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Process Mining Organization (PMO) Modeling and Healthcare Processes

Angelo Rosa [1,*,†] **and Alessandro Massaro** [1,2,†]

[1] LUM, Libera Università Mediterranea "Giuseppe Degennaro", S.S. 100-Km. 18, Parco il Baricentro, 70010 Bari, Italy; massaro@lum.it
[2] LUM Enterprise srl, S.S. 100-Km. 18, Parco il Baricentro, 70010 Bari, Italy
* Correspondence: rosa@lum.it
† These authors contributed equally to this work.

Abstract: Process mining organizatioQn (PMO) is an innovative approach based on artificial intelligence (AI) decision making suitable for designing healthcare processes for human resource (HR) organizations. The proposed work suggests some examples of PMO-based Business Process Modeling and Notation (BPMN) workflows by highlighting the advances in HR management and in risk decrease according to healthcare scenarios. Specifically proposed are different examples of "TO BE" process pipelines related to an upgrade of the organizational healthcare framework, including digital technologies and telemedicine. Important elements are provided to formulate HR management guidelines supporting PMO design. The proposed BPMN workflows are the result of different consulting actions in healthcare institutions based on the preliminary mapping of "AS IS" processes highlighting bottlenecks and needs in HR organization. A pilot experimental dataset is used to show how it is possible to apply AI algorithms providing organization corrective actions. The paper is mainly focused on discussing some validated BPMN models managing HR in the healthcare sector. The methodology is based on the application of the BPMN approach to deploy human resource organizational processes. The results show AI data-driven workflows adopted in healthcare and examples of AI fuzzy c-means outputs addressing organizational actions.

Keywords: PMO; process mining; organization; BPMN-AI; healthcare process engineering; telemedicine; ERAS

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1. Introduction

1.1. Main Scenario of Technologies and Tools Upgrading Processes in Healthcare

Artificial intelligence (AI) plays an important role in the planning of the management of human resources (HR) organization [1,2]; specifically, AI is an important tool improving sustainable organizational performance [1] and HR recruitment [2], important aspects in healthcare. AI-based algorithms are integrated in processes as decision-making engines by generating process mining (PM) workflows. The PM models are, in general, applied for industrial applications and for risk management [3–5] implementing AI decision making in processes managing production, quality, and risks. The PM approach has not yet been applied in healthcare environment. For this purpose, the goal of the present paper is to apply the theoretical approach of PM design to healthcare organizational models. A versatile digital tool to design PM processes is the Business Process Modeling and Notation (BPMN). The BPMN is a standard graphical notation (ISO/IEC 19510:2013) [6,7] suitable for mapping processes; it can, thus, be used to officially standardize operational processes in private and public companies. Concerning healthcare scenarios, BPMN is adopted to design emergency care procedures planning HR healthcare organizations [8], to simulate processes including data-driven decision points [9], and to design integrated home care (IHC) workflows integrating care provision processes [10].

1.2. Main Research Topic: Process Mining Organization (PMO) Modeling

Different management approaches can be followed in healthcare to manage and optimize processes. A typical approach is based on Lean Six Sigma (LSS) providing problem solutions in healthcare for hospital organizations [11]. LSS is a process improvement approach adopting the team collaboration concept to improve performance. A recent upgrade of the LSS approach is named process mining organization (PMO). PMO is defined in a healthcare environment as the workflow optimizing HR organization through an AI decision-making engine. Specifically, in healthcare scenarios, the new concept PMO is based on the integration of AI algorithms in improving the organization, such as for fall-risk management procedures adopted in public hospitals [12].

The upgrade of digital processes through the integration of AI algorithms is possible if a full digital transformation phase is implemented for the healthcare institutions. In this direction, telemedicine and digital tools are fundamental for a tailored process upgrade, because they could include AI decision-making engines improving service care processes through the prediction of the patients' physiological parameters [13]. The merging of digital tools and of AI decision-making engines into organizational workflows allows us to formulate the best PMO model to adopt for HR management efficiency in care services. The main objective of this paper is to provide, using different BPMN workflows, the criteria to formulate BPMN-PMO processes designing advanced workflows useful for HR healthcare organizational models. Elements such as the integration of digital data and AI data processing to formulate intelligent PMO workflows are provided for the first time.

1.3. Alternative Approaches for Process Modeling

Another alternative and widely used approach to adopt for the process modeling is based on the Petri nets managing the orchestration of services [14]. The Petri nets approach has been compared with another important approach, the hypergraph theory approach [15], which is suitable to improve business process performance. In recent years, another approach based on an extension of the Petri nets, called generalized nets, has been successfully used in the modeling of workflow processes for telemedicine/telecare for the monitoring of diabetics [16]. In any case, the BPMN approach is an ISO/IEC standard that could be adopted better to standardize protocols in the dermatopathology medical field [17].

1.4. Importance of Data Interpretations and Data Modeling in Healthcare Processes

Correct data interpretations provided important results during the COVID-19 pandemic, improving patients' chances of recovery [18]. The analysis of data distributions and statistical approaches could support the quality control of processes [19] and the understanding of pandemic conditions [20,21]. The data cross-analysis facilitates the interpretation of the clinical choices, such as the mode of delivery choice [22]. An important upgrade of data processing is provided by machine learning (ML) techniques, decreasing the patient risks [23–25] and, consecutively, optimizing clinical prescreening processes [17]. Correct data interpretation is, thus, fundamental to planning efficiently organizational process.

1.5. Paper Validation Criteria and Vademecum

The proposed workflows have been discussed and validated by different professionals in the healthcare sector. The validation criteria are based on the following points:

- Good process performance deduced using the KPI estimation (decrease in time delays, risk events, patient risk, and in unnecessary care services);
- Workflow matching with priorities and urgencies of the hospitalization units;
- Positive feedback of doctors and of other healthcare personnel regarding the applied operative workflows limiting risks;
- Possibility to formulate an audit form matched with the designed workflows.

The paper is structured as follows:

- Section 2 provides tools and methods regarding BPMN-PMO design and modeling;
- Section 3.1 develops BPMN-PMO examples regarding HR organizations in healthcare environments;
- Section 3.2 provides some examples of BPMN-PMO workflows in HR management to decrease the fall risk of patients and in telemedicine application fields;
- Section 4 provides guidelines for PMO design approach, including process monitoring aspects;
- Section 4 also discusses the advantages, disadvantages, and limits of the proposed theoretical workflows.

2. Materials and Methods

The proposed workflow models are sketched by means of the BPMN standard notation [6,7] digitalizing processes: by using the BPMN approach, the models are suitable for implementation and integration in healthcare protocols. The open-source tool used for the BPMN workflows design is *Draw.io 20.7.4* [26,27]. *Draw.io* is a versatile software containing all the BPMN symbols as integrated libraries, and it is quite simple to use.

