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Impact of Industry 4.0 on decision-making in an operational context

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ABSTRACT

The implementation of Industry 4.0 technologies suggests significant impacts on production systems productivity and decision-making process improvements. However, many manufacturers have difficulty determining to what extent these various technologies can reinforce the autonomy of teams and operational systems. This article addresses this issue by proposing a model describing different types of autonomy and the contribution of 4.0 technologies in the various steps of the decision-making processes. The model was confronted with a set of application cases from the literature. It emerges that new technologies' improvements are significant from a decision-making point of view and may eventually favor implementing new modes of autonomy. Decision-makers can rely on the proposed model to better understand the opportunities linked to the fusion of cybernetic, physical, and social spaces made possible by Industry 4.0.

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1. Introduction

Many researchers have described the potential benefits of Industry 4.0 technologies to improve production systems' productivity and profitability [1-3]. In this sense, there is a close link between Lean and Industry 4.0 as many companies have already partially or fully implemented principles and tools from the Lean management approach [4]. However, previous studies have shown that the principles associated with problem-solving and employees and teamwork currently seem to be little or not improved by Industry 4.0 technologies [5]. However, implementing these high-level principles of Lean and Toyota Production System, as described in the 4 P model proposed by J. Liker [6], is based on a singular decision-making process. Indeed, problem-solving as an element of continuous improvement and learning, is based on decisions taken on the ground (Gemba decisions) in a consensual manner by carefully examining all the options (Nemawashi) before a rapid implementation of the actions resulting from the decisions taken [6]. In the context of the search for complementarities between Lean and Industry 4.0, the impact and role of Industry 4.0 technologies on the decision-making process is of particular interest.

Sari *et al*. [7] point out that the implementation level of Industry 4.0 technologies increases as the manufacturing firms' size increases. While ERP system, Supply Chain Management (SCM) and near real-time production control system can play a vital role for manufacturers in the context of Industry 4.0 especially in transition countries, future research needs to consider the full range of technologies that are considered facilitators of Industry 4.0 [8]. These technologies are numerous. Many authors present different lists of 4.0 technologies [2, 9-13]. They all agree on their capability to enhance communication, flexibility, real-time feedback, and improve how humans make decisions to solve problems in a production context.

Indeed, improving decision-making processes is a recurring focus and a primary objective in deploying these technologies [14-17]. Several research studies focus on production data-based decision-making for process design, scheduling, planning, and control [17]. Different types of autonomy of the production system are possible and are determined by which steps of the decision-making process are (or are not) enhanced. The difficulty of detecting abnormal situations or opportunities for improvements of the current system depends on the complexity of the information being integrated, the number of possible solutions, and the managers' interest in empowering the production systems.

As such, no previous research clearly illustrates how 4.0 technologies can enhance a decision-making process and how it may affect the autonomy of the resources involved. This article addresses this issue by analyzing the impact of Industry 4.0 technologies on decision-making in production systems at the work center level and by proposing a decision-making process model describing different types of autonomy.

The remainder of the paper is structured as follows. The following section presents a literature review on the decision-making process in an operational context. In Section 3, the proposed decision-making process applied to the operational context is described and the different types of autonomy levels. The proposed model is then validated in Section 4, based on a comparison with a set of case studies from the literature. Section 5 presents future works and a conclusion.

2. Literature review

Highlighting the difficulty for manufacturing firms to establish a deployment strategy for industry 4.0 technologies, Osterrieder *et al*. [17] proposed an intelligent factory model around 8 eight distinct thematic perspectives. The authors note that problems related to decision-making are common to several of these categories but stress the need to make it a research focus in its own right to analyze and develop concepts for data-based decision-making situations in manufacturing, using the different technologies of Industry 4.0.

On the other hand, the human decision-making process has been studied in many fields, including psychology and management. It has been analyzed and described by numerous research studies in various operational [18], strategic [19], or crisis contexts [20]. Intuitive and analytical strategies were also investigated in laboratory experiments or field observations to study judgements and decision-making under complex conditions [21-23].

Simon [24] was one of the first to propose a formal decision-making model called IDC. According to this model, a decision goes through three phases: Investigation, Design, and Selection. The Investigation phase consists of formulating the problem and identifying a gap between the current situation and the desired situation. In the Design phase, the subject develops possible actions to resolve the situation and tries to predict these different actions' impact on their environment. In the Selection phase, the different actions are compared, ranked, and selected.

Mintzberg [19] took up ideas from Simon's model but sought to list all the approaches to human decision-making in a specific context, namely strategic corporate decisions. By analyzing 25 decisions from different companies, he proposed a decision-making model that includes all the possibilities that were enumerated. The proposed phases by Mintzberg [19] are similar to Simon [24], but he describes them in terms of seven central "routines": Recognition, Diagnosis, Search, Screen, Design, Evaluation-Choice, Authorisation. Also, he notes three sets of routines that support the central phases, decision control, communication, and political. Mintzberg [19] attempted to present the processes used in human decision-making and not an ideal decision-making process. His model also predicts possible interruptions in the process and the jumps in routines that companies have made.

This interest in describing the actual decision-making process has been followed by a trend towards Naturalistic Decision Making (NDM) [25]. Following this trend, authors have focused on the biases and limitations of human decision-making, particularly in situations of time constraints [26] or crisis [25, 27]. The body of knowledge associated with the NDM that emerged in the 1980s changed the approach to decision-making. There was a shift from "normative" models that describe how rational decisions should be made to models that describe the decisions that are actually made [28]. Some work has highlighted the particularities of decision-making in naturalistic contexts [29] and the unrealistic nature of some of the assumptions underlying rational choice theory [25]. In an operational context, agents are subject to constraints that do not allow them to analyze a large amount of information and consider all of the available choices or make complex calculations to evaluate different options and their potential impacts. Other researchers have described models of decision-making that do not necessarily lead to an optimal decision, but where the decision-making process activities are carried out by humans or through automation [30, 31]. However, this work does not connect or acknowledge various technologies that can be employed. In contrast, other authors have proposed perfect decision-making models, particularly in the literature related to the development of artificial intelligence and intelligent agents, including BDI (Beliefs-Desire-Intention) models [32, 33]. This type of model, inspired by human decision-making models, is then used to design artificial decision-making systems. However, these models rely on targeted technologies, including simulation techniques, massive data analysis, and artificial intelligence. However, none of these models link to the full range of technologies associated with Industry 4.0 by analyzing the opportunities offered by the joint contribution of various technologies.

The DMN (Decision Model and Notation) standard was recently developed by the Object Management Group (OMG) [34] to model decisions in an understandable way and has been adopted by both industry and academia. This standard aims to form a bridge between business process models and decision logic models by introducing a Decision Requirements Diagram that defines the decisions to be made in business processes, their interrelationships, and their requirements for decision logic. It can be used for modeling human decision-making, the requirements for automated decision-making, or for implementing automated decision-making. Group decision-making is always better than individual decisions [35], and DMN models can describe collaborative organizational decisions, their governance, and the business knowledge required for them. This standard is rather dedicated to operational decisions taken as part of daily operational processes, rather than strategic decision-making for which there are fewer rules and representations. This standard defines the word "decision" as the act of choosing among multiple possible options or the option that is chosen. Hasic *et al.* [36] point out that DMN was only studied and implemented in a static fashion despite the dynamic nature of modern knowledge-intensive systems. Decision schema change patterns have not received any attention so far. Therefore, this type of model still seems unsuitable for operational decisions taken in a changing and uncertain environment for which the decision rules, input data, and business knowledge are not pre-established at least in advance. Besides, some articles attempt to link with Decision Support System (DSS) research or show how certain technologies can facilitate the implementation of this standard. Still, none of them encompass the possibilities offered by the full range of technologies in industry 4.0.

