A Framework for Technology Selection and Impact Evaluation of Digitalisation in the Industrial Sector

Maretto L.*, Faccio M.*, Battini D.*

** Dipartimento di Tecnica e Gestione dei Sistemi Industriali, University of Padova, Stradella San Nicola, 3 36100 – Vicenza – Italy (leonardo.maretto@phd.unipd.it, maurizio.faccio@unipd.it, daria.battini@unipd.it)*

Abstract: The wide global competition that manufacturing companies are subjected to is forcing them to invest in the application of digital technologies. Moreover, government initiatives such as Plattform Industrie 4.0 or Made in China 2025 represent another external push for the implementation of the digital transformation in the industrial and manufacturing sector. However, evidence from literature and surveys show that there is still a lack of clarity regarding the economic benefit of digitalisation as well as a lack of guidelines that indicate which industrial process is worth digitalising and with which technology. To address this issue, this work develops a methodological framework that aims to provide guidance in the choice of new digital technologies. The framework is divided into four levels and follows a top-down recursive approach, moving from the strategic level to the digital technology level. Enriched with a mathematical formulation, the framework allows various different multi-criteria decision-making methods to be applied.

Keywords: digitalisation, framework, technology selection, Industry 4.0

1. Introduction

The advent of digital technologies and their increasing interconnection are changing the landscape in which industrial and manufacturing companies are working. As Lasi et al. (2014) suggested, companies face two kinds of pressures: an application pull and a technological push. The former modifies the operating conditions of the companies by introducing a series of new trends such as short development periods, individualization on demand, flexibility, decentralization, and resource efficiency; the latter introduces the innovative technologies that enable the three approaches of the push: mechanization and automation, digitalisation and networking, miniaturization. The application pull and the technology push represent the two main development directions behind Industry 4.0. Despite the existence of a variety of definitions in the literature, Industry 4.0 is now a well-established concept in the field of operations and industrial and manufacturing engineering. It has been adopted by both practitioners and governments: an example of the former is the Boston Consulting Group with the work of Rüßmann et al. (2015), while among the latter group there is the French Government (2015), which introduced a specific program called "Industry of the Future" to fund some of the sectors that are behind the main enabling technologies of Industry 4.0. In the most recent years, the industrial world also witnessed the introduction of new technologies not traditionally linked to the concept of Industry 4.0. This combination of factors, the widespread adoption of Industry 4.0 principles, the push from institutions to modernise the industrial infrastructure and the translation to the industrial world of more advanced technical solutions, results in an unprecedented compulsion for companies to adopt digital technologies. However, companies have a limited amount of time and limited resources so they cannot invest in all digital technologies at once: there needs to be a choice, a moment in which various candidate technologies are considered in all their aspects, evaluated according to a specific set of criteria and, finally, a limited number of technologies are chosen to be implemented. The role of this framework is to help exactly in this phase by providing a structured method to decide the best digital technology to be introduced in a company. Its structure allows to connect different organisational levels that are stakeholders in the introduction of a new digital technology, aligning their different priorities. Moreover, it features a wide usage of Key Performance Indicators (KPIs) at the different levels so that the evaluation of the goodness of a technological implementation is based on the improvement that a certain technology is able to bring to the current state, paving the way for a quantitative based choice. This also enables the framework to provide a first response to one of the issues related to Industry 4.0, and digitalisation in general, as indicated in the work of Ivanov et al. (2020): lack of economic clarity regarding the economic benefit of the adoption of Industry 4.0 technologies.

