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A Multi-Criteria Decision-Making Model Based on Fuzzy Logic and AHP for the Selection of Digital Technologies

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Abstract: The presence of Industry 4.0 national plans and the ever-increasing international competition are forcing companies to embark on digitalization projects of their industrial plants. Time and money, however, are a constraint and, in addition to that, there is a considerable lack of works in the academic literature with regards to specific models for the selection of digital technologies. Starting from our methodological framework, we developed a multi-criteria decision-making model for the digitalization of industrial plants. The model is based on both Fuzzy Logic and AHP and is combined with an existing hierarchical classification of digital technologies in an attempt to highlight the advantage of adopting similar and easily interconnectable technologies. Finally, the model is applied to a simple case study to test its validity.

Keywords: AHP, Fuzzy Logic, digitalization, technology selection, Decision making, Case study of digitization or smart system, Industry 4.0

1. INTRODUCTION

According to Vial (2019), digitalization is “a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies”. The term is also cited by Lasi et al. (2014) in their seminal paper on Industry 4.0 as one of the application pushes that are shaping up the development of the industrial world. The matter has also come to the attention of national and international institutions, which have developed a wide range of digitalization and Industry 4.0 plans. For these reasons, industrial companies are facing an unprecedented pressure to digitalise their plants and processes. However, time and resources are always a factor, forcing companies to make a choice: out of all the available digital technologies, only the most appropriate ones should be implemented. The choice is also complicated by the recent nature of the subject: as pointed out by Ivanov et al. (2021), there is still a lack of clarity regarding the economic benefit of the adoption of digital technologies. To address this issue, we have developed a methodological framework for the selection of digital technologies in the industrial sector. In this paper we will focus on its last level, where the technology selection happens. We have developed a multi-criteria decision-making approach that is based on Fuzzy Logic and AHP and we have combined it with a hierarchical classification of technologies: our model is not only able to indicate the single best performing digital technology but also the most suitable group of similar technologies, aiming to capture the real added value of digitalisation, which lies in the interconnection of different elements of an industrial company.

The rest of the paper is organised as follows: Section 2 contains the Literary Review, Section 3 briefly presents our framework, Section 4 details our decision-making model, Section 5 provides an example of application of the model and Section 6 contains the conclusions and the suggestions for further research.

2. LITERARY REVIEW

Frameworks for technology selection are not a small subject: researching in the Scopus database with the set of keywords (“technology selection” AND framework) yields 161 results in the fields of Engineering and Decision Sciences. If the research is narrowed down by adopting a new set of keywords, (“industry 4.0” OR digitalisation AND “technology selection”), to include only frameworks for the selection of digital technologies in the industrial sector, the number of results drops drastically to 13. Out of these works, only 6 of them are related to our research: Hamzeh et al. (2018), Mämmelä et al. (2018), Beyaz and Yıldırım (2020), Büyüközkan and Gocer (2019), Erbay and Yıldırım (2019), and Garcia-Villareal et al. (2018). Aside from the general lack of contributions, the main findings that can be drawn from these findings are: 1) only Beyaz and Yıldırım (2019) and Erbay and Yıldırım (2019) enrich their frameworks with a classification of digital technologies that is used in the decision process; 2) apart from Erbay and Yıldırım (2019), which adopt a combination of AHP and QFD, there is a lack of clarity on the definition and adoption of specific KPIs, (to be used in the evaluation of the benefits of introducing a new digital technology) and their relation with the existing processes. Hamzeh et al. (2018) also reviewed existing frameworks for technology selection, pointing out the following gaps: 1) lack of a systematic approach in the assessment of the current situation of the organization in the way of embracing Industry 4.0; 2) no consideration of the opportunities and threats of Industry 4.0 key technologies.