The literature associated with Industry 4.0 proposes real-time decision-making in a decentralized but coordinated manner at a global level, with people and machines working together. These developments promote the flexibility and agility of systems at the operational level by increasing their responsiveness and autonomy [10]. However, the research work currently being carried out in this model does not go into the decision-making process's details. It has been largely described by analyzing human decision-making. Still, the questioning of these models and their limits by the introduction of all Industry 4.0 technologies has not yet been studied. Therefore, it seems that no current model studies the reinforcement using 4.0 technologies in the different decision-making process stages, which, in an operational context, can be carried out by an individual or a group to define standard or tailor-made solutions in an increasingly changing and uncertain production environment. This paper, therefore, aims to propose different types of operational decision-making processes based on the use of various technologies.

3. Decision-making model in Industry 4.0 operational context

3.1 Decision-making process

Based on Mintzberg's [19] model described earlier, we propose the following decision-making process in an operational context (Fig. 1).

Like Mintzberg's [19] model, this process consists of 3 phases: Problem or opportunity validation, Solution validation, and Implementation validation. The Problem or Opportunity Validation phase includes the Capture-Measure and Gap recognition steps. The Capture-Measure step consists of collecting information in real-time in the production system. The second step, Gap recognition, consists of recognizing an abnormal situation, i.e., a discrepancy between the current situation and the desired situation that requires a reaction from the production center.

For the Solution validation phase, the Diagnosis, Search, Design, and Selection steps are used. The Diagnosis step corresponds to the Diagnosis step of Mintzberg's [19] model, i.e., understanding cause and effect relationships in the situation under study. Subsequently, depending on whether or not solutions are known to address the identified problem, a choice will be made between the Search or Design steps. If solutions are known, the Search step is used to look among the possible solutions to find those that offer an adequate response to the problem. If no solution is known, the Design step is preferred where it is necessary to design a new solution to the problem or modify a known solution. Afterward, if the Selection step allows, we look to eliminate inappropriate solutions to limit the number of solutions to be evaluated. Then, the Evaluation step allows us to compare the solutions and ensure that the selected solution will solve the situation. Finally, the third phase includes a single step: Authorize. Here, an authorization is issued either by the production center itself (the operator or the machine) or a higher hierarchical entity (a team leader, a manager, or a centralized computer system).

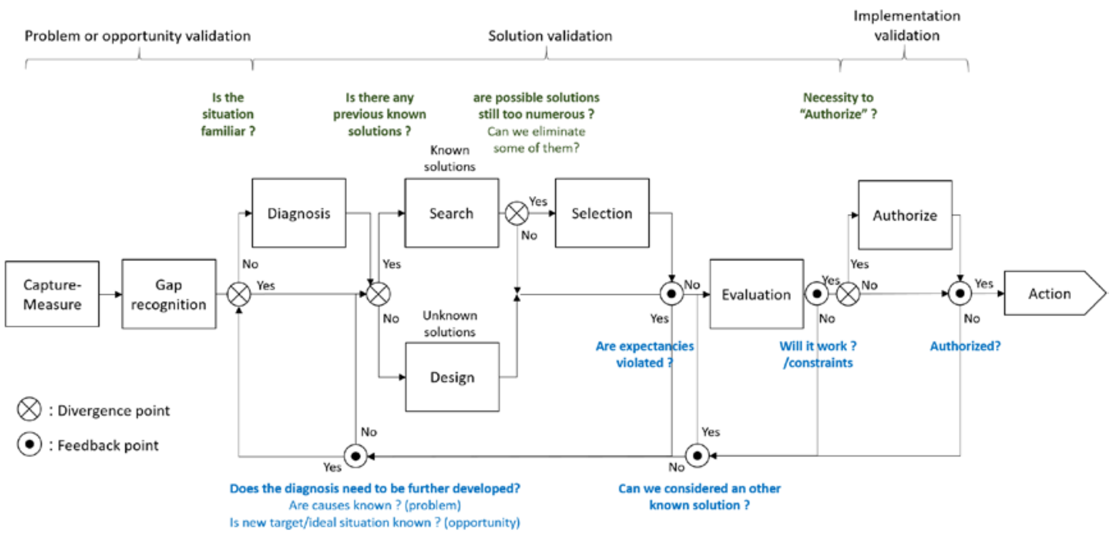

Fig. 1 Proposed decision-making process in an operational context

This decision-making model is non-sequential, and several types of feedback are possible. This is particularly the case when the Selection step leads to eliminating all known solutions identified in the Search step. If the understanding of the situation allows it, the Design step can then be engaged directly to identify a tailor-made solution. Otherwise, the Diagnosis step is undertaken to identify the root causes of the problem, define the target situation precisely, and analyze the conditions for reducing the current situation gap. This same type of feedback can occur if the Evaluation step leads to the rejection of all known or custom-designed solutions or if the Authorize step does not lead to approval for implementing the selected and proposed solution. Shorter feedback can be used to evaluate only solutions that have already been identified but were not evaluated or retained in the first instance.

3.2 Industry 4.0 decision-making support model

Technologies from Industry 4.0 can help operators and/or machines to carry out one or more steps of the decision-making process. Depending on the company's needs and the specific characteristics of the production center, more or fewer steps in the decision-making process may be supported and enhanced by one or more Industry 4.0 technologies.

Porter and Heppelmann [1] propose a model of the various uses of Industry 4.0 technologies but from the perspective of intelligent and connected products rather than a manufacturing production context. More specifically, they propose four levels called capacity levels. These levels are incremental, and each builds on the previous one. These capacity levels are: 1- Monitoring, 2- Control, 3-Optimization, and 4-Autonomy. A few authors have taken these levels, including [2] and [10]. Comparing this highly structured model designed for intelligent products with the decision-making model described above has revealed certain limitations. The Porter and Heppelmann [1] model does not cover some scenarios in complex decision-making processes that generally involve humans. For example, the implementation of the solution Evaluation step differs between standard and custom solutions. The type of enhancement provided by 4.0 technologies is not the same in these two cases. The treatment around the authorization step is also not specified. While this step can be bypassed for decisions made locally on a relatively small perimeter and often of limited complexity, this is not the case when integrating the high levels of autonomy targeted by Industry 4.0. The extended scope of responsibility given to operational teams or systems requires that decisions taken in a decentralized manner remain consistent with optimizing the overall system. New technologies can be mobilized to facilitate and strengthen horizontal, vertical, or end-to-end information exchanges. Depending on the type of decision and the level of autonomy targeted, it is possible to make decision-making more collaborative while maintaining a high level of responsiveness of the operational system.

Inspired by the four capability levels of Porter and Heppelmann's [1] products, seven types of decision-making autonomy are proposed based on Industry 4.0 technologies for manufacturing systems (Fig. 2). For every operational context, a specific type of autonomy should be targeted while considering the more or less stable and predictable nature of the operating environment, the nature and complexity of the decisions to be made, their importance and impact, the skill level and scope of responsibility of the operational teams, the managerial model, and the corporate culture. These seven types of autonomy are therefore not incremental. They are not mutually inclusive and do not present a gradation in terms of intelligence and autonomy. Rather, they respond to different needs for decision-making assistance and enhancement depending on the help needed and whether the solutions are known or not. The seven types of autonomy based on Industry 4.0 technologies in a manufacturing context are as follows: 1) Cyber Monitoring, 2) Cyber Search, 3) Standard Decision Support, 4) Cyber Control, 5) Cyber Design, 6) Customized Decision Support and 7) Cyber Autonomy. These types of autonomy are distinguished according to the possible quantity of solutions sought and according to the specific steps enhanced or supported by the 4.0 technology involved.