The BPMN workflows are designed through interviews performed with different professionals working in the specific sector of the mapped processes. Some subprocesses (modeled by the symbol "Sub-Process, Collapsed" similar to a rectangular box) are detailed into other workflows to enhance the description of the main process. The links between tasks indicate all possible cases by making the process ready for simulation and execution. The integration of AI decision making into the BPMN workflows generates the upgraded BPMN-PMO model, where the organizational impacts and the digital solutions are highlighted. The BPMN workflow design takes into account the use of four main colors to distinguish better the process tasks, such as the following:

- Orange color, identifying digital sources and digital data (it represents the digital transformation of the healthcare institution);
- Red color, representing the AI decision-making engine (AI data prediction or AI data classification/clustering);
- Green color, indicating the PMO outputs or the HR organizational improved models (this color characterizes the organizational impact);
- White color (transparent), modeling the standards tasks or the graphical elements which are retained but are not so important in the design stage.

The BPMN workflow is contained into big rectangular boxes named "pools" (indicating a process or actions performed by a single actor of the system), where the tasks (smaller rectangular boxes) are linked according to a specific data flow or process to follow. The workflow is extended from left to right. For a better comprehension of the workflow, only the following few symbols are considered:

- Event symbols: "Start" (begin of a process); "end" (end of a process); "timer" (periodical evaluation of a part of the process's workflow).
- Gateway symbols: "Exclusive" (logic condition selecting a subprocesses); "exclusive-event-based" (deep checkpoint improving decision-making actions).

The used graphical notation is the ISO/IEC standard [6] applied to PM workflows [3–5]. This standard is appropriate for the design of PMO models addressing the engineering design on innovative research workflows upgraded by the AI decision-making engines. Furthermore, the BPMN facilitates the graphical simulation by taking into account all possible cases merging AI data-processing flows into the processes.

The example discussed in Appendix A (AI data process providing PMO outputs) is a data clustering analysis performed by the fuzzy c-means algorithm [28]. Data clustering is a technique suitable for the deploy of data-driven processes [29] and for showing a possible interpretation of the AI outputs to improve organizational solutions. The Konstanz Information Miner (KNIME) open-source tool [30] is executed to test the PMO approach: discussed in Appendix A are more details about the fuzzy c-means algorithm implementation concerning a case study of an Italian hospitalization unit managing the fall risks of patients. The estimation of the silhouette coefficient [31] is used as a reference metric to define the best number of clusters to process. The choice of the number of clusters is a good compromise between algorithm performance (a silhouette coefficient of 0.136 is estimated for the case study) and the possibility to better interpret results (three clusters are enough to efficiently process a dataset of 5 years of data). The KNIME AI-tool follows the same process flow logic: the flow starts from the left and extends towards the right in its phases.

The workflows of the HR allocation are formulated by following consulting results performed for different hospitalization units, and by analyzing fall-risk data of a specific hospital: data were collected from 2018 to 2022, and include fall numbers, time slot of falls, computerized axial tomography (CAT) analyses, X-ray analyses, ultrasound analyses, number of required external consulting opinions, cases of blunt injuries, cases of major trauma, and cases of falls corresponding to a classified Conley index. Illustrated in Figure 1 are some data of the Conley index evaluation.

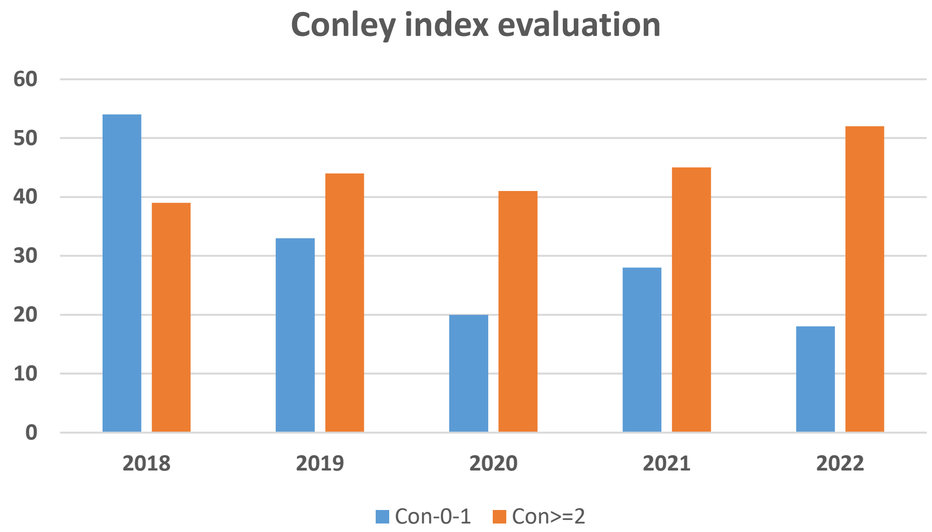

Figure 1. Example of data extracted from the analyzed dataset ("Con 0–1" indicates the low-risk cases of a Conley index value between 0 and 1, and "Con >= 2" is related to the high-risk cases characterized by a Conley index value greater than 2).

The experimental dataset was extracted from reports and documents collected by nurses and doctors registering all fall-risk events and related implications, such as visits following falls and requiring further checks. All data refer to patients having a specific Conley index. The proposed workflows include the activities of surgeons, nurses, doctors, and HR managers collaborating for the case studies.

An example of AI-based data processing is shown in Appendix A. The need to design an AI-based workflow managing HR is to avoid the saturation of the machines of analyses by optimizing the HR allocation criteria and HR operations at the same time. An important aspect that emerged in the preliminary "AS IS" analysis (and planned in the "TO BE" process) is to reskill or upskill HR due to the limited number of available health personnel. Furthermore, the "AS IS" analysis enhanced the existence of urgent and nonurgent cases requiring a re-engineering of the HR allocation procedure and of the organization actions described in the proposed workflows. Finally, as a further solution to avoid the overcrowding of hospitals, telemedicine workflows suggested by doctors activating hospitalization care paths and post-surgery patient control processes were designed.

Concerning the hospitalization process, the adopted BPMN workflows integrate patient queue management processes based on the priority of care paths requiring more attention (elderly patients with comorbidities, patients in the postoperative phase, etc.).

3. Workflow Results: Design of PMO Healthcare Processes

This section provides three typologies of BPMN models tailoring HR management processes of medical staff in healthcare environments. The topic of the first, more generic, example addresses a BPMN-PMO decision-making process integrating an AI engine to improve the HR organizational model. The topic of the second type of examples refers to the HR management process optimizing fall risks of patients in healthcare structures. Finally, the topic of the third example is related to the BPMN-PMO telemedicine model optimizing care paths and, consecutively, the HR organization. All the discussed examples were designed by taking into account the frameworks of healthcare units and interviews with different professionals working in hospitals.

3.1. HR Management through Data-Driven Approach

The HR manager has an important role of optimizing HR activities in a healthcare infrastructure. The first step to designing a data-driven workflow supporting HR management is the identification of the data-processing phase. Illustrated in Figure 2 is the BPMN-PMO workflow of an HR manager deciding which HR to allocate. The workflow enhances the integration of the AI algorithms (see red color) and the digital data flux (see orange color) into the whole main process, with the goal of optimizing the organizational model (see green color). The data-processing phases are defined by the following task priorities:

1. Preliminary dataset analysis: The attributes of the analyzed dataset are selected based on the analysis to perform (in this phase, data cleaning and/or data filtering, preparing digital data for processing, can be executed).
2. Algorithm selection: The selection of the AI algorithm depends on dataset typology (AI unsupervised algorithms are preferred for a dataset with a high number of attributes and that has difficulty finding the key attributes to extract more useful information; additionally, AI supervised algorithms are indicated when an significant attribute is to be supervised as a class to classify or to predict).
3. The AI algorithm is executed, and the results are interpreted to find solutions about HR allocation, HR procedures to actuate, and, in general, to update the organizational model.