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With regards to specific multi-criteria decision-making models, the combination of Fuzzy Logic and AHP appears to be a rather vast topic, with 8,391 document results on Scopus. However, restricting the research only to the combination of Fuzzy Logic and AHP applied to the selection of digital technologies shrinks the numbers considerably: only 29 results are obtained with the set of keywords (fuzzy AND ahp AND ("digital technologies" OR digitalization OR "industry 4.0")). Only 4 of these works adopt a wide set of digital technologies as an element of the decision-making process. Büyüközkan and Güler (2020) and Büyüközkan et al. (2020) follow a similar approach, where success factors in aviation 4.0 and significance factors in Digital Maturity Models appear as criteria to evaluate companies and not as alternatives. Güler and Büyüközkan (2019) have developed a combination of Fuzzy Logic and AHP to select the most suitable digital transformation strategy, applying it to the banking sector. Finally, Jamwal et al. (2021) proposed a sustainability framework for Industry 4.0: the selection process is based on Fuzzy AHP and DEMATEL and the enablers to sustainability in Industry 4.0 appear as a set of criteria.

To the best of our knowledge, ours is the first work that adopts a KPI-based approach and applies Fuzzy Logic and AHP to select the best performing digital technology in the industrial sector, It is also the first work that tries to capture the added value of adopting similar and interconnected technologies by referring to an existing hierarchical classification in the literature.

3. THE FRAMEWORK

To address the lack of contributions in the literature, we have developed a methodological framework, which is briefly presented in this section. It is characterised by a top-down approach, starting from strategies, and ending with digital technologies. The framework is divided in three steps or levels, each having the same structure, as shown in Fig.1.

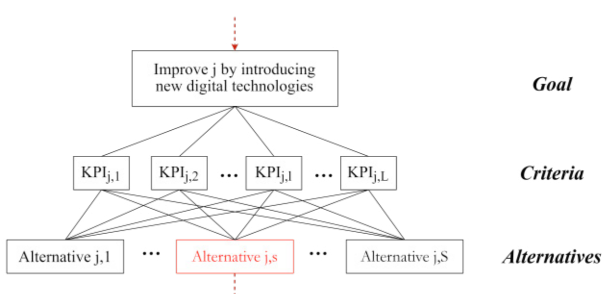

Fig. 1. Structure of each level of the framework

The structure is the following: a goal, a set of criteria and a set of alternatives. Although its structure resembles the classical AHP outline, the framework is flexible and can accommodate other multi-criteria decision-making tools. The KPI-based approach consists in the adoption of KPIs as criteria in each level: the alternatives are chosen according to their contribution or the potential improvement they can bring to the current performance. The best-ranked alternative then becomes the input of the successive level. In the first level, the strategies of the company and their KPIs are the criteria while the internal processes of the company represent the alternatives. The process that has the highest impact on the KPIs of the main strategy is chosen as the best alternative, becoming the input of the second level. At the second level, the best process is broken down into its KPIs and subprocesses, with the latter representing the alternatives. The subprocess that has the highest impact on the performances of the main process becomes the input for the third level. Here, the digital technologies are the alternatives, and they are evaluated according to the improvement they can bring to the current subprocess. The decision-making process that is presented in this paper operates at this third level.

4. FUZZY LOGIC AND AHP FOR THE SELECTION OF DIGITAL TECHNOLOGIES

4.1 AHP and Fuzzy Logic

The analytical hierarchy process (AHP) is a structured technique applied to solve multi-criteria decision making-problems (Saaty, 1980): it decomposes a decision problem into a hierarchical structure that comprises a goal, criteria and sub-criteria and the alternatives to choose from. Criteria, sub-criteria and alternatives are then subjected to pairwise comparisons by a panel of expert decision-makers.

For the pairwise comparisons, the traditional AHP method applies a set of crisp, clear-cut numbers, ranging from 1 to 9. However, this approach does not take ambiguity and uncertainty into account, which are elements that are generally always present in expert judgments and particularly when evaluation is performed *ex-ante*. To address this issue, a valid alternative is represented by the adoption of Fuzzy Logic. Fuzzy Logic stems from the theory of fuzzy sets, which was introduced for the first time by Zadeh (1965). In our model, all the evaluations provided by experts are expressed through linguistic judgments, which are converted into fuzzy sets, defined by Trapezoidal Fuzzy Numbers. These sets are described by trapezoidal membership functions, hence their name. A trapezoidal membership function is usually described in this way:

$$f_{SET}(x, l, m_1, m_2, u) = \\ = \begin{cases} (x-l)/(m_1-l) & l \le x < m_1 \\ 1 & m_1 \le x \le m_2 \\ (u-x)/(u-m_2) & m_2 < x \le u \\ 0 & otherwise \end{cases} \qquad (1)$$

where l, m_1, m_2, u are the parameters of the membership function, which are graphically represented in Fig. 2. The parameters of the membership functions which make up the fuzzy sets that are applied in our model to convert the linguistic judgments are shown in Table 1.