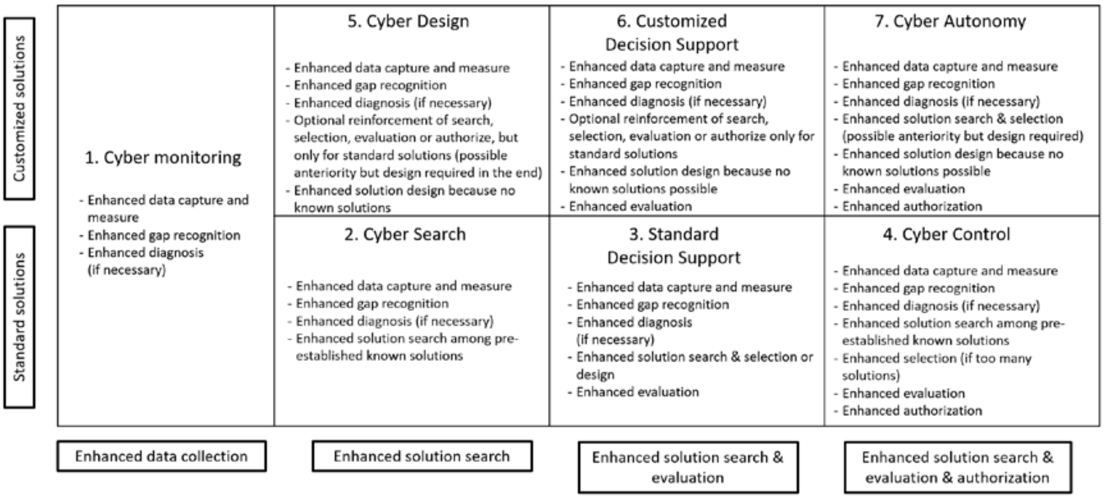

Fig. 2 Model of types of autonomy: an Industry 4.0 decision-making support model

The following figures highlight each type of autonomy, the steps of the decision-making process that can be enhanced, optionally or not, by the different Industry 4.0 technologies. Some types of autonomy do not mobilize certain steps, which then appear as hatched. The main questions managed at divergence points appear in green and those conditioning the crossing of the feedback points appear in blue.

The Cyber Monitoring type corresponds to the enhancement of the Capture and Measure and Gap recognition steps. Here, we allow for an improvement in the collection of production data and analyzing this data to detect an abnormal situation or an opportunity for improvement. Any technology does not enhance the search for solutions in Industry 4.0, and the other steps of the decision-making process are left to humans. However, in some cases, the Diagnosis step can be enhanced to prepare better the steps dedicated to searching for standard or customized solutions. Fig. 3 shows the application of Cyber Monitoring to the proposed decision-making process.

The Cyber Search type corresponds, like the Cyber Monitoring type, to enhance the Capture-Measure and Gap recognition steps using 4.0 technologies, but adding optional support for the Diagnostic step if the reasons behind the observed deviation are not immediately recognized. Also, if the system knows solutions to resolve the situation, the Search step is enhanced to find the possible solution(s) to be applied. A human user provides the following steps. Fig. 4 shows the application of the Cyber Search type to the proposed decision-making process.

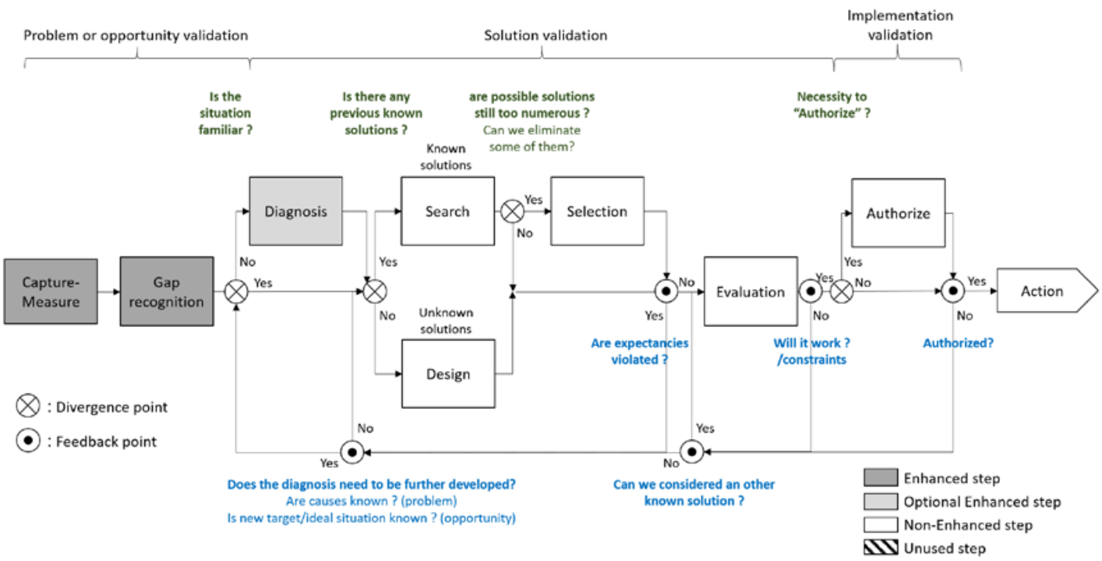

Fig. 3 Enhanced steps in the Cyber Monitoring type

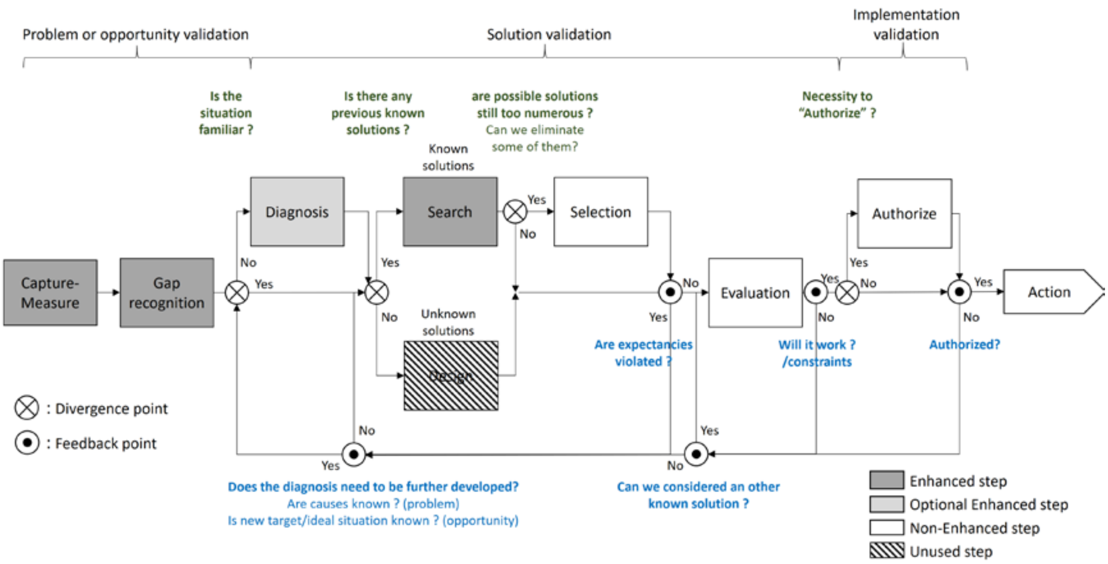

Fig. 4 Enhanced steps in the Cyber Search type

The Standard Decision Support type shown in Fig. 5 is similar to the Cyber Search type and subsequently supports the Selection and Evaluation decision-making steps. Thus, for a situation where solutions are known, a search for solutions (Search step) is carried out. The Selection step follows this if more than one solution is possible. This step aims to limit the number of solutions that will then be evaluated by eliminating what is unfeasible. The Evaluation step is also enhanced to determine the most appropriate solution, notably by anticipating the consequences of implementing the solutions identified in the Search step and filtered by the Selection step.

The Cyber Control type assists in all of the decision-making steps if solutions are known. The final step, authorizing the action, is also enhanced to facilitate the action's commitment when it has to be approved at a level other than the perimeter from which the chosen solution emanates. Fig. 6 shows the application of Cyber Control to the proposed decision-making process.

