{S_{i^-} + S_{i^+}} \text{ where } 0 \le C_i \le 1$$

Negative and positive separation measures based on normalized Euclidean distance for each alternative of our case are reported in Table 8.

Step 8. Rank the alternatives.

After the relative closeness coefficient of each alternative is determined, alternatives are ranked according to descending order of C_i. The final ranking is the following:

D–H–I–G–C–F–B–E–A.

The first four technologies are external to the Business Division, as well as the last two. C, F and B are internal. This ranking indicates that the first four technologies are very important according to both the two investigated macro-issues, i.e. attractiveness and technological competitiveness. Given their outstanding position with respect to the other two external technologies (E and A), the firm is evaluating different forms of sourcing. Specifically, although excluding equity forms for any of the external technologies, the firm is conceiving, for the first four,

Table 7
The intuitionistic fuzzy positive and negative ideal solutions.

	A +			A −		
	μ	ν	π	μ	ν	π
Potential improvement of the performance of the existing products	0.549	0.324	0.127	0.187	0.721	0.092
Recurring costs reduction	0.402	0.469	0.130	0.113	0.832	0.055
Non-recurring costs reduction	0.358	0.510	0.132	0.126	0.805	0.069
Life cycle cost reduction	0.337	0.545	0.118	0.126	0.818	0.056
External TRL	0.535	0.338	0.127	0.238	0.652	0.110
Internal TRL	0.297	0.373	0.330	0.030	0.338	0.632
Competitive intensity	0.095	0.364	0.541	0.245	0.376	0.379
Range of applications opened by the technology	0.380	0.234	0.386	0.074	0.213	0.713
Number of new products opened by the technology	0.358	0.268	0.374	0.036	0.231	0.733
Patents number	0.336	0.512	0.153	0.089	0.534	0.377
Difference between external and internal TRL	0.276	0.412	0.312	0.441	0.379	0.180
Market volume opened by the technology	0.555	0.189	0.256	0.207	0.216	0.576
Implementation risks	0.152	0.462	0.386	0.250	0.460	0.290
Complexity	0.093	0.455	0.452	0.238	0.459	0.303
Innovative degree	0.341	0.297	0.362	0.108	0.291	0.601
Public support to development	0.384	0.396	0.220	0.137	0.415	0.448
Barriers to imitation	0.023	0.466	0.511	0.266	0.486	0.248

Table 8
Separation measures and the relative closeness coefficient.

	A	B	C	D	E	F	G	H	I
S +	0.189	0.178	0.186	0.133	0.179	0.179	0.153	0.154	0.164
S −	0.144	0.150	0.175	0.207	0.147	0.153	0.168	0.182	0.181
C_i	0.432	0.458	0.484	0.608	0.451	0.460	0.523	0.542	0.525

sourcing modes characterized by greater levels of integration than for the last two (Chiesa and Manzini, 1998). In particular, for the first four technologies, forms like alliances, networking and joint R & D are evaluated, while for technologies E and A the firm is pondering sourcing forms like outsourcing and R & D contracts which indeed, respect to the previous forms, produce a minor impact on the firm, have a shorter time horizon, are more flexible and require less commitment in terms of control over people and activities, and time/costs required for the definition of the collaboration.

4. Discussion and conclusion

This paper proposes and applies a modified version of IF-TOPSIS multi-criteria decision making method proposed by Boran et al. (2009) and Aloini et al. (2014) to a to a challenging and complex decision problem –technology evaluation – which is usually subjected to uncertainty and evaluation from multiple experts. In fact, managers need to decide which technologies they intend to foster and fund; they are aware that this decision produces relevant effects on firms' present and future core competencies (Torkkeli and Tuominen, 2002). Given these premises and following the recommendations of the extant literature, technology assessment requires that many criteria and actors are considered and involved in the decision process. The empirical test we assess also provides an interesting proof of the method suitability in a real business context.

On the one hand, as required by several authors in literature (see Jolly, 2012; Yoon et al., 2002; Kelley and Rice, 2002; Levitas et al., 2006; Lee et al., 2009), the suggested MCDA method has allowed to include into the decision process a wealth of different and relevant criteria capable of seizing the complexity of the choice.

On the other hand, using IFS scale and IFWA operator, we allow a peer-based voting procedure for assessing the final group evaluation which avoids the need of a “supra-decision maker”.