4.2 Classification of digital technologies

With regards to the list of digital technologies that is used as the list of alternatives in the last level of the framework, we decided to adopt the classification of Industry 4.0 technologies proposed by Frank et al. (2019). This classification has two main advantages: 1) it is rather wide and comprehensive, listing up to 36 different applications of digital technologies; 2) it is organised in a hierarchical structure rather than a simple list where technologies appear to be seemingly unrelated. This second point is particularly important since an effective digitalisation process is not represented by a blind application of a single digital technology. The real added value of such process lies instead in the interconnection and data sharing between different technological applications within a plant. Therefore, it is important to adopt a technology classification that reflects functional relationships or similarities.

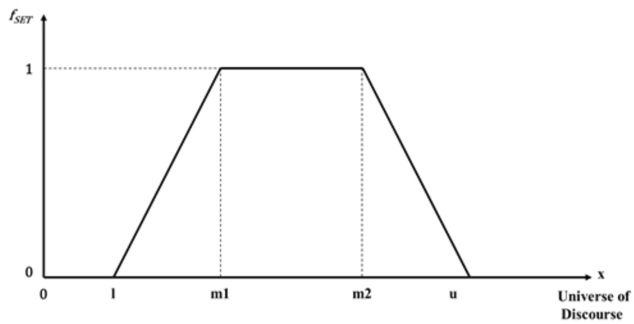

Figure 2 Membership function diagram of a Trapezoidal Fuzzy Number

Table 1. Trapezoidal fuzzy conversion scale

Linguistic Scale	Triangular fuzzy scale
Very Low	(0, 0, 0.10, 0.25)
Low	(0.10, 0.25, 0.35, 0.50)
Medium	(0.25, 0.45, 0.55, 0.75)
High	(0.50, 0.65, 0.75, 0.90)
Very High	(0.75, 0.90, 1.00, 1.00)

According to Frank et al. (2019), the candidate technologies can be grouped in the following way:

- Smart Manufacturing Technologies
  - Vertical Integration: Sensors, actuators and Programmable Logic Controllers (PLC), Supervisory Control and Data Acquisition (SCADA), Manufacturing Execution System (MES), Enterprise Resource Planning (ERP), Machine-to-machine communication (M2Ma)
  - Virtualization: Virtual commissioning, Simulation of processes (e.g. digital manufacturing), Artificial Intelligence for predictive maintenance, Artificial Intelligence for planning of production
  - Automation: Machine-to-machine communication (M2Mb), Robots (e.g. Industrial Robots, Autonomous Guided Vehicles, or similar), Automatic nonconformities identification in production
  - Traceability: Identification and traceability of raw materials, Identification and traceability of final products
  - Flexibility: Additive manufacturing, Flexible and autonomous lines
  - Energy Management: Energy efficiency monitoring system, Energy efficiency improving system
- Smart Working Technologies: Remote monitoring of production, Remote operation of production, Augmented Reality (AR) for Maintenance, Virtual reality (VR) for workers training, Augmented and virtual reality (A&VR) for product development, Collaborative robots
- Smart Supply Chain Technologies: Digital platforms with suppliers, Digital platforms with customers, Digital platforms with other company units

The original classification also includes a set of Smart Product Technologies. Since our focus is on the production system, rather than the product itself, these technologies can be delisted. In addition, Frank et al. (2019) also present a list of Base Technologies: Internet of Things, Cloud, Big Data and Analytics. These technologies are named "Base" because they offer the platform over which all the other groups of technologies can operate. Consequently, due to their nature of enabling factors rather than elements of choice and for a matter of simplicity, they are not considered as alternatives.

4.3 The Decision-Making Model

A well-established combination of Fuzzy Logic and AHP already exists, and it is called Fuzzy AHP, as described by Chang (1996). However, for the sake of our purpose, which includes the adoption of the specific hierarchical classification proposed by Frank et al. (2019), Fuzzy AHP would be impractical: due to the high number of possible alternatives, the resulting pairwise comparison matrix would be rather large (dimension 27×27), driving up considerably the number of single pairwise comparisons to perform. For this reason, we decided to adopt a model which is derived from the work of Kapoor and Tak (2005): this methodology operates with fuzzy numbers and, despite still following the hierarchical structure of AHP, better handles a high number of alternatives.