At the basis of the development of the framework there is the idea of developing a method to help companies to choose the most suitable technology for a certain process. Moreover, the framework has the intention to define a coherent theoretical background for a future deeper analysis of the decision-making process in technology selection at different organisational levels, examining the main decisional factors and the impact of the technologies over such levels. To tackle this combination of topics, we first conducted a research of existing frameworks for technology selection in the literature, with a special focus on digital technology selection in the industrial sector. The method behind the design of the framework is a general top-down approach that starts from the strategy and ends with the technology selection. The selection process at each level can be supported by traditional multi-criteria decision-making techniques such as AHP or TOPSIS. However, due to the wide variety of strategies, processes and technologies and their rapidly changing nature, also methods that deal with uncertain data and imprecise knowledge, such as fuzzy logic, represent a valid alternative. The novelty of the paper is represented by its top-down flux and the subdivision of the process into subprocess, with the consequent connection between subprocesses and technologies. This is due to the fact that many digital technologies (e.g. such as Virtual Reality, Augmented Reality etc. in an assembly line) have an immediate impact on a single subprocess rather than the entire process itself (or the improvement of the process is determined mainly by improved performance of a single subprocess). In addition, despite the wide variety of technology selection frameworks, there is only a handful of these works that is dedicated to the selection of digital technologies in the industrial sector.

The work is organised as follows: Section 2 presents the results of our Literary Review and lists the main works in the field of technology selection for industrial purposes. Section 3 presents the proposed framework, with a description of all its elements and the attached mathematical formulation, Section 4 is a discussion of the structure of the framework and its potential implementation and Section 5 provides the closing remarks and the potential future research alleys.

2. Literary Review

The research for existing academic contributions on frameworks for technology selection was conducted on Scopus. Searching with a set of general keywords, such as "technology selection" AND "framework" in the abstract, title and keywords yields a considerable number of results: 318. Limiting the contributions to the subject areas of Engineering and Decision Sciences, the number of results reduces to 161. Narrowing down the research even further, with an enriched set of keywords ("industry 4.0" OR digitalisation AND "technology selection"), in order to find existing frameworks that deal with the selection of digital technologies in the industrial sector, yields only 13 results. After careful reading of these 13 works, 7 of them can be eliminated because they are not related to the topic of this research. The remaining 6 contributions are described below and collected in Table 1.

Hamzeh et al. (2018) reviewed a set of frameworks for technology selection in the industrial sector: by analysing the works of Kengpol and O'Brien (2001), Gouvea Da Costa et al. (2006), Thomassen et al. (2014), Farooq and O'Brien (2015) and Deja et al. (2017), the authors were able to identify a series of gaps in the literature which include 1) a 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 support for the inclusion of internal and external factors in the selection process, 3) no consideration of the opportunities and threats of Industry 4.0 key technologies and a 4) failure to incorporate risk calculations. The proposed solution is a six-step framework that comprises the evaluation of the current situation, the identification of the critical strategic factors for the implementation of Industry 4.0, the definition of the planning range for the implementation, the choice of the manufacturing technology, a detailed evaluation of the identified technology (using a wide variety of suggested multicriteria decision making techniques, ranging from scoring models to fuzzy techniques) and a final risk assessment of the technology alternatives.

Table 1: literary research results recap

Authors	Methods	General	Sector
Hamzeh et al. (2018)	Various	Yes	-
Mämmelä et al. (2018)	Design Science	Yes	-
Beyaz and Yıldırım (2020)	TOPSIS	No	Automotive
Buyukozkan and Gocer (2019)	TOPSIS with Intuistic Fuzzy	No	Turkish Logistics
Erbay and Yıldırım (2019)	AHP + QFD	No	Automotive and IT
Garcia-Villareal et al. (2018)	Action Research	No	German medical equipment manufacturers

Mämmelä et al. (2018) proposed a technology evaluation approach based on Design Science in order to determine which information is needed to evaluate the cost and the value of technology in the manufacturing industry. The importance of intentions, which are guided by the company strategy, is based on their role as evaluation criteria for technology exploitation. These strategic aspects are linked to the technology through the product. The effects of technology exploitation are evaluated through a series of elements that include the knowledge of the technical system intentions and business intentions, product life-cycle phases, technology characteristics and the potential effect of technology related to the product. These elements are all somewhat corresponding to the elements that were introduced in our framework.