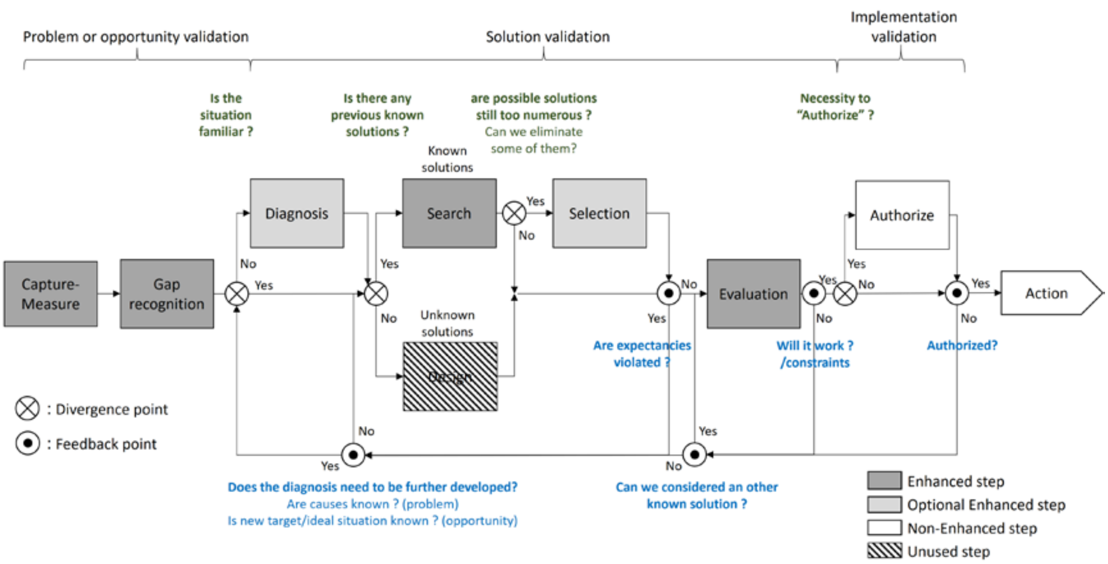

Fig. 5 Enhanced steps in the Standard Decision Support type

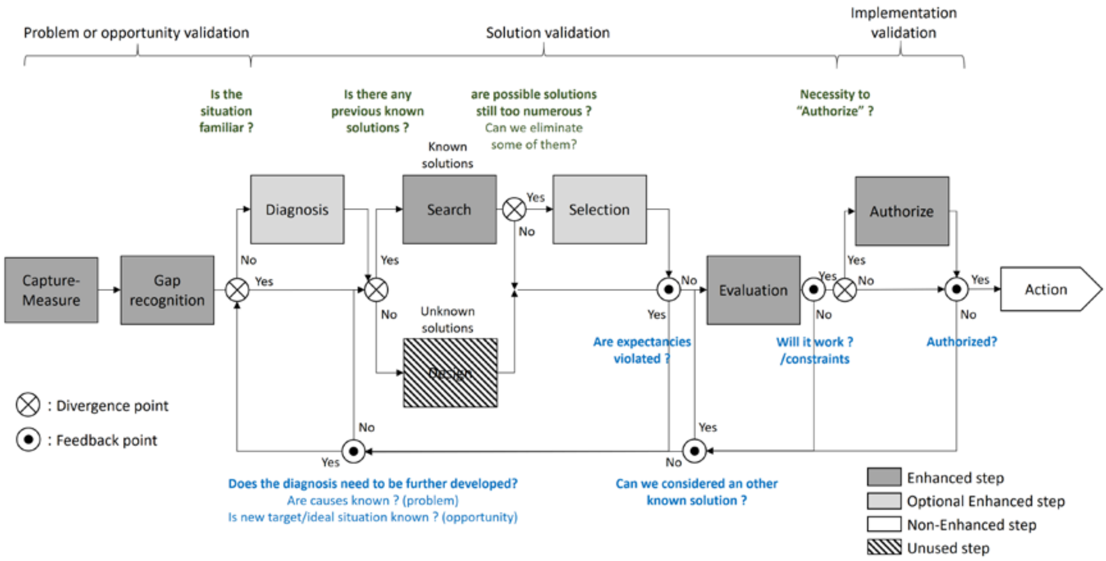

Fig. 6 Enhanced steps in the Cyber Control type

The Cyber Design type is similar to the Cyber Search type, but in a situation where no possible solution is known. Here, it is the Design step that is enhanced to design a tailor-made solution. The search for a standard solution based on the optional enhancement of the Search, Selection, Evaluation, and Authorize steps may sometimes have preceded the design step's mobilization but without success. The preferred technologies 4.0 must build a new solution that would reduce the gap in the production system. The steps that follow the Design step are then left to the human's responsibility without any special assistance. Fig. 7 shows the application of the Cyber Design type to the proposed decision-making process.

The Customized Decision Support type is similar to the Cyber Design type, with the addition of the Evaluation step enhancement. The Search and Selection steps could have been activated beforehand to identify known solutions that proved to be either unsuitable or ineffective. Feedback then leads to a search for a tailor-made solution at the Design step. The evaluation step's enhancement is more complex than in the Standard Decision Support type because this process must evaluate tailor-made solutions that are not known beforehand. The Authorization step remains the only one that is the responsibility of the human without any assistance. Fig. 8 shows the application of the Customized Decision Support type to the proposed decision-making process.