Thus, the advanced procedure allows a more systematic and structured decision process supporting a democratic peer voting system which potentially enhances the achievement of a wider consensus. In so doing, a multiplicity of decision makers with diverse perspectives is fairly and effectively included into the process possibly reducing the bias (Linstone, 2010). In fact, the absence of a single DM endowed with the rights to determine the DMs weights limits that wrong impressions of the supra-decision maker about other DMs may might dramatically affect the evaluation process. Biased DMs' weights on their turn could affect the final result. Conversely, a more democratic procedure reduces this risk in that the ranking is more independent from individual impression.

As concerning the case study, we show evidence about the suitability and potential value of the method in supporting and driving the decision process in the investigated application context. Specifically, outcomes of the evaluation were appreciated by the DMs: the final evaluation of managers was to invest in the selected technologies. Also, evidence has convinced them to extend the application of the MCDA approach to the other six technological areas of the company. Thus, we can conclude that Intuitionistic Fuzzy Logic combined with TOPSIS theory has revealed again as a suitable way to deal with uncertainty in very heterogeneous contexts.

Finally, this study has indirectly contributed on the debate about the management of technologies since it provides researchers and managers with an initial set of relevant evaluation criteria for assessing the technologies, which – at our best knowledge – were missing in the literature.

Whether not fully comprehensive, the proposed criteria are easily generalizable; in this sense they make a step forward respect to the vast majority of the contributions in the literature which propose criteria tailored on specific industries/technologies (Akkineni et al., 1990; Khouja, 1995; Subba Raju et al., 1995).

In this direction, it is valuable to notice that we considered both its contribution to the creation of value and to the firm's competitiveness (Harris et al., 1981); also, according to the open innovation literature, we considered not only internal or co-developed technologies, but also technologies to be sourced from external partners (Gassmann and Enkel, 2004).

Main limitations of this work can be summarized in the following points:

- Firstly, we assumed each DM can vote every criterion autonomously so that we associate a single aggregated weight to each DMs. Nevertheless, weights could be customized according to the specific DM's field of expertise.
- Second, the case study proofs the utility and applicability of the methodology in the specific application context but it does not allow attempting any generalization. This is also because Intuitionistic Fuzzy Set Theory, as well as other MCDA methods, can effectively support decision makers to face a number of methodological criticalities but it is also strongly dependent by the knowledge elicitation process.

Further research associated with this work includes possible extensions to other technological area and different research fields, possible comparisons of the advanced MCDM approach with other methods, especially as concerning the achievement of a wide consensus on the final output, as well as the possibility to accomplish a sensitivity analysis on the weights of DMs and criteria.

Appendix A

Table A.1
Description and sources of the selected criteria.

Criteria	Description	Sources
Market volume opened by the technology	The greater is the market volume, the greater is the market potential. The volume depends on the geographical coverage, the dynamism of the demand, the time horizon and the benefits obtained by consumers	Shen et al. (2009), Jolly (2003, 2012)
Range of applications opened by the technology	It measures the number of applications, new functions and new market segments, opened by the technology. The higher is this variable, the higher is the market potential because of risk diversification: it is reduced the risk that the failure in an application/function/segment will result in a total failure	Shen et al. (2009), Jolly (2003, 2012), Prahalad (1993)