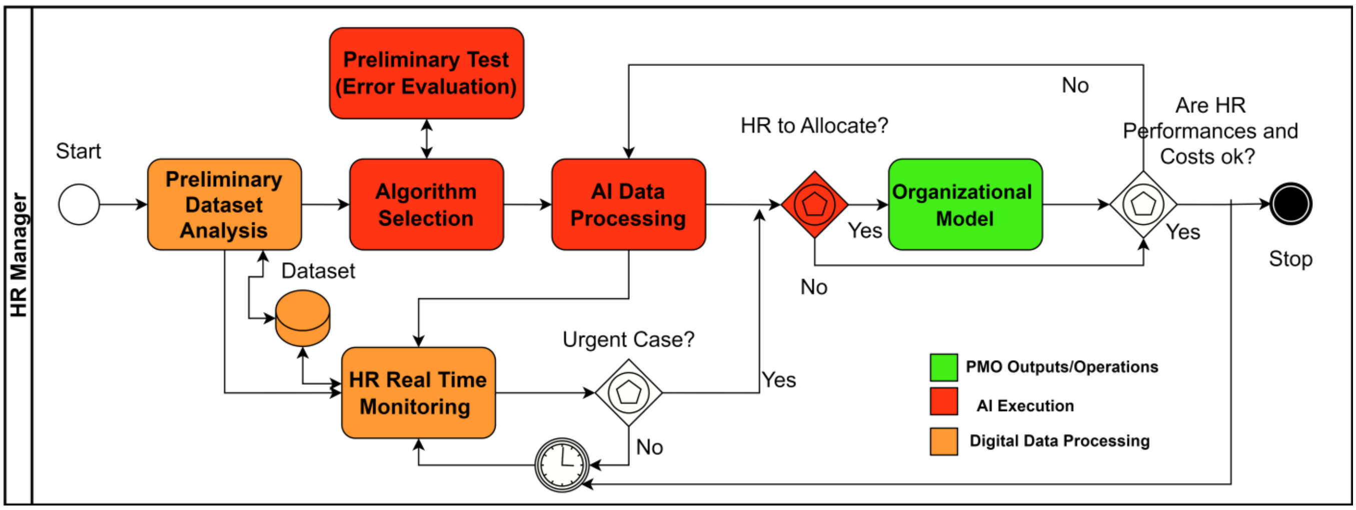

Figure 2. BPMN graph modeling a PMO workflow tailoring HR allocation.

The workflow is linked to provide real-time monitoring of HR (activities in progress, tasks pending, task to perform, actual presence/allocation, etc.). A new HR allocation is performed in accordance with the best HR efficiency and the possible emergences of urgent cases. AI data analysis driving the process can be a new risk classification, a risk prediction, or an HR classification (HR skilled to avoid a possible risk). The process terminates when it has found good HR performances and optimizations of HR management costs. The examples discussed in Sections 3.2 and 3.3 indicate more detailed PMO-based organization models.

3.2. Application Field: Fall Risks and HR Management

The proposed example in Figure 3 is related to a PMO model oriented to patient fall-risk management and improvement of the medical staff actions. The workflow is structured into sequential tasks based on priority roles. Specifically, to avoid the fall risk in hospitals, three main sequential actions are defined (see Action 1, Action 2, and Action 3 of the "exclusive-event-based" gateways of Figure 3):

1. **Action 1** (learning plan actuation in long periods): If necessary, a formative plan is enabled (training plan, execution of the plan, and test of nurse upskill/reskill) when it is found that the medical staff have no experience in preventing patients' falls. The formation is important to know and for better application of the security procedures (Conley risk evaluation [24], actions to prevent risks, mechanical tools to add on beds, use of sensors and digital tools for patient monitoring, etc.).
2. **Action 2** (HR displacement in short/medium period): If a formative plan is not enough, and if necessary, a reallocation of nurses is performed (allocation of nurses in specific rooms with patients with high risk, allocations of nurses in time slots characterized by a high fall probability, movement of nurses from other departments, etc.).
3. **Action 3** (HR addition in short/medium period): If it is not possible or not necessary to activate Action 1 or Action 2, a last solution is the addition of new skilled nurses but with an increase in costs of the hospitalization unit.

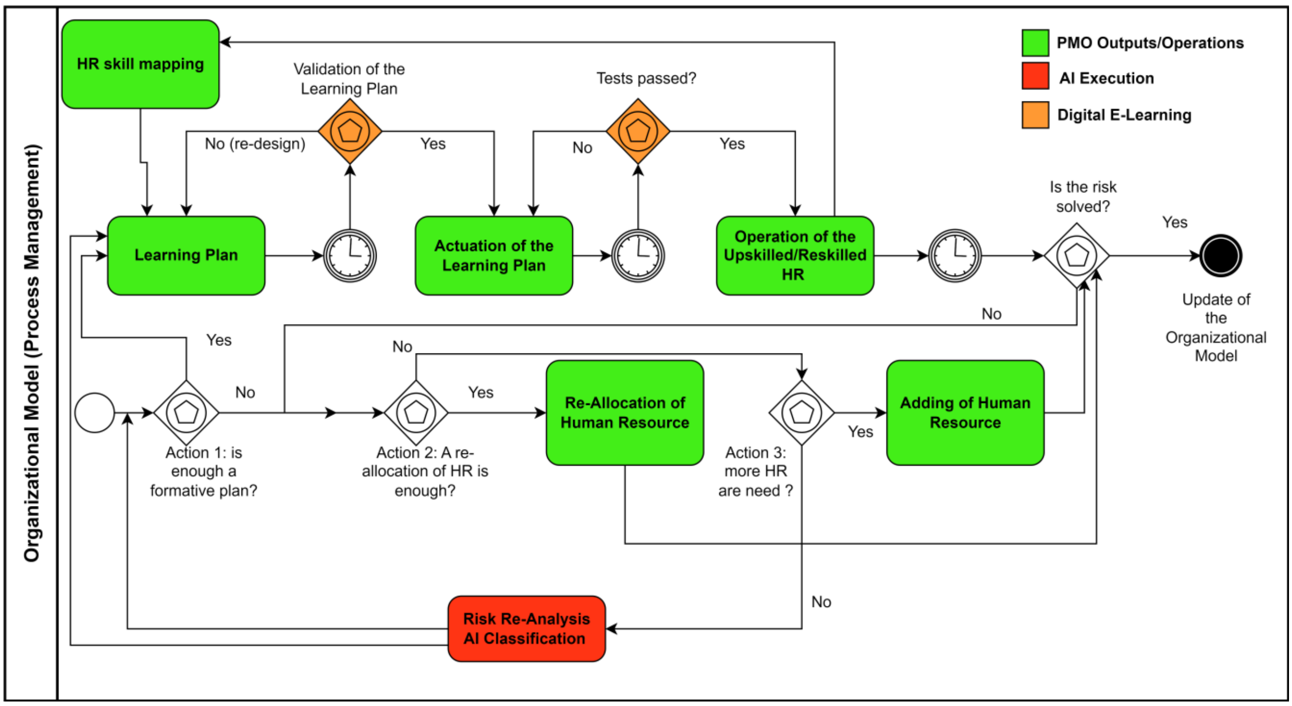

Figure 3. BPMN-PMO workflow of HR (medical staff) management according to AI risk assessment (risk reanalysis).