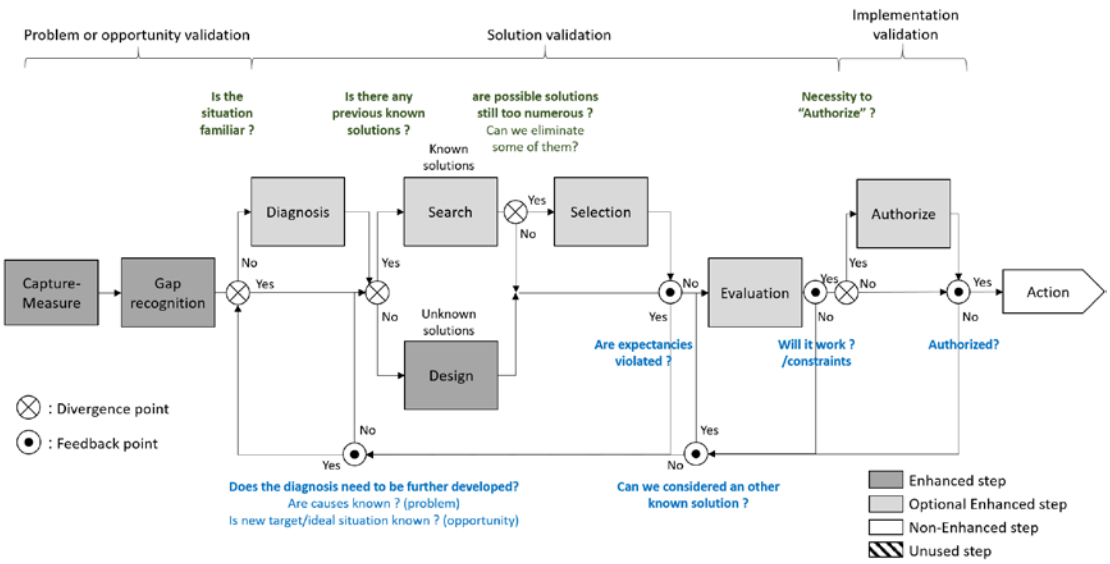

Fig. 7 Enhanced steps in the Cyber Design type

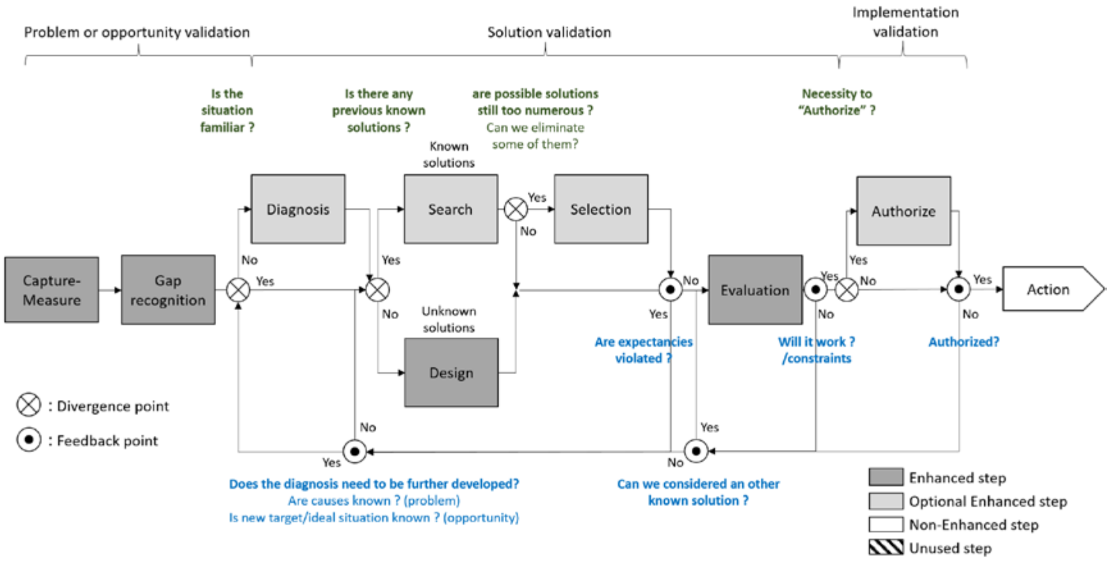

Fig. 8 Enhanced steps in the Customized Decision Support type

Finally, the Cyber Autonomy type is based on the Customized Decision Support type, with the addition of the Authorize step's enhancement. In this case, as with the Cyber Control type, no step is performed by human users without assistance. However, any type of situation corresponding to problems or opportunities associated with known or unknown solutions can be handled autonomously throughout the operational teams' decision-making process. Fig. 9 shows the application of the Cyber Autonomy type to the proposed decision-making process.

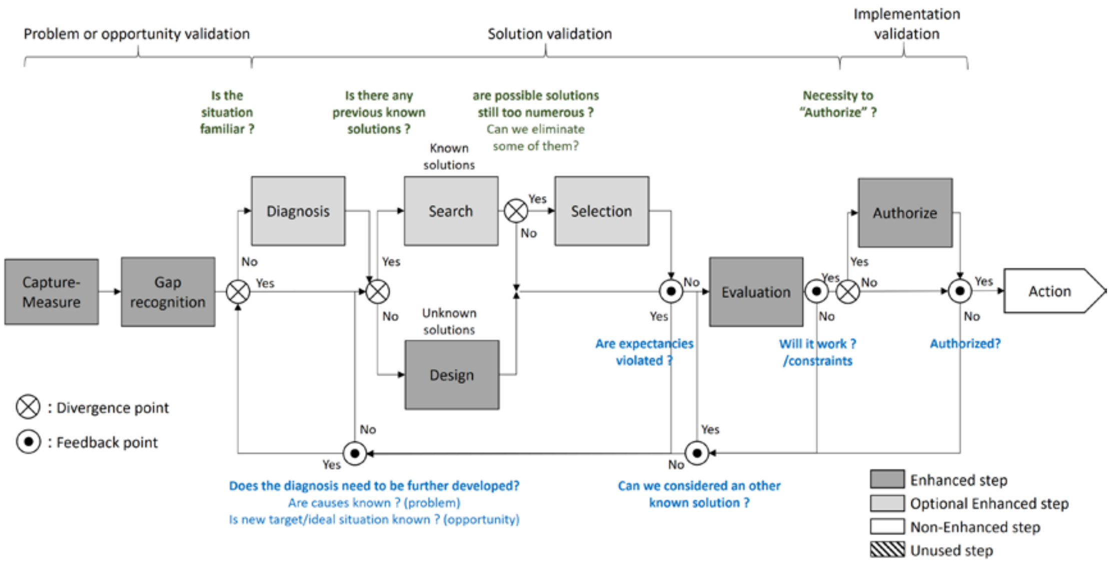

Fig. 9 Enhanced steps in the Cyber Autonomy type

4. Model validation

For validation purposes, the model was compared with case studies found in the literature. These cases were targeted using the keywords "industry 4.0" OR "industry 4.0" AND "use case" OR "case study" in the SCOPUS database. By focusing on articles related to the theme "Decision Sciences", we were able to identify 180 papers, over a third (69) of which were related to engineering and production. An analysis of these articles led to the exclusion of 37 articles for the following reasons:

- the use cases were associated with the technical validation of the implementation of one or more technologies of the industry 4.0 and not how they are used to support or control an operational system,
- the use cases did not make a direct link to identify decision-making in an operational context,
- the use cases did not sufficiently detail the use of industry 4.0 technologies or were not sufficiently described.

The remaining 32 articles identified 41 cases in which the application of technologies from Industry 4.0 could be linked to one of the seven types of autonomy based on the technologies proposed in our model. It should be noted that very few application cases are dated before 2017, and their number has been increasing since then. Their connection to the different types of autonomy has been achieved by an in-depth reading of the articles and a systematic questioning in relation to the conditions of activation of the steps and branches specific to each type of autonomy of the model. Another researcher carried out a double analysis to verify the reproducibility of the proposed linkage. Table 1 presents the result of this analysis, making it possible to confirm that the proposed model can cover all of the described application cases.

It has emerged from this analysis that 2 out of every 3 cases today correspond to Cyber monitoring. Conversely, some types of autonomy still seem very far from being mature. For example, no application case could be linked to the Standard decision support type. This may seem surprising at first glance because operational excellence and continuous improvement approaches, already widely used in operational contexts, encourage capitalizing on the solutions identified during problem resolution to turn them into reaction standards. Although cases of Cyber search applications have been identified to enhance the search for already known standard solutions, the evaluation of these solutions is still mainly carried out by humans.

Several cases correspond to Cyber control but relate to decisions that are still relatively uncomplicated or related to a still limited scope of responsibility. We have found articles that foresee future developments corresponding to the Cyber design type but without any real implementation at the moment. For example, some applications concern the feedback and analysis of information from the field to continually readjust the design of highly customized products or continuously adapt the rules applied by a maintenance department to monitor equipment. This implies a strengthening of interoperability between different information systems, which in many cases is still a major technological barrier. The Customized support decision type always seems to be reserved for applications in process industries. This is probably explained by the need to have already a large database and the high level of complexity and cost associated with implementing this type of autonomy.

We find cases of Cyber autonomy for applications realized in an experimental framework and the realization of precise actions for which the choice of the chosen solution depends on clearly identified and measurable parameters. As the possibility of achieving this level of autonomy is often evoked in the literature, we did not find any already functional application cases for more complex decisions for which the interdependencies between data and variables are either unknown or uncertain or when the data, constraints, objectives or knowledge are non-explicit.

The distribution of application cases across the different types of autonomy is now very unbalanced. The dominant weight of Cyber monitoring marks the fact that the priority today is to enhance the detection of problems and opportunities to start the decision-making process as early as possible. It also marks the potential for further progress in deploying new technologies to enhance the entire decision-making process. The mass of data that many companies are currently building up through the implementation of Cyber monitoring is a capital that is still poorly valued. It seems to us that this will inevitably call for an extension of the digitization approaches already undertaken to aim for types of autonomy that would cover a greater part of the steps in the decision-making process. However, the complexity of implementing certain types of autonomy, the associated risks, particularly in terms of cybersecurity, the related costs, a sometimes low ROI, the repercussions at the managerial and social levels, and the consideration of environmental issues are all reasons that may not necessarily justify enhancing all steps of the decision-making process.

Therefore, we can expect to gradually migrate towards a more balanced distribution of the application cases over the different types of autonomy in the years to come, without necessarily converging towards types of autonomy such as Cyber control or Cyber autonomy.