Number of new products opened by the technology	It measures the number of products opened by the technology. The greater is the number of products, the greater is the expected commercial reward	Shen et al. (2009), Jolly (2003, 2012), Prahalad (1993)
Potential improvement of the performance of the existing products	It measures the potential contribution of the technology to the improvement of the performance of existing products. This improvement is achieved by using in already existing products/families technologies unused until then in such products/families	Shen et al. (2009)
Reduction of recurring costs	It measures the potential contribution to the reduction of the recurring costs of existing products	Shen et al. (2009)
Reduction of non-recurring costs	It measures the potential contribution to the reduction of the non-recurring costs of existing products	Shen et al. (2009)
Reduction of life-cycle-cost	It measures the potential reduction of the Life Cycle Cost of existing products. This evaluation extends to all costs (costs of installation, management, maintenance and upgrade, as well as the residual value at the end of life) except for the initial costs (included in the non-recurring costs)	Shen et al. (2009)
Implementation risks	It measures the uncertainty for a technology to achieve the results and objectives within the defined constraints of cost, time and quality	Shen et al. (2009)
Complexity	The extent to which a development process of the technology can be programmed so that it can be controlled and become predictable.	Shen et al. (2009)
Innovative degree	Evaluation of the innovativeness of the technology. A more innovative technology will be more attractive and will create greater value	Shen et al. (2009), Rohrbeck (2010)
Technology maturity: internal technology readiness level – TRL	It measures the TRL, i.e. the level of maturity reached by the examined internal technology (internal TRL)	Rohrbeck (2010)
Technology maturity: external technology readiness level – TRL	It measures the TRL, i.e. the level of maturity reached by the examined external technology (external TRL)	Rohrbeck (2010)
Public support to development	A technology which receives financial support from public authorities will be able to create more value and will be more attractive	Jolly (2003, 2012), Hsu et al. (2009)
Difference between external and internal TRL	It measures how far the firm is ahead of the competitors in the development of a technology	Shen et al. (2009), Jolly (2003, 2012)
Number of owned patents (and in general of IPPMs)	The firm's ability to protect from imitation is important for improving positioning relative to competitors. The greater the number of patents (and in general of IPPMs), the greater the competitiveness	Jolly (2003, 2012), Teece (1986), Ernst (1998), Allarakhia and Walsh (2011)
Competitive intensity	It measures the concentration of the market of the investigated technology. A higher concentration implies less competition and hence greater profits and higher profitability	Jolly (2003, 2012)
Barriers to imitation	Competitors protect their technology from imitations through barriers such as IPPMs. Lower barriers enable the company to imitate more easily and be more competitive	Jolly (2003, 2012)

Table A.2a
The aggregated IF decision matrix R (Alternatives A, B, …, I represent the technologies to be assessed).

Criteria	A			B			C			D			E		
	μ	ν	π	μ	ν	π	μ	N	π	μ	ν	π	μ	ν	π
Potential improvement of the performance of the existing products	0.692	0.212	0.096	0.832	0.097	0.071	0.900	0.050	0.050	0.650	0.250	0.100	0.593	0.304	0.103
Recurring costs reduction	0.150	0.800	0.050	0.229	0.701	0.070	0.534	0.367	0.099	0.484	0.412	0.104	0.534	0.367	0.099
Non-recurring costs reduction	0.307	0.607	0.086	0.400	0.500	0.100	0.650	0.250	0.100	0.520	0.376	0.105	0.229	0.701	0.070
Life cycle cost reduction	0.150	0.800	0.050	0.150	0.800	0.050	0.150	0.800	0.050	0.400	0.500	0.100	0.150	0.800	0.050
External TRL	0.400	0.500	0.100	0.400	0.500	0.100	0.400	0.500	0.100	0.400	0.500	0.100	0.900	0.050	0.050
Internal TRL	0.400	0.500	0.100	0.400	0.500	0.100	0.400	0.500	0.100	0.400	0.500	0.100	0.900	0.050	0.050
Competitive intensity	0.653	0.247	0.100	0.754	0.159	0.087	0.722	0.186	0.092	0.714	0.193	0.093	0.650	0.250	0.100
Range of applications opened by the technology	0.645	0.257	0.098	0.758	0.157	0.085	0.832	0.097	0.071	0.405	0.500	0.096	0.645	0.257	0.098
Number of new products opened by the technology	0.900	0.050	0.050	0.637	0.262	0.101	0.832	0.097	0.071	0.900	0.050	0.050	0.853	0.082	0.065
Patents number	0.694	0.212	0.094	0.150	0.800	0.050	0.558	0.342	0.099	0.150	0.800	0.050	0.338	0.571	0.091
Difference between external and internal TRL	0.150	0.800	0.050	0.400	0.500	0.100	0.150	0.800	0.050	0.150	0.800	0.050	0.150	0.800	0.050
Market volume opened by the	0.405	0.500	0.096	0.495	0.404	0.101	0.637	0.262	0.101	0.229	0.701	0.070	0.581	0.318	0.101

technology															
Implementation risks	0.400	0.500	0.100	0.400	0.500	0.100	0.593	0.304	0.103	0.426	0.475	0.099	0.563	0.333	0.104
Complexity	0.593	0.304	0.103	0.593	0.304	0.103	0.722	0.186	0.092	0.426	0.475	0.099	0.563	0.333	0.104
Innovative degree	0.563	0.333	0.104	0.692	0.212	0.096	0.754	0.159	0.087	0.484	0.412	0.104	0.491	0.404	0.104
Public support to development	0.264	0.659	0.077	0.650	0.250	0.100	0.470	0.429	0.101	0.229	0.701	0.070	0.413	0.491	0.096
Barriers to imitation	0.900	0.050	0.050	0.491	0.404	0.104	0.791	0.129	0.080	0.702	0.203	0.095	0.563	0.333	0.104

Table A.2b
The aggregated IF decision matrix R (Alternatives A, B, …, I represent the technologies to be assessed).