The model is described as follows:

1) Apply the AHP structure to the criteria and alternatives that are derived from our framework: the goal is to improve the subprocess under examination through the application of digital technologies; criteria are represented by a set of relevant KPIs of the subprocess; the alternatives have already been listed and classified in Section 4.2.

2) A panel of expert decision-makers is asked to assign a relative weight to each criterion, according to the perceived importance of each KPI in expressing the performance of the subprocess. The experts' judgments are conveyed through the linguistic scale indicated in Table 1 and then converted into the corresponding Trapezoidal Fuzzy Numbers. Each relative weight is indicated as follows:

$$W_{cd} = (l_{cd}, m1_{cd}, m2_{cd}, u_{cd}) \quad (1)$$

where W_{cd} is the relative weight assigned to criteria c by decision-maker d, l_{cd}, $m1_{cd}$, $m2_{cd}$, u_{cd} are the parameters of weight W_{cd} expressed as a trapezoidal fuzzy number, c = *1, ..., C* is the index of the criterion and *d=1, ..., D* is the index of the decision-maker.

3) The aggregated weights of the criteria are calculated by averaging the relative weights of the criteria over the number of decision-makers. The mean operator is applied to each one of the four parameters that describe the relative weight of a criterion:

$$W_c = (\sum_{d=1}^{D} W_{cd})/D \qquad \forall c = 1, \dots, C \tag{2}$$

$$W_C = (l_c, m1_c, m2_c, u_c) = = (\frac{\sum_{d=1}^{D} l_{cd}}{D}, \frac{\sum_{d=1}^{D} m1_{cd}}{D}, \frac{\sum_{d=1}^{D} m2_{cd}}{D}, \frac{\sum_{d=1}^{D} u_{cd}}{D}) \tag{3}$$

where W_c is the aggregated weight for criterion *c.*

4) The panel of decision-makers is asked to provide a judgement on the positive impact that every one of the alternatives can bring to each KPI-criterion. The alternatives are represented by the list of 27 digital technologies indicated in Section 4.2. The judgements are expressed in the linguistic scale shown in Table 1 and then converted into Trapezoidal Fuzzy Numbers. Each judgement can be expressed through a variable named Value of Goodness (VoG), shown below:

$$VoG_{acd} = (l_{acd}, m1_{acd}, m2_{acd}, u_{acd}) \tag{4}$$

where VoG_{acd} represents the evaluation on the improvement that the implementation of alternative *a* can have on KPI-criterion *c*, according to decision-maker *d.*

5) In a similar way as in step 3), for each criterion, the aggregated Values of Goodness of each alternative are calculated by averaging the Values of Goodness over the number of decision-makers.

$$VOG_{ac} = (\sum_{d=1}^{D} VOG_{acd})/D \qquad \forall a = 1, \dots, A \quad \forall c = 1, \dots, C \tag{5}$$

$$VOG_{ac} = (l_{ac}, m1_{ac}, m2_{ac}, u_{ac}) = = (\frac{\sum_{d=1}^{D} l_{acd}}{D}, \frac{\sum_{d=1}^{D} m1_{acd}}{D}, \frac{\sum_{d=1}^{D} m2_{acd}}{D}, \frac{\sum_{d=1}^{D} u_{acd}}{D}) \tag{6}$$

where VOG_{ac} is the aggregated Value of Goodness of alternative *a* with respect to criterion *c.*

6) The Fuzzy Score of each alternative is calculated by weighting the aggregated Value of Goodness of each alternative with the aggregated weights of the relative criteria:

$$FS_a = \frac{\sum_{c=1}^{C} (VOG_{ac} \otimes W_c)}{C} \qquad \forall a = 1, \dots, A \tag{7}$$

where FS_a is the Fuzzy Score of alternative *a.* The algebraic operation $\otimes$ can be approximated as follows:

$$(l_1, m1_1, m2_1, u_1) \otimes (l_2, m1_2, m2_2, u_2) \approx \approx (l_1 \times l_2, m1_1 \times m1_2, m2_1 \times m2_2, u_1 \times u_2) \tag{8}$$