Table 1 Distribution of the use cases on the different types of autonomy

	1. Cyber monitoring	2. Cyber Search	3. Standard Decision Support	4. Cyber Control	5. Cyber Design	6. Customized Decision Support	7. Cyber Autonomy
Soic R., Vukovic M., Skocir P., Jezic G. (2020) [37]	X						
Aliev K., Antonelli D., Awouda A., Chiabert P. (2019) [38]	X						
Antón S.D., Schotten H.D. (2019) [39]	X						
Bakakeu J., Brossog M., Zeitler J., Franke J., Tolksdorf S., Klos H., Peschke J. (2019) [40]	X						X
Burow K., Franke M., Thoben K.-D. (2019) [41]	X						
Chiacchio F., D'Urso D., Compagno L., Chiarenza M., Velardita L. (2019) [42]	X						
Conzon D., Rashid M.R.A., Tao X., Soriano A., Nicholson R., Ferrera E. (2019) [43]							X
Giehl A., Schneider P., Busch M., Schnoes F., Kleinwort R., Zaeh M.F. (2019) [44]	X						
Loske M., Rothe L., Gertler D.G. (2019) [45]	X						
Miehle D., Meyer M.M., Luckow A., Bruegge B., Essig M. (2019) [46]				X			
Pusch A., Noël F. (2019) [47]	X	X					
Rabelo R.J., Zambiasi S.P., Romero D. (2019) [48]	X	X				X	
Sala R., Pirola F., Dovere E., Cavalieri S. (2019) [49]	X						
Subramanian D., Murali P., Zhou N., Ma X., Cesar Da Silva G., Pavuluri R., Kalagnanam J. (2019) [50]						X	
Cagnin R.L., Guilherme I.R., Queiroz J., Paulo B., Neto M.F.O. (2018) [51]				X			
Freitag M., Wiesner S. (2018) [52]	X						
Luetkehoff B., Blum M., Schroeter M. (2018) [53]	X						
Mittal S., Romero D., Wuest T. (2018) [54]	X						
Molka-Danielsen J., Engelseth P., Wang H. (2018) [55]	X						
Monizza G. P., Rojas R.A., Rauch E., Garcia M.A.R., Matt D.T. (2018) [56]							X
Nesi P., Pantaleo G., Paolucci M., Zaza I. (2018) [57]	X						
Roda I., Macchi M., Fumagalli L. (2018) [58]	X						
Serrano D. C., Chavarría-Barrientos D., Ortega A., Falcón B., Mitre L., Correa R., Moreno J., Funes R., Gutiérrez A. M. (2018) [59]	X						
Badarinath R., Prabhu V.V. (2017) [60]	X			X			
Dragičevic N., Ullrich A., Tsui E., Gronau N. (2017) [61]	X			X			
Durão L.F.C.S., Haag S., Anderl R., Schützer K., Zancul E. (2017) [62]	X						
Innerbichler J., Gonul S., Damjanovic-Behrendt V., Mandler B., Strohmeier F. (2017) [63]	X						
Lall M., Torvatn H., Seim E.A. (2017) [64]	X						
Saldivar A.A.F., Goh C., Li Y., Yu H., Chen Y. (2017) [65]	X						
Sandor H., Genge B., Haller P., Graur F. (2017) [66]	X						
Tedeschi S., Emmanouilidis C., Farnsworth M., Mehnen J., Roy R. (2017) [67]	X						
Adeyeri M.K., Mpofu K., Adenuga Olukorede T. (2015) [68]	X	X		X			X
	27	3	0	5	0	2	4

5. Conclusion and future developments

A model of seven types of autonomy associated with the decision-making process in an operational context and based on Industry 4.0 technologies for manufacturing systems was proposed. The model contributes to the current literature on Industry 4.0 by clearly demonstrating how 4.0 technologies can enhance decision-making processes and how they affect the autonomy of the resources involved at an operational level.

From a practical point of view, this model can help industrial establish a structured and coherent roadmap for the deployment of Industry 4.0 technologies. Decision-makers can rely on this model to target the type of autonomy they wish to see entrusted to operational teams to improve the production system's responsiveness to the problems and opportunities encountered in the field. This implies drawing up an initial list of critical decisions that the operational teams must or should manage and the main obstacles and errors usually encountered.

It should be noted that the proposed model is not adapted to respond to large-scale and complex unexpected disruptions such as health or financial crisis. Indeed, such cases involve a set of decisions taken at different strategic, tactical, and operational levels, whereas the proposed model is limited to an operational scope. However, the coupling of this model with other types of models such as DMN (Decision Model and Notation) models could constitute an answer to this type of situation. In this respect, it seems that this could constitute a new and particularly promising research axis in the future.

In the next step of this research, we will study the contribution of Industry 4.0 technologies to the implementation of these different types of autonomy through the enhancement of the various steps of the decision-making process. It is important to note that the proposed model was developed as part of a larger study to investigate the integration of Industry 4.0 technologies into Lean production systems. In this regard, an earlier study on the linkages between Industry 4.0 and Lean approaches showed that some Lean principles currently appear to show little or no improvement by Industry 4.0 technologies. This is particularly the case for Lean principles related to employees and teamwork, continuous improvement, stable and standardized processes, and the Toyota model philosophy [5]. Among future research, a practical case is being formalized to test the proposed model of autonomy types and to study the conditions of acceptance of Industry 4.0 technologies that contribute to reinforcing the decision-making process. It is based on a learning factory and uses existing Lean management training modules designed in partnership with several manufacturers. Various Industry 4.0 technologies such as IoT, cloud computing, Big data analysis, machine learning, simulation, augmented reality, and data visualization will be progressively deployed. Within this framework, the different types of empowerments of operational teams in decision-making will be tested to manage the production problems encountered in real-time. This will constitute the next step in validating our model before implementing it in a real production unit.

Among other issues that must be addressed within the proposed approach, the impact of change resistance toward Industry 4.0 technologies needs further study. As stated by Klein [69], decision support systems are generally not well received by those who are supposed to use them, as they are not necessarily aware of certain cognitive biases or do not perceive any real interest in being assisted. Anchoring these technologies' deployment within continuous improvement approaches and training teams in people-centered use of these new technologies is essential. This implies a more detailed analysis of the physical, sensing, cognitive, and collaborative capabilities that Industry 4.0 technologies can reinforce at the operational level to compare them with the needs that can be perceived or expressed by operators 4.0 and team 4.0.

References

[1] Porter, M.E., Heppelmann, J.E. (2015). How smart, connected products are transforming companies, *Harvard Business Review*, Vol. 93, No. 10, 96-114.

[2] Moeuf, A., Pellerin, R., Lamouri, S., Tamayo-Giraldo, S., Barbaray, R. (2017). The industrial management of SMEs in the era of Industry 4.0, *International Journal of Production Research*, Vol 56, No. 3, 1118-1136, doi: 10.1080/00207543.2017.1372647.

[3] Pacchini, A.P.T., Lucato, W.C., Facchini, F., Mummolo, G. (2019). The degree of readiness for the implementation of Industry 4.0, *Computers in Industry*, Vol. 113, Article No 103125, doi: 10.1016/j.compind.2019.103125.

[4] Buer, S.-V., Strandhagen, J.O., Chan, F.T.S. (2018). The link between Industry 4.0 and lean manufacturing: Mapping current research and establishing a research agenda, *International Journal of Production Research*, Vol. 56, No. 8, 2924-2940, doi: 10.1080/00207543.2018.1442945.

[5] Rosin, F., Forget, P., Lamouri, S., Pellerin, R. (2019). Impacts of Industry 4.0 technologies on lean principles, *International Journal of Production Research*, Vol. 58, No. 6, 1644-1661, doi: 10.1080/00207543.2019.1672902.

[6] Liker, J.K. (2004). *The Toyota way: 14 management principles from the world's greatest manufacturer,* McGraw-Hill Education, New York, USA.