Beyaz and Yıldırım (2020) proposed a multi-criteria decision-making model for digital transformation in the automotive sector. Starting with methods such as Value Stream Mapping and Waste analysis, the problems of the process are identified. Then, the problems are matched with a panel of technologies with the help of specialists. Then, the feasibility of the technology implementation is split into four dimensions: financial, organizational, technological, and legal. After the evaluation of each technology under each step, the final selection is made using the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method, introduced for the first time by Hwang and Yoon (1981).

Buyukozkan and Gocer (2019), after assessing the absence of relevant works about the technology selection problem in the context of multi criteria decision making, developed an approach, validated in a Turkish logistics company, based on TOPSIS under the Intuitionistic Fuzzy environment. The latter, introduced by Atanassov (1986), is an extension of traditional fuzzy logic which, alongside membership functions, defines non-membership functions. A set of eleven criteria are used to evaluate the options: flexibility, security, functionality, usability, cost, compliance, transferability, reliability, complexity, performance and scalability.

Erbay and Yıldırım (2019) introduced a multi criteria decision making model that combines AHP and the adaptation of QFD (Quality Function Deployment) proposed by Herron and Braiden (2006). In the latter work, the selection of the most appropriate lean manufacturing tool is governed by a three-step methodology: the first is the Productivity Needs Analysis, which identifies the key productivity measures for a manufacturing plant, the second is the Manufacturing Needs Analysis, which associates the plant problems with the appropriate tools, and the third is a Training Needs Analysis. In particular, the output of the Productivity Needs Analysis is a matrix that combines problems, processes, tools and KPIs and explores and weighs their relative relationships.

Finally, Garcia-Villareal et al. (2018) developed a technology selection framework using action research in order to support the Sales and Operations Planning department of German medical equipment manufacturers.

The analysis of the literature presents us with two main gaps:

1) Despite for a handful of works, there is a lack of contributions that deal with the issue of digital technologies selection in the industrial and manufacturing sector.

2) Apart from Hamzeh et al. (2018) and Mämmelä et al. (2018), the other existing works are models that employ specific decision-making techniques within specific contexts rather than more general frameworks. (Columns "General" and "Sector" of Table 1)

Our work fits into this gap, providing a general framework for the selection of digital technologies in the industrial sector, which does not apply one specific decision-making technique and adopts a KPI-based-top-down approach.

3. The Framework

The proposed framework is divided into four levels and it can work in a recursive fashion. Its objective is to provide a decision-making process that is based on logic and data and that can be traceable, meaning that decisions taken at each level can be explained and supported by evidence. The framework was first defined graphically, following the logical flow of the decision-making process. In a second phase, the model was enriched with a mathematical formulation. This formulation is provided alongside the presentation of the model in this section while the graphical representation is shown in Figure 1.

3.1 First Level

The first level of the framework connects the strategy with the processes of the company. The first assessment that the company must do is to review its strategies and long-term plans and provide a list of strategic objectives that directly or indirectly impact the operations of the manufacturing department. Examples of these strategic objectives are: increasing the productivity of the manufacturing plants, increasing the product mix, decreasing the stock, expanding through acquisitions or building of new plants, etc. The objectives should be accompanied with their respective performance indicators: where possible, each objective should come with its specific list of key performance indicators (KPIs). The KPIs form an intermediate level between the respective strategic objective and the processes. The company, then, must examine its internal operative processes and compile a list that collects them, especially but not exclusively those which are thought to be impacted by the introduction of digital technologies or which are targeted as the candidates for digitalisation. Therefore, the inputs of the first level of the framework are represented by a list of strategic objectives, each with their own list of KPIs, and a second list of industrial processes. These two lists should be compiled with the aid of expert knowledge and any attempt at a quick quantification of the impact of digitalisation on the elements of the lists should be avoided since such an evaluation will be performed later within the framework. A multicriteria analysis is then performed, using the strategic objectives as criteria and their KPIs as subcriteria and where the processes represent the alternatives; the output of the analysis is a weighted ranking of the processes according to their influence on the strategic objectives as quantified by their respective KPIs. Two other additional outputs of this level, that can be useful for the company, are: a weighted ranking of the strategic objectives, that lists all the objectives according to their importance, and a weighted ranking of the KPIs for each objective, which indicates the most important KPIs that are used to monitor the progress in the achievement of said objective. From a mathematical standpoint, the inputs of the level are:

$$S_i \qquad \text{with } i = 1, 2, \ldots, I$$

$$P_j \qquad \text{with } j = 1, 2, \ldots, J$$

where S_i is the i-th element in the list of strategies, I is the index of the last element in the list of strategies, P_j is the j-th element in the list of processes and J is the index of the last element in the list of processes. Additionally, the list of KPIs for each strategy can be represented as:

$$\forall i \qquad KPI_{i,k} \qquad \text{with } k = 1, 2, \ldots, K$$

where $KPI_{i,k}$ indicates the k-th KPI used to monitor strategic objective i and K is the last element of the KPI list. The process of the multicriteria decision analysis can be summarised with three functions. The first one is a function f that, given the list of strategic objectives, returns a weighted ranking of the same objectives, representing the selection of the most important strategies according to the company:

$$f(S_i) = R_i \qquad \text{with } i = 1, 2, \ldots, I$$

where R_i is the i-th element of the weighted rank of the strategic objectives. The selection of the most important KPIs for a given strategy is summarised through a second function g which, for each strategic objective, given its KPIs returns their weighted rank:

$$\forall i \qquad g\,(R_i, KPI_{i,k}) = W_{i,k} \qquad \text{with } k = 1, 2, \dots, K$$

$$\text{such as } \textstyle\sum_k W_{i,k} = 1 \qquad \forall i$$

where $W_{i,k}$ is the k-th element of the KPI rank for strategy i. Finally, the last step of the analysis is represented by a third function h that, given the list of processes and the strategic KPI ranking, returns a weighted rank of the processes according to their influence on the most important strategic KPIs:

$$h\,(P_j, W_{i,k}) = R_j \qquad \text{with } j = 1, 2, \dots, J$$

where R_j is the j-th element of the weighted rank of the processes.

3.2 Second Level

The main output of the first level of the framework represents the input of the second level. In fact, the main input of the second level is represented by the operative processes that have the largest influence on the main strategic objectives as shown by their weighted ranking, introduced above as R_j. At this stage, a thorough examination of those main processes is required: each process must be broken down into several subprocesses. Each one of these subprocesses represents a set of operations that, altogether, compose a part of the original process. An example of process in a manufacturing company is represented by the assembly while its subprocesses are: feeding of the materials and parts, manual assembly in a set of stations, automatic assembly in another set of stations, material handling between the stations and control & testing; another example can be the order processing in a retail warehouse, which is broken down into picking, single order packing, multiple order packing and shipment. The depth of the breakdown of the processes should be agreed upon within the company. Then, a list of the main KPIs under which each process is evaluated has to be compiled. Once the lists are completed, another multicriteria analysis is performed for each process, where its KPIs are used as criteria and the subprocesses are the alternatives. The aim of this second analysis is to indicate, for each process, which are the KPIs that are the most important for the evaluation of the process itself and which are the subprocesses that have the largest impact on those KPIs. Hence, the main output of the second level is represented by a weighted ranking of the subprocesses, according to the impact that they have on the main KPIs of a certain process. An additional output of the second level is a weighted ranking of the KPIs, which measures their importance in capturing the performance of the process according to the practitioners' judgement. With regards to the mathematical formulation, the inputs of the second level are:

$$R_j \qquad \text{with } j = 1, 2, \dots, J$$

$$\forall j \qquad KPI_{j,l} \qquad \text{with } l = 1, 2, \dots, L$$

$$\forall j \qquad P_{j,s} \qquad \text{with } s = 1, 2, \dots, S$$

where, R_j is the weighted rank of the processes, $KPI_{j,l}$ is the l-th element of the list of KPIs of process j and L is the index of the last element in this list of KPIs, $P_{j,s}$ is the s-th element of the list of subprocesses of process j and S is the index of the last element in the list of subprocesses of process j. The last two lists, in particular, are the ones compiled in this level, as mentioned above. The multicriteria analysis is represented by two functions, one less than in the previous level, because in this case there are no subcriteria. Both functions are applied to one process j at a time, hence the symbol $\forall j$. The first is a function m which, given the list of KPIs for process j, returns their weighted ranking according to their relative importance:

$$\forall j \qquad m\,(KPI_{j,l}) = W_{j,l} \qquad \text{with } l = 1, 2, \dots, L$$

$$\text{such as } \textstyle\sum_l W_{j,l} = 1 \qquad \forall j$$

where $W_{j,l}$ is the l-th element of the KPI rank for process j. This function represents a step in the multicriteria analysis where the KPIs of the process are compared with relation to their importance in the monitoring of the process. Then, a second function n accounts for the last steps of the analysis: for each process j, given its weight, the weighted rank of the KPIs of that process and the subprocesses of process j, the function returns a weighted rank of the subprocesses:

$$\forall j \qquad n\,(R_j, W_{j,l}, P_{j,s}) = R_{j,s} \qquad \text{with } s = 1, 2, \dots, S$$

where $R_{j,s}$ is the s-th element of the weighted rank of the subprocesses of process j. For a matter of simplicity, it is possible for the company to perform the analysis of the second level exclusively on the best ranked process or on a restricted set of highly ranked processes, according to the weighted rank R_j.

3.3 Third Level

The third level of the framework is where the actual technology selection happens. This level starts from the subprocesses that have the largest impact on the KPIs of the respective process, which in turn is one of the processes that have the highest influence on the main KPIs under which the most important strategic objectives are evaluated by the company. In this way, the selection of the most suitable technologies is linked to each one of the upper levels, especially the first one that comprehends the main strategic targets, and is quantity-based thanks to the use of level-specific-KPIs as selection criteria. First of all, for each one of the principal subprocesses, as indicated by the list $R_{j,s}$, the company has to collect all the KPIs and put them in a list. Then, the company has to define a list of all the digital technologies that are candidate for adoption. The various candidate technologies can be grouped according to a categorisation proposed by Frank et al. (2018): Smart Manufacturing, Smart Supply Chain and Smart Working Technologies, as listed below.

- 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 (M2M)
  - 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 (M2M), 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 for maintenance, Virtual reality for workers training, Augmented and virtual reality for product development, Collaborative robots
- Smart Supply Chain Technologies: Digital platforms with suppliers, Digital platforms with customers, Digital platforms with other company units

Smart Product Technologies are not considered since their influence is mainly on the product itself rather than the productive system. With regards to the Base Technologies of the same classification, they are left out as well, since they represent enabling factors that are common to all the Front-End Technologies, hence the element of choice is less central. Once the two input lists are completed, another multicriteria analysis can be performed for each subprocess: using the relative subprocess KPIs as criteria, the analysis defines the principal KPIs for the evaluation of the subprocess and then looks for the technology that have the largest impact on those main KPIs. This is the crucial part of the framework, where the analysis should be performed as carefully as possible: a deep internal knowledge of the operations of the subprocess and a wide and extensive knowledge of the capabilities of the candidate technologies are both required; in addition, the evaluation of the impact of the technologies on the KPIs should follow as much as possible a quantitative approach, preferring formulas and direct correlations to scores and expert judgement. The main output of the third level is a weighted ranking of the candidate technologies, according to their ability to improve the performances of the relative subprocess. Another important output of this level is a weighted ranking of the KPIs of the relative subprocess, which lists them according to the priority assigned to them by the company. In terms of mathematical formulation, the inputs of the level are:

$$\forall j,s \qquad \begin{array}{ll} R_{j,s} & \text{with } s = 1, 2, \ldots, S \\ KPI_{j,s,r} & \text{with } r = 1, 2, \ldots, R \\ T_z & \text{with } z = 1, 2, \ldots, Z \end{array}$$