A first useful and interesting outcome of this approach is that the Fuzzy Scores of each alternative coincide with Trapezoidal Fuzzy Numbers (even if they are not Trapezoidal Fuzzy Numbers). Thus, it is possible to write:

$$FS_a = (a_a, b_a, c_a, d_a) \tag{9}$$

where a_a, b_a, c_a, d_a, are four defining values (which coincide with the parameters of a Trapezoidal Fuzzy Number) of the Fuzzy Score of alternative *a.*

7) In the last step, in order to associate each alternative with a single, crisp value and to establish a consequent ranking, the Fuzzy Scores are defuzzified. The Weighted Average Method is applied, where each landmark value of the Fuzzy Score is weighted by the maximum relative membership function value:

$$DS_a = \frac{\sum_{i=1}^{4} (f_a(lv_{ia}) \times lv_{ia})}{\sum_{i=1}^{4} f_a(lv_{ia})} \tag{10}$$

where f_a is the membership function, lv_{ia} is the *i*-th landmark value of alternative *a,* and DS_a is the Defuzzified Score of alternative *a.* The landmark values suggested for the calculation are shown below:

$$lv_{ia} = = (a_a + (b_a - a_a)/2, b_a, c_a, c_a + (d_a - c_a)/2) \tag{11}$$

where a_a, b_a, c_a, d_a, are the four defining values of alternative *a.* Therefore, the final formulation is:

$$DS_a = = \frac{\begin{pmatrix} (a_a + (b_a - a_a)/2) \times 0.5 + b_a \times 1 + c_a \times 1 + \\ + \left(c_a + \frac{d_a - c_a}{2}\right) \times 0.5 \end{pmatrix}}{(0.5 + 1 + 1 + 0.5)} \tag{12}$$

8) The alternatives are then compared according to their DS_a and the digital technology with the highest value is considered as the single best candidate for adoption.

9) The Fuzzy Score of each single technology is combined with the scores of all the other technologies that belong to the same group, according to Frank's et al. (2019) classification. Compared to an application of AHP that adopts the groups of similar technologies as alternatives, our approach offers a deeper evaluation: in fact, the score of each group is derived from the capability of each single technology to improve the performance of the current subprocess; a higher-level approach would not be able to capture the improvement that a single technology can bring to a subprocess as the groups of technologies are too general *per se* to perform such an estimation. The Fuzzy Scores of the digital technologies that belong to the same group are modified as follows:

$$FS_g = (a_g, b_g, c_g, d_g) \qquad \forall g = 1, \dots, G \tag{13}$$

where

$$a_g = min_a(a_a) \qquad \forall a = 1, \dots, A_g |\ a \in Gr.g \tag{14}$$

$$b_g = \frac{1}{A_g} \sum_{a=1}^{A_g} b_a \qquad \forall a = 1, \dots, A_g |\ a \in Gr.g \tag{15}$$

$$c_g = \frac{1}{A_g}\sum_{a=1}^{A_g} c_a \qquad \forall a = 1, \dots, A_g | \; a \in Gr.g \qquad (16)$$

$$d_g = max_a(d_a) \qquad \forall a = 1, \dots, A_g | \; a \in Gr.g \qquad (17)$$

In the previous equations, FS_g is the Fuzzy Score of technology group g, a_g, b_g, c_g, d_g, are the defining values of FS_g, and A_g is the number of alternatives that belong to Group g.

10) The Fuzzy Scores for each group are then defuzzified with (12) according to the Weighted Average Method, resulting in DS_g, the Defuzzified Score of group g.

11) The groups are then compared and evaluated according to their Defuzzified Scores

5. EXAMPLE OF APPLICATION

Consider an example where an industrial company is embarked in a digitalization process and wants to improve its processes through the implementation of digital technologies. The company has already detected the candidate subprocess for digitalisation following the steps of our proposed framework. The company forms a panel composed of 3 decision-makers, who indicate three hypothetical KPIs as criteria for the evaluation of digital technologies: KPI_1, KPI_2, KPI_3. The judgements of the three decision-makers were simulated and were expressed in the linguistic scale shown in Table 1 (the judgements can be provided upon request). The model is then implemented according to what is shown in section 4.3. The resulting Defuzzified Scores of all the alternatives are listed in Table 2.