[7] Sarı, T., Güleş, H.K., Yiğitol, B. (2020). Awareness and readiness of Industry 4.0: The case of Turkish manufacturing industry, *Advances in Production Engineering & Management*, Vol. 15, No. 1, 57-68, doi: 10.14743/apem2020.1.349.

[8] Medić, N., Anišić, Z., Lalić, B., Marjanović, U., Brezocnik, M. (2019). Hybrid fuzzy multi-attribute decision-making model for evaluation of advanced digital technologies in manufacturing: Industry 4.0 perspective, *Advances in Production Engineering & Management*, Vol. 14, No. 4, 483-493, doi: 10.14743/apem2019.4.343.

[9] Boston Consulting Group (2015). Industry 4.0: The future of productivity and growth in manufacturing industries, from *https://image-src.bcg.com/Images/Industry_40_Future_of_Productivity_April_2015_tcm9-61694.pdf*, accessed December 7, 2021.

[10] CEFRIO (2016). Prendre part à la révolution manufacturière? Du rattrapage technologique à l'Industrie 4.0 chez les PME, from *https://espace2.etsmtl.ca/id/eprint/14578/1/Prendre-part-%C3%A0-la-r%C3%A9volution-manufacturi%C3%A8re-Du-rattrapage-technologique-%C3%A0-l%E2%80%99Industrie-4.0-chez-les-PME.pdf*, accessed December 7, 2021.

[11] Mayr, A., Weigelt, M., Kühl, A., Grimm, S., Erll, A., Potzel, M., Franke. J. (2018). Lean 4.0 – A conceptual conjunction of lean management and Industry 4.0, *Procedia CIRP,* Vol. 72, 622-628, doi: 10.1016/j.procir.2018.03.292.

[12] Sanders, A., Elangeswaran, C., Wulfsberg, J. (2016). Industry 4.0 implies lean manufacturing: Research activities in Industry 4.0 function as enablers for lean manufacturing, *Journal of Industrial Engineering and Management,* Vol. 9, No. 3, 811-833, doi: 10.3926/jiem.1940.

[13] Wagner, T., Herrmann, C., Thiede, S. (2017). Industry 4.0 impacts on lean production systems, *Procedia CIRP*, Vol. 63, 125-131, doi: 10.1016/j.procir.2017.02.041.

[14] Lu, Y., Morris, K.C., Frechette, S. (2016). Current standards landscape for smart manufacturing systems, *National Institute of Standards and Technology*, *NISTIR,* Vol. 8107, 39, doi: 10.6028/NIST.IR.8107.

[15] Jardim-Goncalves, R., Romero, D., Grilo, A. (2017). Factories of the future: Challenges and leading innovations in intelligent manufacturing, *International Journal of Computer Integrated Manufacturing*, Vol. 30, No. 1, 4-14.

[16] Zhou, J., Li, P., Zhou, Y., Wang, B., Zang, J., Meng, L. (2018). Toward new-generation intelligent manufacturing, *Engineering*, Vol. 4, No. 1, 11-20, doi: 10.1016/j.eng.2018.01.002.

[17] Osterrieder, P., Budde, L., Friedli, T. (2019). The smart factory as a key construct of Industry 4.0: A systematic literature review, *International Journal of Production Economics*, Vol. 221, Article No. 107476, doi: 10.1016/j.ijpe.2019.08.011.

[18] Klein, G.A., Orasanu, J., Calderwood, R., Zsambok, C.E. (1993). *Decision making in action: Models and methods,* Ablex Publishing Corporation, Norwood, USA.

[19] Mintzberg, H., Raisinghani, D., Théorêt, A. (1976). The structure of "unstructured" decision processes, *Administrative Science Quarterly*, Vol 21, No. 2, 246-275, doi: 10.2307/2392045.

[20] Cannon-Bowers, J.A., Salas, E. (1998). *Making decisions under stress: Implications for individual and team training*, American Psychological Association, Washington, USA, doi: 10.1037/10278-000.

[21] Hammond, K.R., Hamm, R.M., Grassia, J., Pearson, T. (1987). Direct comparison of the efficacy of intuitive and analytical cognition in expert judgment, *IEEE Transactions on Systems, Man, and Cybernetics*, Vol. 17, No. 5, 753-770, doi: 10.1109/TSMC.1987.6499282.

[22] Kahneman, D., Klein, G. (2009). Conditions for intuitive expertise: A failure to disagree, *American Psychologist*, Vol. 64, No. 6, 515-526, doi: 10.1037/a0016755.

[23] Gigerenzer, G., Gaissmaier, W. (2011). Heuristic decision making, *Annual Review of Psychology*, Vol. 62, 451-482, doi: 10.1146/annurev-psych-120709-145346.

[24] Simon, H.A. (1960). *The new science of management decision,* Harper & Brothers, New York, USA, doi: 10.1037/13978-000.

[25] Klein, G. (2008). Naturalistic decision making, *Human Factors: The Journal of the Human Factors and Ergonomics Society*, Vol. 50, No. 3, 456-460, doi: 10.1518/001872008X288385.

[26] Power, D.J., Cyphert, D., Roth, R.M. (2019). Analytics, bias, and evidence: The quest for rational decision-making, *Journal of Decision Systems*, Vol. 28, No. 2, 120-137, doi: 10.1080/12460125.2019.1623534.

[27] Okoli, J., Watt, J. (2018). Crisis decision-making: The overlap between intuitive and analytical strategies, *Management Decision*, Vol. 56, No. 5, 1122-1134, doi: 10.1108/MD-04-2017-0333.

[28] Schraagen, J.M. (2018). Naturalistic decision-making, In: Ball, L.J., Thompson, V.A. (eds.), *The Routledge international handbook of thinking and reasoning,* Routledge/Taylor & Francis Group, New York, USA, 487-501.

[29] Orasanu, J., Connolly, T. (1993). The reinvention of decision-making, In: Klein, G.A., Orasanu, J., Calderwood, R., Zsambok, C.E. (eds.), *Decision making in action: Models and methods*, Ablex Publishing Corporation, Norwood, USA, 3-20.

[30] Rasmussen, J., Goodstein, L.P. (1987). Decision support in supervisory control of high-risk industrial systems, *Automatica*, Vol. 23, No. 5, 663-671, doi: 10.1016/0005-1098(87)90064-1.

[31] Naikar, N. (2010). A comparison of the decision ladder template and the recognition-primed decision model, Defence science and technology organization, Australian Government, Department of Defence, Victoria, Australia.

[32] Rao, A.S., Georgeff, M.P. (1995). BDI agents: From theory to practice, In: *Proceedings of the First International Conference on Multiagent Systems, ICMAS 1995,* California, USA, 312-319.

[33] Kinny, D., Georgeff, M., Rao, A. (1996). A methodology and modelling technique for systems of BDI agents, In: Van de Velde, W., Perram, J.W. (eds.), *Agents breaking away. MAAMAW 1996, Lecture notes in computer science (Lecture notes in artificial intelligence*), Vol. 1038, Springer, Berlin, Heidelberg, 56-71, doi: 10.1007/BFb0031846.

[34] Object Management Group. Decision Model and Notation, from *https://www.omg.org/spec/DMN*, accessed December 7, 2021.

[35] Chakraborty, P.S., Sarkar, B., Majumdar, G. (2013). Group decision making for a manufacturing organization considering intensity of preference, *Advances in Production Engineering & Management*, Vol. 8, No. 3, 149-156, doi: 10.14743/apem2013.3.162.

[36] Hasić, F., Corea, C., Blatt, J., Delfmann, P., Serral, E. (2020). Decision model change patterns for dynamic system evolution, *Knowledge and Information Systems*, Vol. 62, No. 9, 3665-3696, doi: 10.1007/s10115-020-01469-w.