Criteria	F			G			H			I		
	μ	ν	π	μ	ν	π	μ	N	π	μ	ν	π
Potential improvement of the performance of the existing products	0.653	0.247	0.100	0.495	0.404	0.101	0.413	0.491	0.096	0.307	0.607	0.086
Recurring costs reduction	0.229	0.701	0.070	0.307	0.607	0.086	0.307	0.607	0.086	0.338	0.577	0.085
Non-recurring costs reduction	0.236	0.693	0.071	0.413	0.491	0.096	0.413	0.491	0.096	0.405	0.500	0.096
Life cycle cost reduction	0.150	0.800	0.050	0.307	0.607	0.086	0.307	0.607	0.086	0.229	0.701	0.070
External TRL	0.400	0.500	0.100	0.400	0.500	0.100	0.400	0.500	0.100	0.400	0.500	0.100
Internal TRL	0.400	0.500	0.100	0.400	0.500	0.100	0.400	0.500	0.100	0.400	0.500	0.100
Competitive intensity	0.653	0.247	0.100	0.563	0.333	0.104	0.563	0.333	0.104	0.484	0.412	0.104
Range of applications opened by the technology	0.645	0.257	0.098	0.600	0.300	0.100	0.413	0.491	0.096	0.405	0.500	0.096
Number of new products opened by the technology	0.900	0.050	0.050	0.405	0.500	0.096	0.405	0.500	0.096	0.405	0.500	0.096
Patents number	0.551	0.347	0.102	0.150	0.800	0.050	0.150	0.800	0.050	0.150	0.800	0.050
Difference between external and internal TRL	0.150	0.800	0.050	0.400	0.500	0.100	0.400	0.500	0.100	0.400	0.500	0.100
Market volume opened by the technology	0.307	0.607	0.086	0.338	0.577	0.085	0.338	0.577	0.085	0.338	0.577	0.085
Implementation risks	0.400	0.500	0.100	0.426	0.475	0.099	0.426	0.475	0.099	0.426	0.475	0.099
Complexity	0.593	0.304	0.103	0.426	0.475	0.099	0.426	0.475	0.099	0.426	0.475	0.099
Innovative degree	0.491	0.404	0.104	0.495	0.404	0.101	0.405	0.500	0.096	0.405	0.500	0.096
Public support to development	0.264	0.659	0.077	0.563	0.333	0.104	0.563	0.333	0.104	0.439	0.462	0.100
Barriers to imitation	0.900	0.050	0.050	0.338	0.577	0.085	0.338	0.577	0.085	0.338	0.577	0.085

Table A.3a
The aggregated weighted IF decision matrix (Alternatives A, B, …, I represent the technologies to be assessed).