If the fall risk is not solved by the three actions, the workflows restart iteratively to evaluate the last two actions. The task of "Risk Reanalysis AI Classification" (enhanced by the red color) is used to classify risks and to update the risk assessment: the AI analysis is triggered when all the three actions are unsatisfactory to decrease the fall risk. This is an indicator that risks should be reclassified and re-evaluated (update of the risk assessment model through AI classification). Other important aspects of the organizational model are HR skill mapping and the use of e-learning platforms to improve and track the formation plan (see orange color), and the ability to provide further digital data, updating the skill maps.

The risk assessment in the short and medium terms can be improved by the AI risk prediction and the AI risk classification according to the scheme in Figure 4, where an example of risk assessment triggered by AI is shown. The AI decision making process is able to active the following two cases:

- **Case A** (nonurgent actions): The nonurgent actions are performed when alerting conditions estimated by the AI algorithm are found;
- **Case B** (urgent actions): The urgent actions are executed when a high risk is assessed.

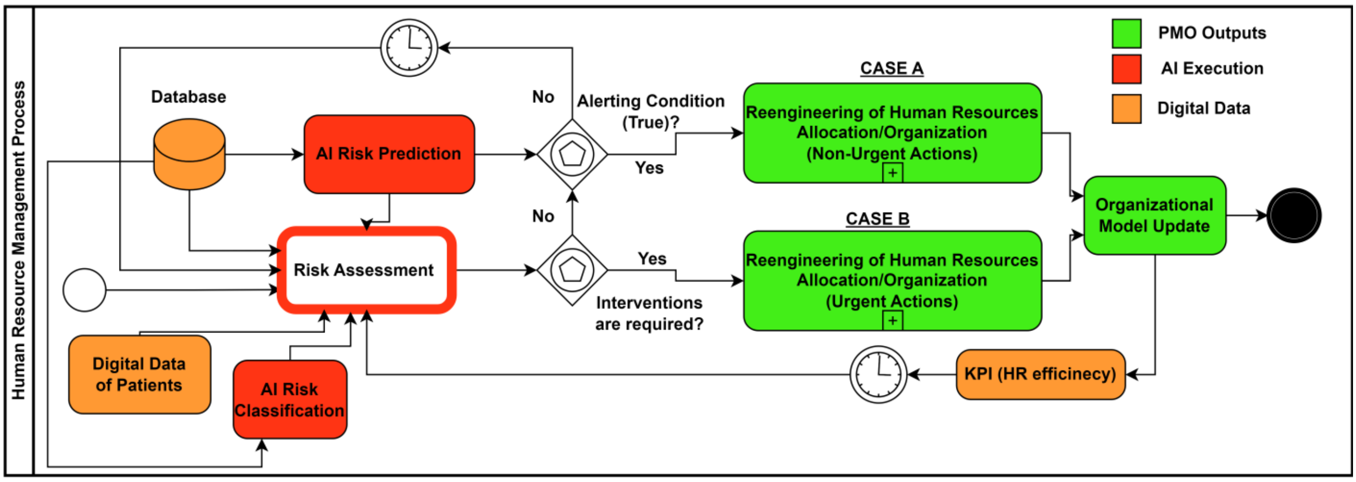

Figure 4. BPMN-PMO workflow of HR management according to risk assessment for urgent and nonurgent actions (planning of interventions in the medium and short terms).

The executions of both the tasks (Case A and Case B) provide results to optimally update the organizational model and the risk assessment preliminary based on the standalone evaluation of the Conley index [32]. The risk assessment considers different digital information (collected into a database) such as risk prediction, risk classification, KPI of the medical staff, and patient data.

The subprocess of Case A (nonurgent case) is deployed in the workflow of Figure 5 by taking the case into account before the HR availability check (waiting for the availability in a negative case) and successively enabling the HR displacement after the acceptance.

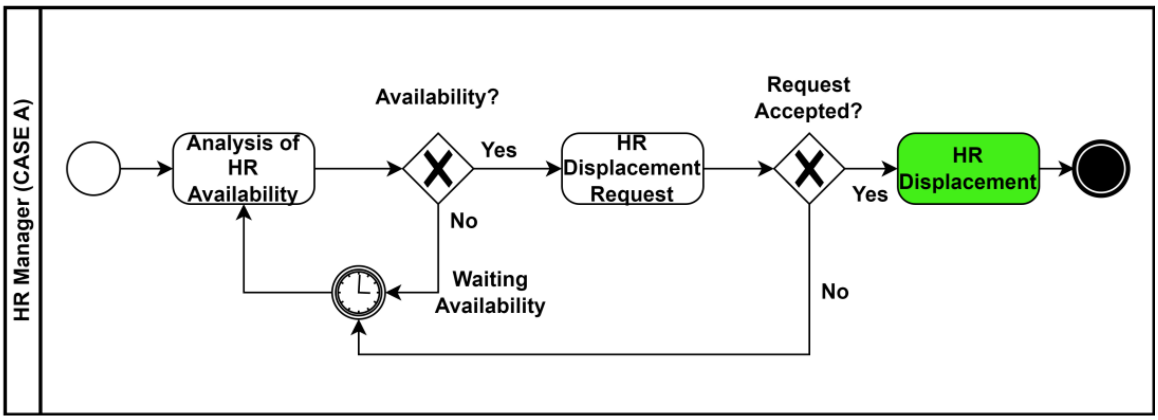

Figure 5. BPMN-PMO Case A of Figure 4 (nonurgent case).

More details of the subprocess of Case B (urgent case) are sketched in Figure 6, which considers, in cases of not immediate availability, an evaluation of the impacts following an HR displacement coming from another department (an high impact requires an external call of HR, increasing the costs).