where $R_{j,s}$ is the weighted rank of the subprocesses, $KPI_{j,s,r}$ is the r-th element of the list of KPIs of subprocess s of process j and R is the index of the last element in this list of KPIs, T_z is the z-th element of the list of candidate technologies and Z is the index of the last element in the list of technologies. The lists compiled in this level are the last two, in the same way as for the second level. Again, the multicriteria analysis is summarised by two functions. The two functions are applied consecutively, one subprocess s at a time, hence the symbol $\forall s$. p is the first one of the two functions which, given the list of KPIs of a given subprocess, returns their weighted ranking according to their relative importance:

$$\forall s \qquad p\,(KPI_{j,s,r}) = W_{j,s,r} \qquad \text{with } r = 1, 2, \ldots, R$$

$$\text{such as } \textstyle\sum_r W_{j,s,r} = 1 \qquad \forall s$$

where $W_{j,s,r}$ is the is the r-th element of the KPI rank for subprocess s of process j. The second function q accounts for the technology selection and is the most important of the framework. For each subprocess s, given its weighted rank, the weighted ranking of its KPIs and the list of technologies, the function returns a weighted ranking of the technologies, which are ordered according to their impact on the KPIs:

$$\forall s \qquad q\,(R_{j,s}, W_{j,s,r}, T_z) = R_z \qquad \text{with } z = 1, 2, \ldots, Z$$

where R_z is the z-th element of the weighted rank of technologies. In the same way as for the second level, for the sake of simplicity it possible to perform the analysis on just one subprocess: the best ranked according to $R_{j,s}$.

3.4 Fourth Level

The last level of the framework represents a connection between the resulting technology ranking and the rest of the framework, starting from the top. In fact, in order to obtain more robust results, it is possible to start a new iteration of the framework: the multicriteria analysis can be performed again at each level, starting from the relative weights of the various criteria. The result of running the framework another time is a new technology ranking which, again, is put under the examination of the experts of the company and can be compared with the previous one. The iterations can be repeated until convergence of the weighted ranks of the technologies is reached or the results are deemed satisfying enough by the company.

4. Discussion

Our framework proposes a recursive top-down multi-criteria decision-making structure to select the most suitable digital technology in a manufacturing company. This framework serves as the basis for a future expansion of the research, offering a methodological frame for a successive deeper examination of the decision-making process at each level.

The model works with a top-down approach, where technologies are chosen according to their ability to enhance the performance of the current system rather than from an evaluation based exclusively on the various properties of the technology itself.

The model attempts to be as general as possible, so that it can be applied and modelled to different productive sectors, with their specific processes and subprocesses and their own KPIs. There is also no definition of the multi-criteria decision-making technique to be used within each level: a wide variety of approaches are available, as long as they can produce weighted ranks. As mentioned above, good alternatives are AHP, TOPSIS or the application of fuzzy logic.

With regards to the KPIs, in our model they are either strategic-specific, process-specific and subprocess-specific. However, the general and recursive structure of the model does not prevent to add new KPIs that are directly correlated to the introduction of a new technology. For example, after the first iteration of the framework, a certain technology is chosen; this technology allows to monitor the performances of the subprocess in a new way, adding a novel KPI; in the second iteration of the model, this KPI can be added to the criteria of the third level selection and the consequent improvement should be modelled accordingly.

At a first glance, the framework would initially not look like taking the cost of a certain technology into account in the decision-making process, since the criteria used are relative to a subprocess. However, the cost can be added to the criteria by considering the cost of running the subprocess in question: each technology will then be evaluated according to the esteemed cost that it will take to run the subprocess with that implemented technology.