Table 2. Defuzzified Scores and overall rank of the 27 digital technologies

Technology	Group	DS_a	Rank
1. PLC	Vertical Integration	0.3736	8
2. SCADA		0.3085	13
3. MES		0.1275	22
4. ERP		0.1955	20
5. M2Ma		0.3842	6
6. Virtual Commissioning	Virtualization	0.0908	23
7. Simulation of processes		0.2435	17
8. AI for predictive maintenance		0.3863	5
9. AI for planning of production		0.4198	2
10. M2Mb	Automation	0.3721	9
11. Robots		0.3033	14
12. Aut. nonconf. identification		0.3650	10
13. Traceability of raw materials	Traceability	0.2221	18
14. Traceability of final products		0.3744	7
15. Additive Manufacturing	Flexibility	0.0450	25
16. Flex. and aut. lines		0.4026	3
17. Energy eff. Monitoring syst.		0.2131	19
18. Energy eff. Improving syst.	Energy Management	0.2540	16
19. Remote monitoring of prod.	Smart Working	0.3274	12
20. Remote operation of prod.		0.4493	***1***
21. AR for maintenance		0.2934	15
22. VR for workers training		0.4008	4
23. A&VR for prod. development		0.0642	24
24. Cobots		0.3593	11
25. Digital plat. with suppliers	Smart Supply Chain	0.0372	26
26. Digital plat. with customers		0.0372	26
27. Dig. plat. with company units		0.1650	21

The Defuzzified Scores of the groups of technologies, according to Frank et al. (2019), are shown in Table 3.

Table 3 Defuzzified Scores of the groups of technologies

Group	DS_g
Vertical Integration	0.2795
Virtualization	0.2877
Automation	0.3468
Traceability	0.3025
Flexibility	0.2341
Energy Management	0.2352
Smart Working	0.3156
Smart Supply Chain	0.0887

The Defuzzified Scores of the single digital technologies show that Remote Operation of Production ($DS_a = 0.4493$) is the best alternative in terms of potential improvement of the three KPIs which describe the performance of the subprocess under examination.

Before commenting the scoring of the groups of technologies, a brief clarification is needed. As shown in section 4.2, Frank's et al. (2019) classification has three main macro-groups. The macro-group Smart Manufacturing Technologies is divided into six sub-groups of related technologies; the other two macro-groups, however, are not divided into sub-groups. It would be ideal to make the comparison at sub-group level; however, for the sake of this purpose, we considered Smart Working and Smart Supply Chain at the same level of sub-groups of technologies, since they both include a limited (respectively 5 and 3) number of closely related technologies, in a similar way as for the sub-groups of Smart Manufacturing Technologies.

Table 3 shows that the best candidate group of technologies is represented by Automation, with $DS_g = 0.3468$. Automation shows a higher score than Smart Working, the group that includes the single best performing technology.

The managers in charge of the digitalisation project are now faced with three options:

1. If a short-term action is required, adopt the single best ranked technology, the Remote operation of production

2. Define a long-term plan to implement the technologies that belong to the Automation group, in order to exploit the benefit of adopting digital technologies that are similar, where interconnection and intercommunication is easier.

3. Adopt the Remote operation of production for short-term gain and implement the Automation technologies for long-term advantage.

6. CONCLUSIONS

In this paper we adapted an existing multi-criteria decision-making model, based on Fuzzy Logic and AHP, to the selection of digital technologies. The model is also coupled with a structured classification of Industry 4.0 technologies taken from the literature, in order to capture the multiplying effect of adopting similar and interconnected technologies. The results show that the single best technology does not necessarily belong to the group of technologies that, combined, can best improve the performances of the production system. Considering the outcome of this work, we were able to identify the following suggestions for further research:

1. Apply the model to a real-life case study of a company that is undergoing a process of digital transformation and compare the results of the two different approaches.

2. Conduct a large-scale survey among companies to get data about mostly used KPIs and sector-specific strategies, processes and subprocesses.

3. Develop a scoring system for already implemented digital technologies, with the aim of using it to update the Fuzzy Scores of new candidate technologies that belong to the same group or that share a high degree of interconnection.

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