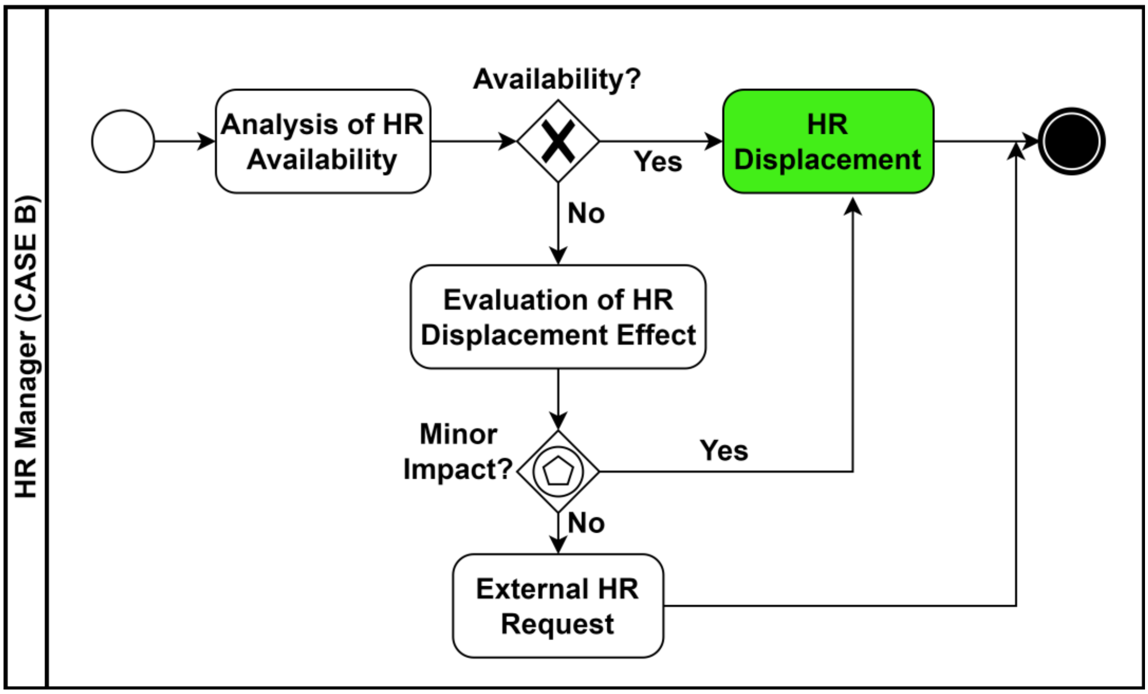

Figure 6. BPMN-PMO Case B of Figure 4 (urgent case).

3.3. Telemedicine Impacting Organizational Models

A continuous patient monitoring home care process could imply a possible hospitalization care process actuation, especially for patients with high health risk. An efficient care process requires real-time patient monitoring, suggesting hospitalization only in necessary cases, thus giving the medical staff more freedom to work on other urgent cases. This aspect is also very important because the doctors and their availability times are generally limited. A digital solution, upgrading hospitalization decision making and HR efficiency, is the telemedicine platform integrating the patient data into a unique information system and improving the medical staff coordination, as proven in the experimental case of [33] related to the COVID-19 pandemic period. Illustrated in Figure 7 is an example of a BPMN-PMO workflow merging the homecare assistance telemedicine monitoring tools with hospitalization decision-making processes. The workflow activates the care hospitalization path only when an alerting condition is found; thus, tailoring HR works for the ordinary activities performed in the hospital. The alert conditions are the output of the AI-based telemedicine platform, behaving as a decision support system (DSS) and working in different alerting levels [13] (AI is able to predict patient risk conditions).

Another application of telemedicine is in the enhanced recovery after surgery (ERAS) management processes regarding the monitoring of patients after surgical operations. In this scenario, telemedicine could support the triggering of the posthospitalization process, optimizing the HR management (management of surgeons and of patients with high risk of complications).

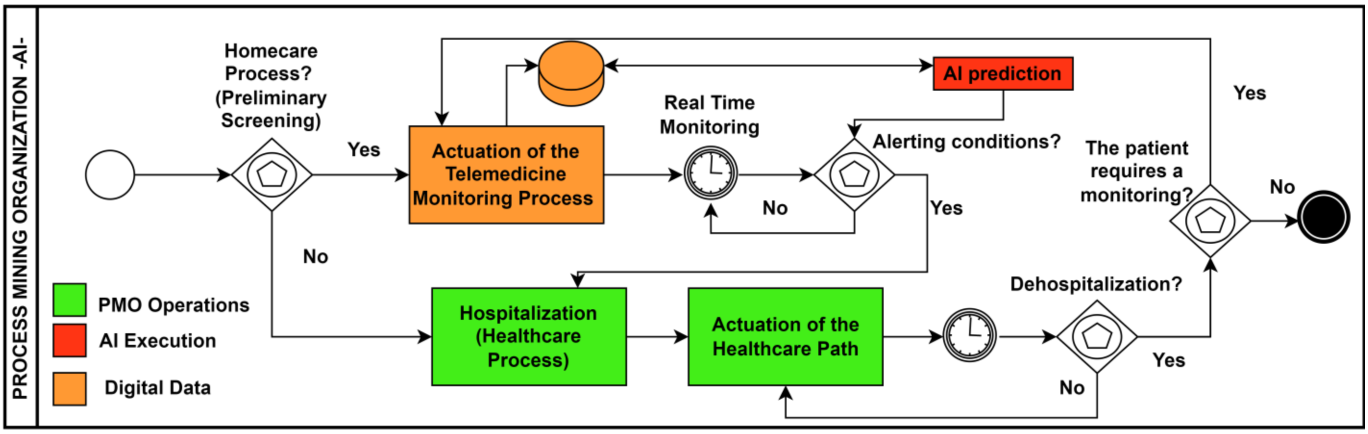

Figure 7. Telemedicine BPMN-PMO workflow: decision making about homecare assistance and hospitalization path care actuation.

Illustrated in Figure 8 is a workflow of the ERAS process, starting with the interview of surgeons and the formulation of clinical tests. In this case, the surgeon is called to check the patient only when the telemedicine sensors provide an alert condition. The proposed procedure will optimize the surgeon's work. Furthermore, the workflow of Figure 8 considers the analysis of priorities of the alerting cases to assign the surgeons making decisions about the rehospitalization of the patient. The proposed theoretical model can be applied for different clinical postsurgical cases.

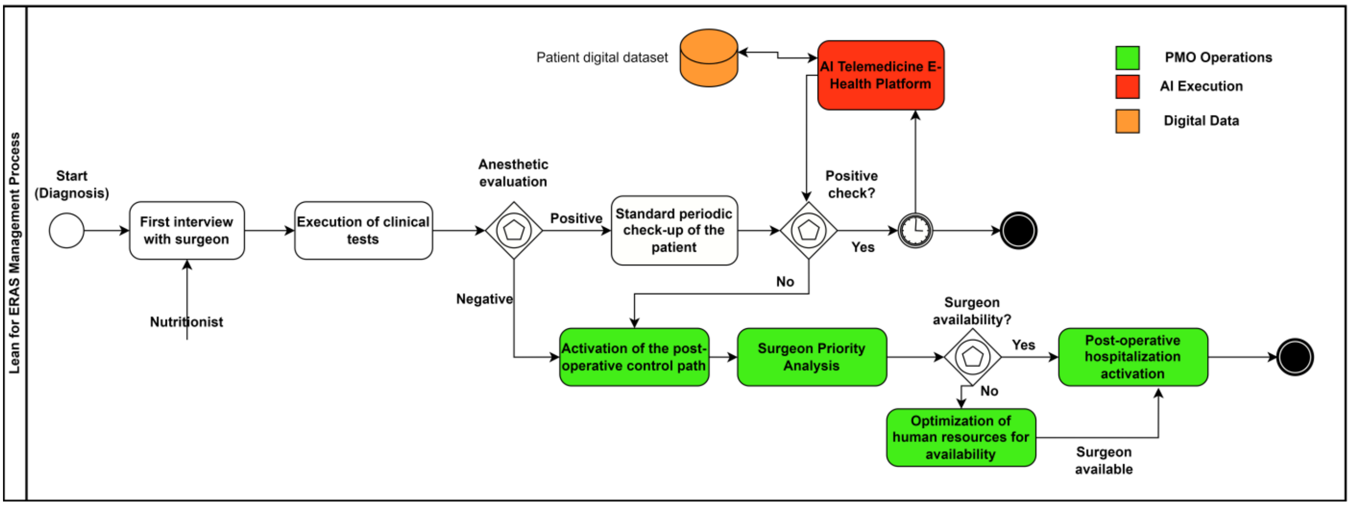

Figure 8. BPMN-PMO ERAS workflow integrating AI-based telemedicine.