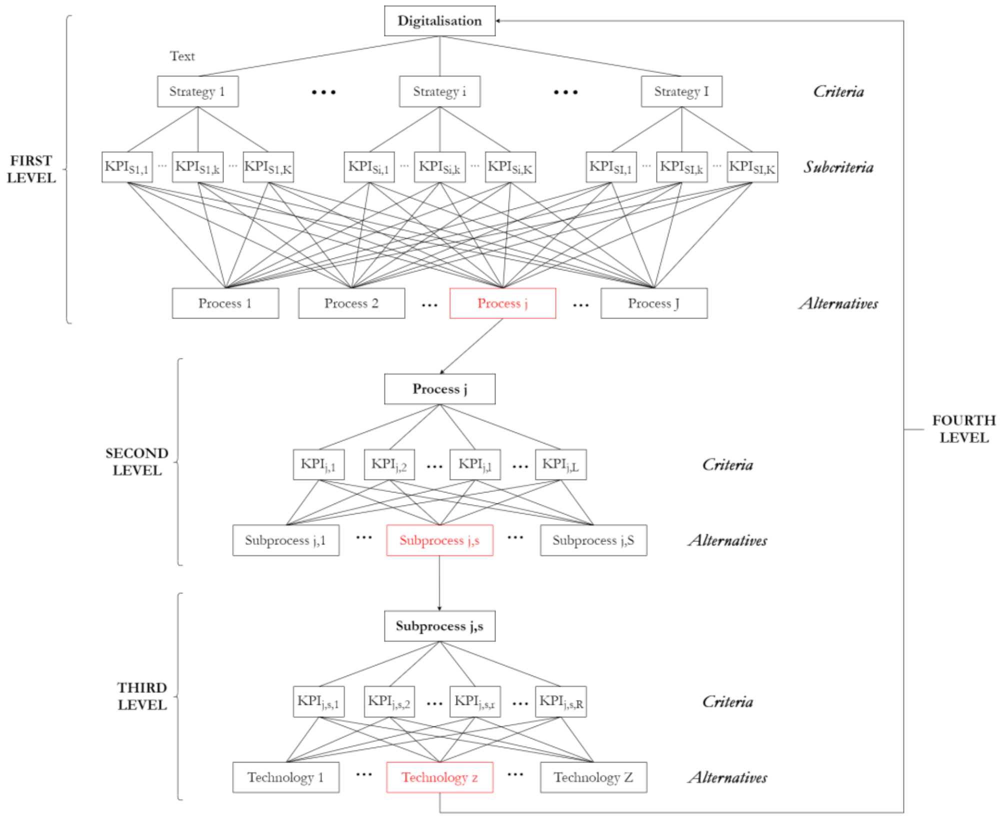

Figure 1: The graphical representation of the framework. The elements in red represent a single chosen process, subprocess and technology for each level as results of the decision-making process at each level. Those shown in the picture are not AHP trees but are just representations of the relationships between the elements of each level.

5. Conclusion

In this work we developed a framework for the selection of digital technologies in the industrial and manufacturing sector. We started from an analysis of the literature which showed a lack of frameworks for technology selection within the environment of digitalisation and Industry 4.0. To address this gap, we developed a recursive framework that can work by iteration. The approach of the framework is top-down since it starts from the strategic objectives and ends with the technology selection; moreover, the choice of the alternatives at each level is made according to the improvement that they can bring to the output of the upper level. It also allows to have specific rankings of the criteria and the alternatives at the end of each level-specific analysis. The elective digital technologies are classified into a structure that follows the classification proposed by Frank et al. (2018). Finally, it splits processes into subprocesses so that the technology selection can be made at the level where the impact is greater. To the best of our knowledge this is the first approach of this kind in the literature for the selection of digital technologies in the industrial environment.

Since the main aim of this framework is to be a theoretical platform for successive research, the possibilities for further research are wide and many. For example, the framework can be adopted to real cases to test its validity, also offering the chance to understand how its implementation changes according to different industrial sectors. Another interesting theme can be the examination of the principal KPIs and decision variables that are used at the various levels to choose the best alternative, with a special focus on the level of technology selection. New mathematical models can be built using this framework a reference, modelling the impact of technologies on different processes according to their characteristics or the interactions between the different levels in a digitalised environment. Finally, adopting fuzzy techniques seems an interesting approach to the problem due to the intrinsic uncertainty that is behind the choice of a never-implemented-before technology.

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