Criteria	A			B			C			D			E		
	μ	ν	π	μ	ν	π	μ	N	π	μ	ν	π	μ	ν	π
Potential improvement of the performance of the existing products	0.422	0.439	0.139	0.507	0.358	0.135	0.549	0.324	0.127	0.396	0.467	0.137	0.361	0.505	0.134
Recurring costs reduction	0.113	0.832	0.055	0.172	0.749	0.079	0.402	0.469	0.130	0.364	0.506	0.130	0.402	0.469	0.130
Non-recurring costs reduction	0.169	0.743	0.087	0.220	0.673	0.106	0.358	0.510	0.132	0.286	0.592	0.122	0.126	0.805	0.069
Life cycle cost reduction	0.126	0.818	0.056	0.126	0.818	0.056	0.126	0.818	0.056	0.337	0.545	0.118	0.126	0.818	0.056
External TRL	0.238	0.652	0.110	0.238	0.652	0.110	0.238	0.652	0.110	0.238	0.652	0.110	0.535	0.338	0.127
Internal TRL	0.297	0.373	0.330	0.297	0.373	0.330	0.297	0.373	0.330	0.297	0.373	0.330	0.030	0.338	0.632
Competitive intensity	0.147	0.373	0.480	0.095	0.364	0.541	0.110	0.368	0.522	0.115	0.368	0.517	0.149	0.373	0.478
Range of applications opened by the technology	0.196	0.236	0.568	0.120	0.225	0.656	0.074	0.213	0.713	0.380	0.234	0.386	0.196	0.236	0.568
Number of new products opened by the technology	0.036	0.231	0.733	0.187	0.272	0.540	0.070	0.248	0.683	0.036	0.231	0.733	0.059	0.243	0.698
Patents number	0.089	0.534	0.377	0.336	0.512	0.153	0.144	0.537	0.319	0.336	0.512	0.153	0.239	0.533	0.228
Difference between external and internal TRL	0.441	0.379	0.180	0.276	0.412	0.312	0.441	0.379	0.180	0.441	0.379	0.180	0.441	0.379	0.180
Market volume opened by the technology	0.395	0.212	0.393	0.320	0.216	0.464	0.207	0.216	0.576	0.555	0.189	0.256	0.252	0.217	0.532
Implementation risks	0.250	0.460	0.290	0.250	0.460	0.290	0.152	0.462	0.386	0.238	0.459	0.303	0.166	0.463	0.371
Complexity	0.152	0.462	0.386	0.152	0.462	0.386	0.093	0.455	0.452	0.238	0.459	0.303	0.166	0.463	0.371
Innovative degree	0.227	0.304	0.469	0.144	0.297	0.558	0.108	0.291	0.601	0.281	0.304	0.415	0.276	0.304	0.420
Public support to development	0.361	0.401	0.238	0.137	0.415	0.448	0.235	0.416	0.349	0.384	0.396	0.220	0.269	0.413	0.318
Barriers to imitation	0.023	0.466	0.511	0.187	0.496	0.317	0.059	0.482	0.458	0.094	0.491	0.415	0.154	0.496	0.350

Table A.3b
The aggregated weighted IF decision matrix (Alternatives A, B, …, I represent the technologies to be assessed).

Criteria	F			G			H			I		
	μ	ν	π	μ	ν	π	μ	ν	π	μ	ν	π
Potential improvement of the performance of the existing products	0.398	0.464	0.137	0.302	0.576	0.122	0.251	0.638	0.111	0.187	0.721	0.092
Recurring costs reduction	0.172	0.749	0.079	0.231	0.670	0.099	0.231	0.670	0.099	0.254	0.645	0.101
Non-recurring costs reduction	0.130	0.799	0.071	0.227	0.667	0.105	0.227	0.667	0.105	0.223	0.673	0.104
Life cycle cost reduction	0.126	0.818	0.056	0.259	0.642	0.099	0.259	0.642	0.099	0.193	0.728	0.079
External TRL	0.238	0.652	0.110	0.238	0.652	0.110	0.238	0.652	0.110	0.238	0.652	0.110
Internal TRL	0.297	0.373	0.330	0.297	0.373	0.330	0.297	0.373	0.330	0.297	0.373	0.330
Competitive intensity	0.147	0.373	0.480	0.198	0.376	0.426	0.198	0.376	0.426	0.245	0.376	0.379
Range of applications opened by the technology	0.196	0.236	0.568	0.229	0.238	0.534	0.374	0.234	0.392	0.380	0.234	0.386
Number of new products opened by the technology	0.036	0.231	0.733	0.358	0.268	0.374	0.358	0.268	0.374	0.358	0.268	0.374
Patents number	0.145	0.539	0.316	0.336	0.512	0.153	0.336	0.512	0.153	0.336	0.512	0.153
Difference between external and internal TRL	0.441	0.379	0.180	0.276	0.412	0.312	0.276	0.412	0.312	0.276	0.412	0.312
Market volume opened by the technology	0.480	0.203	0.316	0.457	0.203	0.340	0.457	0.203	0.340	0.457	0.203	0.340
Implementation risks	0.250	0.460	0.290	0.238	0.459	0.303	0.238	0.459	0.303	0.238	0.459	0.303
Complexity	0.152	0.462	0.386	0.238	0.459	0.303	0.238	0.459	0.303	0.238	0.459	0.303
Innovative degree	0.276	0.304	0.420	0.276	0.301	0.423	0.341	0.297	0.362	0.341	0.297	0.362
Public support to development	0.361	0.401	0.238	0.182	0.418	0.399	0.182	0.418	0.399	0.253	0.415	0.332
Barriers to imitation	0.023	0.466	0.511	0.266	0.486	0.248	0.266	0.486	0.248	0.266	0.486	0.248

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