4. Discussion

The proposed workflows are deduced using the real needs of healthcare organizations. The first step necessary to construct the workflow is the definition of the requirements of the "AS IS" process mapping the main process and showing possible bottlenecks. The preanalysis of the critical problems to solve helps to construct the "TO BE" workflows illustrated in Figures 1–7. Focusing the attention on HR management in healthcare processes, the main goal of the PMO is to define possible solutions to optimize the medical staff's work, thus consecutively optimizing the healthcare services. Detailed in Table 1 is a PMO framework describing possible actions to execute, deduced from the previous PMO models. Furthermore, PMO advantages/disadvantages and limitations/perspectives are described in Tables 2 and 3, respectively.

Table 1. PMO framework and action guidelines.

HR Intervention Typology	Goal	Possible Correlated Negative Impact	Action Guidelines
Training	Decrease in the health risk of the patient in hospitals.	Legal impact (compensation of patients in cases of inadequately trained personnel).	Reskill and upskill of the medical staff according to the specific risk to control.
HR allocation and displacement	• Optimization of medical staff improving processes and care protocols; • Switching of HR processes according to priorities; • Decrease in time gaps due to unnecessary waiting times (such as for presurgical patient preparation processes).	Imbalances due to the movement of staff between different departments or different healthcare units.	Controlling of the staff displacement according to priorities and to real needs (use of the telemedicine supporting the medical staff management).
HR recruitment	Recruitment of new skilled medical staff, improving care services and clinical processes.	Increase in HR costs.	Recruitment is executed according to a preliminary analysis of needs and possible improvement in the care service quality.
Definition of new responsibilities and roles	Definition of new procedures and protocols by designating new staff roles or assigning new responsibilities.	• Initial HR imbalances to follow the new procedures and protocols; • Fear of taking on new responsibilities.	Preliminary discussion with the whole staff about the new roles; design of the new protocols, comparing all HR opinions.
HR for control room (telemedicine applied to homecare assistance)	Designation of some of the medical staff to remotely monitor patients at home.	Adhesion of patients to wear medical sensors at home.	Implementation of the telemedicine platform according to privacy laws and linking electronic health records.

Table 2. Main advantages and disadvantages of the PMO.

PMO Corrective Action	PMO Advantages	PMO Disadvantages
Training	• Decrease in the health risk of the patient in hospitals; • Improvement of the risk assessment.	Improvement in organizational process about training plan and execution (an initial mapping of the HR skills is required to optimize the training plan).
HR allocation and displacement	• Optimization of medical staff improving processes and care protocols; • Switching of HR processes according to priorities, decrease in time gaps due to unnecessary waiting times (such as for presurgical patient preparation processes); • Correct use of medical machinery (only in cases of need).	Possible increase in the management impact decreasing the efficiency of other departments/sections moving their staff (decrease in the care service quality).
Monitoring of task execution of HR	The HR traceability allows the estimation of KPIs regarding HR efficiency.	A major control of HR activities could generate fear in the staff, thus decreasing the care service efficiency.

Table 3. Limitations and perspectives of PMO.

PMO Limits	Description	PMO Perspectives
Implementation of the AI data-driven processes	The adoption of supervised and unsupervised AI algorithms for the execution of processes requires a high level of expertise in the field of AI and process engineering (a strong HR upskill is required and only few professional figures could work for an AI-based audit).	A future use of digital processes could enable specified automatisms, thus optimizing time delays and HR allocation responses of the hospitals.
Digital solution integration	• The integration of digital solutions (electronic health records, databases, telemedicine platforms, tablet data entry, etc.) requires that HR should be "digital responsive". Usually, this is not the case for some of the employed staff; • Privacy policies could block data integration in database systems; • The digital transformation in hospitalization units is typically slow.	Future use of a full digital platform controlling HR organization and patients (including telemedicine care services).
Digital dataset available	AI-supervised algorithms require a large number of digital data (optimization of learning model). Digital transformation processes of healthcare units are typically slow.	Advanced solutions such as big data tools (data collection and data fusion) and augmented data (creation of artificial dataset to increase the initial performance of the training models) are useful to improve the AI performance.

In order to overcome the problem of the availability of healthcare personnel skilled in AI topics, practical cases have highlighted the possibility of using only specific algorithms with already trained models. The problem of integrating digital solutions into the information system of a hospital unit introduced the possibility of collecting digital data by means of a simple mobile app. Finally, concerning the availability of a large enough dataset, a practical case related to the monitoring of diabetics proved the possibility of using augmented data, thus increasing the efficiency of the training models of artificial neural networks (ANNs).

The adoption of BPMN protocols allows HR responsibilities and roles to be fixed in the "AS IS" process and new ones to be established in the "TO BE" process. Three main categories of organizational actions can be executed. The categories are HR training, HR allocation/displacement, and HR monitoring. BPMN-PMO workflows could be implemented as synoptic panels (as interactive dashboards) monitoring the healthcare processes in real time, thus making the processes operational. The BPMN approach is a versatile tool because it provides the possibility of simulating the process workflow first before actuating it. AI decision-making data-driven processes could be automated in the future to avoid time delays and to accelerate processes through a DSS activating a multilevel alerting condition system [13]. Possible limitations of PMO implementations are related to data privacy management, the amount of available digital data to process, decreasing the AI algorithm's error, and the availability of skilled staff able to correctly interpret AI outputs. As the digital transformation of healthcare units is typically slow, the digital data availability is poor at the beginning of the digital transformation. This problem is overcome by adopting data augmentation techniques [34,35] and increasing AI efficiency for few available digital data. Discussed in Appendix A is an example of an AI unsupervised PMO decision-making algorithm related to a case study of a healthcare unit managing fall risks. New advances include the implementations of BPMN-PMO in prescreening of tumors [17] by activating new organizational procedures to execute clinical protocols.

The proposed BPMN examples of Figures 1–7 were constructed by the following steps:

1. The actors of the systems and the number of pools were defined;
2. The preliminary interviews to define the process were performed;

3. The main tasks to highlight in the main process were defined and the whole BPMN workflow was simplified;
4. The preliminary BPMN workflows were sketched;
5. The workflow was simulated by considering all possible cases;
6. The final BPMN workflow was optimized;
7. An audit form was estimated to control the "TO BE" clinical processes (an example of the audit form is given in Appendix B).

The workflows of Figures 2–5 emerged from the case study discussed in [12]: the HR organizational models proposed in this paper were furthermore improved based on the fall-risk assessment supported by AI data processing (see the results of Appendix A highlighting the need for a training plan to execute and a possible reallocation of the medical staff according to data processing). The workflow of Figure 7 was designed following the case study discussed in [13] regarding the telemedicine monitoring processes for homecare assistance. Finally, the workflow of Figure 8 was derived from the actual problem in different hospitalization units regarding the limited availability of surgeons.

The real challenge of PMO in healthcare is the use of a decision-making engine based on AI algorithms. This generates some problems in terms of the responsibility of those who implement the process, thus requiring a probable approval from an ethical–scientific committee. A possible way to overcome this main roadblock is for the final decision to be attributed to the process manager, following the organizational chart of responsibilities.

5. Conclusions

The proposed paper provides useful elements to design an optimized organizational process in healthcare settings. Different theoretical workflows were discussed to consider as basic "templates" to design more complex workflows or to adapt them to a specific case study. The goal of the work was to enhance the matching between digital technologies and AI in healthcare organizational models for application to risk assessment, HR management, and care optimization. The work is also useful for understanding the new PMO approach, substituting the traditional LSS one and upgrading the tailoring of healthcare processes. The "TO BE" workflows discussed in the paper were designed after the identification of bottlenecks in healthcare organizations through the mapping of the "AS IS" status. A first approach adopted to process data highlighted the potential use of AI algorithms to drive processes: a basic example of AI unsupervised algorithm data processing was shown to provide corrective actions in a healthcare organization (Appendix A). The proposed "TO BE" processes will be validated after the KPI evaluation about the HR efficiency, the resource management efficiency, and health risk decrease. Furthermore, the paper proposed an audit framework (Appendix B) representing a benchmark (audit form) for the AI-based KPI evaluation addressing material management, HR corrective actions, and planning strategies. The proposed framework is able to monitor how the "TO BE" processes impact healthcare organizations. At least two years of data collection are required to obtain a first significant evaluation of the optimized organizational processes. In any case, it is preferable to control the process executions using different milestones (checkpoints) through specific KPIs. The number of milestones is a function of the complexity of the process to be implemented.

Future works will discuss the process validation approaches to follow to optimize the operative workflows.

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Appendix A

The analyzed example considers the application of the AI fuzzy c-means algorithm applied to an experimental dataset of a hospital unit. The dataset was structured using the following yearly selected attributes (five years of data, from 2018 to 2022):

- A: number of falls;
- B: number of falls that happened between 8 p.m. and 8 a.m.;
- C: number of falls that happened between 8 a.m. and 8 p.m.;
- D: number of performed computerized axial tomography (CAT) analyses;
- E: number of X-ray analyses;
- F: number of ultrasound analyses;
- G: number of external consulting;
- H: checked blunt injuries due to a fall;
- I: events related to major trauma;
- J: low-risk cases (0 < Conley index [20] < 1);
- K: high-risk cases (Conley index > 2).

Shown in Figure A1 is an example of fuzzy c-means calculus (number of falls versus the winner clusters).

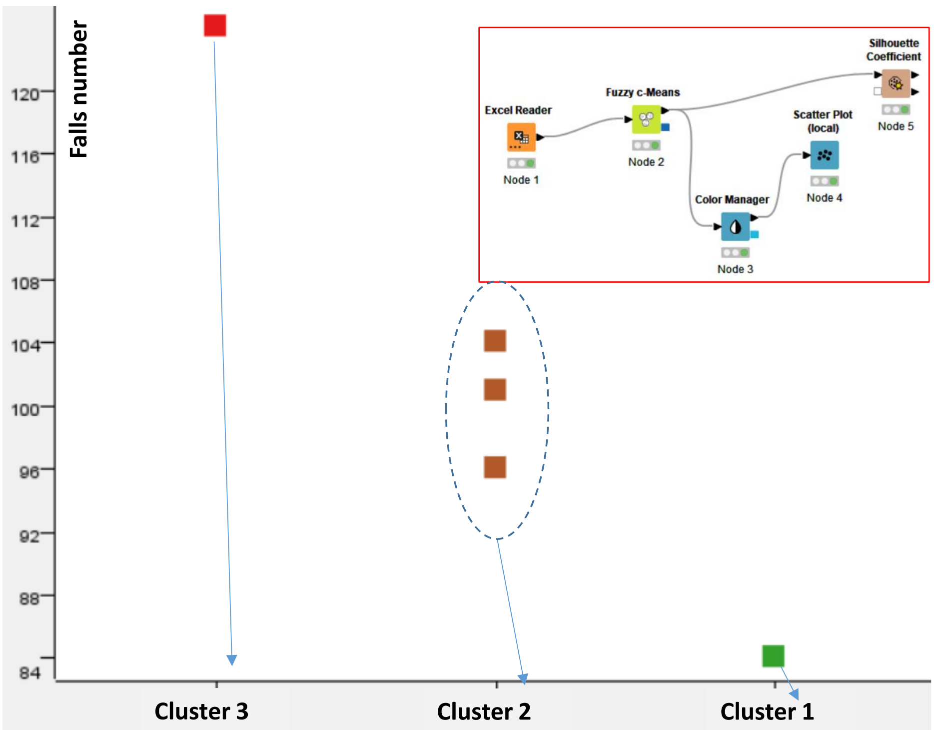

Figure A1. Example of clusters versus falls number. Inset: KNIME workflow executing fuzzy c-means AI unsupervised algorithm. The colored points indicate the number of falls (color red: cluster 3; color brown: cluster 2; color green: cluster 1). The dashed ellipse indicate the grouping of different falls number in the cluster 2. Inset: KNIME workflow executing the AI unsupervised algorithm of fuzzy c-means.

Shown in Table A1 is an example of fuzzy c-means data interpretation defining possible PMO outputs.

Table A1. Data-processing results: data analysis interpretation and possible PMO actions (data-driven processes).

Cluster	Cluster Features	PMO Outputs
Cluster 1	• Low A, D, F, J; • high C.	Best cluster indicating the year 2020. No particular corrective actions are required. The medical stuff is more present in the time slot when the patient falls occur (low risk).
Cluster 2	• Mainly low F, C; • average low J; • mainly high G; • average high K.	The years 2019, 2021, and 2022 appertain to this cluster (moderate risk). • A training of the medical staff about medications (light injuries) allows a decrease in external consulting. • Assignment of specific rooms supporting monitoring patients having a high Conley index (possible reallocation of nurses to control these rooms). • Monitoring of patients using sensors and cameras (application of telemedicine facilities).
Cluster 3	• High A, D, F, J.	Worse cluster related to the year 2018. A specific action concerns the management of the clinical machines and their HR operators.

Appendix B. AI-Based Consulting Audit Framework

Shown in Figures A2 and A3 are the example of audit form monitoring PMO processes, and of the dashboard as results of the same audit form, respectively. The proposed framework is able to monitor how the proposed workflows impacts healthcare organizations and takes into account the further ranking due to the AI prediction, which could overcome the benchmark value (positive condition). The framework is structured into the following five classes (phases to monitor):

- Materials choosing;
- Preparing and implementation;
- Monitoring;
- Standardization;
- Sustainability.

The audit form was constructed by starting with a basic LSS audit form, changing some voices, and integrating a further AI score supporting the process evaluation.

ZONA/Hospital			Audit PMO						Results	AI (wheight)	Total Score	benchmark			
SETTING															
SCORE			AUDITOR:	DATE											
5 S	**NO**	**CHECKING ITEM**	**HR Mangement and Organizational Criteria**	**0**	**1**	**2**	**3**	**4**	**1**			**4**	**PMO- Main HR actions**	**WHO**	**Alternative WHO (AI Skill Matrix)**
1 :Choosing	1	Materials	HR and wharehouse management					4	2			**4**	Planning for human responsabilities		
	2	Tools and materials 1/2 YES=4 NO=0	HR involved in tools selections and use				3		3			**4**	Identification for staff tools and related use whith whekly scheduling		
	3	Tools and materials 2/2 YES=4 NO=0	Is there a check about needs and use of materials?					4	4			**4**	Introduce a quality check staff for material supply analysis:		
	4	Impediments Check	Are there any impediments materials and/or tools?				3		3			**4**	Organize displacement of machines or tools to avoid impediments		
	5	Material Digital Data YES=4 NO=0	Data storage of toolls and materials				3		3			**4**	Pre-check and post-check of care materials; AI predictions of materials; Ai		
2 :Preparing and Implementation	6	Materials	Hard are ready to use?				3		3			**4**	Triggering for materials setting up		
	7	Layout spatial organization SI=4 NO=0	Optimizations of HR internal movements				3		3			**4**	Gemba Walk		
	8	Quality KPI	Materials triggers for actions				3		3			**4**	Quality staff for materials		
	9	Digital storage	Storage of used materials				3		3			**4**	HR allining planned materials and used ones		
	10	Tools and Materials	Are materials and tools arranged according to the choices made?				3		3			**4**	Check-point optimizations and process implementations		
3.Monitoring	11	Work Station YES=4 NO=0	Is worked station allined whith plan?					4	4			**4**	Organization for alignment monitoring		
	12	Waste materials YES=4 NO=0	Waste material check ofr using analisy and sanitisation					4	3			**4**	Special waste disposal organisation and time for cleaning (Surgery rooms)		
	13	Medical Equipment and instruments	Are there non-functional tools/equipment on the workstation?					4	4			**4**	Machine predictive maintenance planning and optimization		
	14	Materials spatial organization	Are they well identified and allocated					4	4			**4**	Operative layout organization		
	15	Availability kanban YES=4 NO=0	Check of correct availability					4	2			**4**	Check-point optimizations and process implementations		
4. Standardization	16	Standardization 1/2 YES=4 NO=0	Time standards are monitoring and followed?					4	4			**4**	It is necessary to carry out 'time and method' planning for individual activities that become the methodological support for AI		
	17	Standardization 2/2 YES=4 NO=0	Matching between skills and time slots (HR compatibilities)					4	1			**4**	Upgade of skills classifications whith AI		
	18	Digital Data YES=4 NO=0	Are necessary of corrective interventions on workstation					4	3			**4**	Corrective actions about workstations		
	19	Update of HR availability YES=4 NO=0	Updating available human resources and acquired skills (useful for training to improve knowledge and skills)					4	4			**4**	Planning half-yearly skill-matrix update reports		
	20	Alignment whith previous audit YES=4 NO=0	Gap analisys between audit					4	2			**4**	Audit form optimization		
5. Sustainability	21	Strategic Management YES=4 NO=0	Monitoring the level of involvement in implementation				3		3			**4**	Planning six-monthly meetings with strategic management for policy alignment		
	22	Middle Managmenet YES=4 NO=0	Monitoring the level of involvement in implementation				3		3			**4**	Schedule quarterly meetings to see if there are any organisational misalignments between the planning part (middle management) and the programming part (operational staff)		
	23	Leadership YES=4 NO=0	Analysing different leadership styles within different UU.OO.					4	4			**4**	From the leadership style analysis, it is important to plan the training and planning phase		
	24	System Control (Telemedicine) YES=4 NO=0	Time optimizations of clinical activities			3			3			**4**	Future use of a full digital platform controlling HR organization and patients		

Figure A2. Example of audit form monitoring PMO processes.

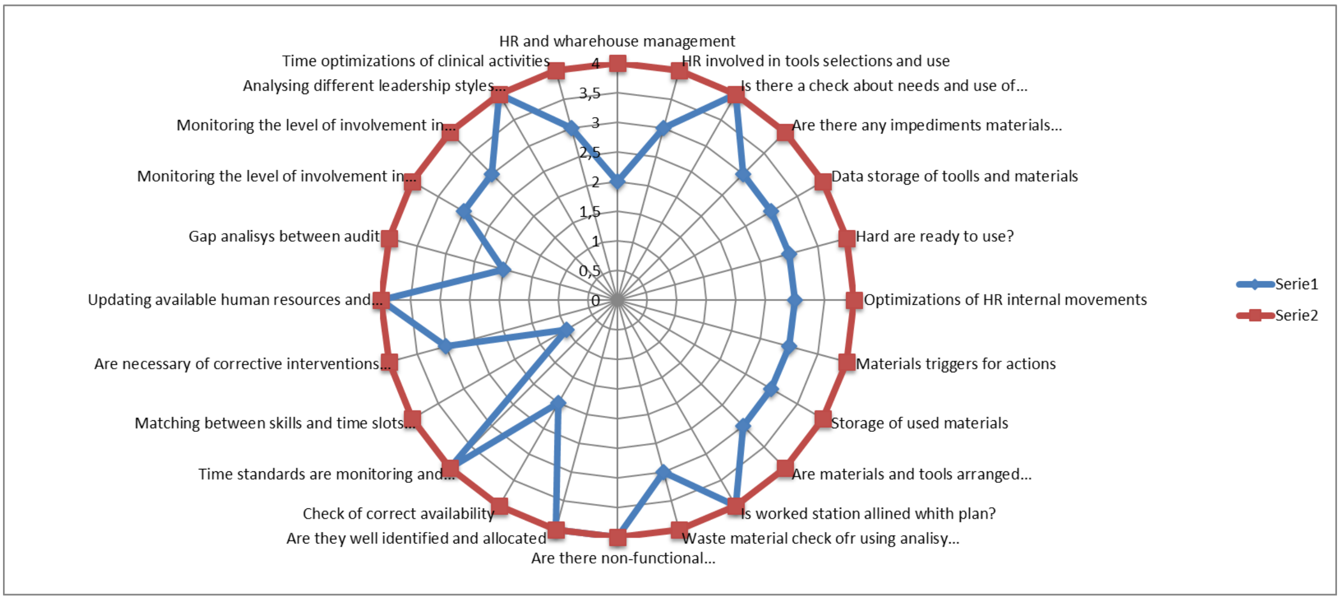

Figure A3. Example of dashboard as results of audit form. The brown graph represents the benchmark value which could be overcome by adding the AI score to the basic score.

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