[37] Soic, R., Vukovic, M., Skocir, P., Jezic, G. (2020). Context-aware service orchestration in smart environments, In: Jezic, G., Chen-Burger, Y.H., Kusek, M., Šperka, R., Howlett, R., Jain, L. (eds.), *Agents and multi-agent systems: Technologies and applications 2019. Smart innovation, systems and technologies*, Vol 148. Springer, Singapore, doi: 10.1007/978-981-13-8679-4_3.

[38] Aliev, K., Antonelli, D., Awouda, A., Chiabert, P. (2019). Key performance indicators integrating collaborative and mobile robots in the factory networks, In: Camarinha-Matos, L., Afsarmanesh, H., Antonelli, D. (eds.), *Collaborative networks and digital transformation. PRO-VE 2019. IFIP advances in information and communication technology,* Vol. 568, Springer, Cham, Switzerland, 635-642, doi: 10.1007/978-3-030-28464-0_56.

[39] Antón, S.D.D., Schotten, H.D. (2019). Putting together the pieces: A concept for holistic industrial intrusion detection, *Computer Science, Cryptography and Security,* Cornell University, *https://arxiv.org/abs/1905.11701v1*.

[40] Bakakeu, J., Brossog, M., Zeitler, J., Franke, J., Tolksdorf, S., Klos, H., Peschke, J. (2019). Automated reasoning and knowledge inference on OPC UA information models, In: *Proceedings of 2019 IEEE International Conference on Industrial Cyber Physical Systems (ICPS),* Taipei, Taiwan, 53-60, doi: 10.1109/ICPHYS.2019.8780114.

[41] Burow, K., Franke, M., Thoben, K.D. (2019). 5G-ready in the industrial IoT-environment, In :Ameri, F., Stecke, K., von Cieminski, G., Kiritsis, D. (eds.), *Advances in production management systems. Production management for the factory of the future. APMS 2019. IFIP advances in information and communication technology,* Vol. 566, Springer, Cham, Switzerland, 408-413, doi: 10.1007/978-3-030-30000-5_51.

[42] Chiacchio, F., D'urso, D., Compagno, L., Chiarenza, M., Velardita, L. (2019). Towards a blockchain based traceability process: A case study from pharma industry, In: Ameri, F., Stecke, K., von Cieminski, G., Kiritsis, D. (eds.), *Advances in production management systems. Production management for the factory of the future. APMS 2019. IFIP advances in information and communication technology,* Vol. 566, Springer, Cham, Switzerland, 451-457, doi: 10.1007/978-3-030-30000-5_56.

[43] Conzon, D., Rashid, M.R.A., Tao, X., Soriano, A., Nicholson, R., Ferrera, E. (2019). BRAIN-IoT: Model-based framework for dependable sensing and actuation in intelligent decentralized IoT systems, In: *Proceedings of 2019 4th International Conference on Computing, Communications and Security (ICCCS),* Rome, Italy, 1-8, doi: 10.1109/CCCS.2019.8888136.

[44] Giehl, A., Schneider, P., Busch, M., Schnoes, F., Kleinwort, R., Zaeh, M.F. (2019). Edge-computing enhanced privacy protection for industrial ecosystems in the context of SMEs, In*: Proceedings of 2019 12th CMI Conference on Cybersecurity and Privacy (CMI),* Copenhagen, Denmark, 1-6, doi: 10.1109/CMI48017.2019.8962138.

[45] Loske, M., Rothe, L., Gertler, D.G. (2019). Context-aware authentication: State-of-the-art evaluation and adaption to the IIoT, In: *Proceedings of 2019 5th World Forum on Internet of Things (WF-IoT),* Limerick, Ireland, 64-69, doi: 10.1109/WF-IoT.2019.8767327.

[46] Miehle, D., Meyer, M.M., Luckow, A., Bruegge, B., Essig, M. (2019). Toward a decentralized marketplace for self-maintaining machines, In: *Proceedings of 2019 IEEE International Conference on Blockchain (Blockchain)*, Atlanta, USA, 431-438, doi: 10.1109/Blockchain.2019.00066.

[47] Pusch, A., Noël, F. (2019). Augmented reality for operator training on industrial workplaces – Comparing the Microsoft hololens vs. small and big screen tactile devices, In: Fortin, C., Rivest, L., Bernard, A., Bouras, A. (eds.), *Product lifecycle management in the digital twin era. PLM 2019. IFIP advances in information and communication technology,* Vol. 565. Springer, Cham, Switzerland, 3-13, doi: 10.1007/978-3-030-42250-9_1.

[48] Rabelo, R.J., Zambiasi, S.P., Romero, D. (2019). Collaborative softbots: Enhancing operational excellence in systems of cyber-physical systems, In: Camarinha-Matos, L., Afsarmanesh, H., Antonelli, D. (eds.), *Collaborative networks and digital transformation. PRO-VE 2019. IFIP advances in information and communication technology,* Vol. 568, Springer, Cham, Switzerland, 55-68, doi: 10.1007/978-3-030-28464-0_6.

[49] Sala, R., Pirola, F., Dovere, E., Cavalieri, S. (2019). A dual perspective workflow to improve data collection for maintenance delivery: An industrial case study, In: Ameri, F., Stecke, K., von Cieminski, G., Kiritsis, D. (eds.), *Advances in production management systems. Production management for the factory of the future. APMS 2019. IFIP advances in information and communication technology,* Vol. 566, Springer, Cham, Switzerland, 485-492, doi: 10.1007/978-3-030-30000-5_60.

[50] Subramanian, D., Murali, P., Zhou, N., Ma, X., Da Silva, G.C., Pavuluri, R., Kalagnanam, J. (2019). A prediction-optimization framework for site-wide process optimization, In: *Proceedings of 2019 IEEE International Congress on Internet of Things (ICIOT),* Milan, Italy, 125-132, doi: 10.1109/ICIOT.2019.00031.

[51] Cagnin, R.L., Guilherme, I.R., Queiroz, J., Paulo, B., Neto, M.F.O. (2018). A multi-agent system approach for management of industrial IoT devices in manufacturing processes, In: *Proceedings of 2018 IEEE 16th International Conference on Industrial Informatics (INDIN)*, Porto, Portugal, 31-36, doi: 10.1109/INDIN.2018.8471926.

[52] Freitag, M., Wiesner, S. (2018). Smart service lifecycle management: A framework and use case, In: Moon, I., Lee, G., Park, J., Kiritsis, D., von Cieminski, G. (eds.), *Advances in production management systems. Smart manufacturing for Industry 4.0. APMS 2018. IFIP advances in information and communication technology,* Vol. 536, Springer, Cham, Switzerland, 97-104, doi: 10.1007/978-3-319-99707-0_13.

[53] Luetkehoff, B., Blum, M., Schroeter, M. (2018). Development of a collaborative platform for closed loop production control, In: Camarinha-Matos, L., Afsarmanesh, H., Rezgui, Y. (eds.), *Collaborative networks of cognitive systems.*

PRO-VE 2018. IFIP advances in information and communication technology, Vol. 534, Springer, Cham, Switzerland, 278-285, doi: 10.1007/978-3-319-99127-6_24.
[54] Mittal, S., Romero, D., Wuest, T. (2018). Towards a smart manufacturing toolkit for SMEs, In: Chiabert, P., Bouras, A., Noël, F., Ríos, J. (eds,), *Product lifecycle management to support Industry 4.0. PLM 2018. IFIP advances in information and communication technology,* Vol. 540, Springer, Cham, Switzerland, 476-487, doi: 10.1007/978-3-030-01614-2_44.
[55] Molka-Danielsen, J., Engelseth, P., Wang, H. (2018). Large scale integration of wireless sensor network technologies for air quality monitoring at a logistics shipping base, *Journal of Industrial Information Integration*, Vol. 10, 20-28, doi: 10.1016/j.jii.2018.02.001.
[56] Pasetti Monizza, G., Rojas, R.A., Rauch, E., Garcia, M.A.R., Matt, D.T. (2018). A case study in learning factories for real-time reconfiguration of assembly systems through computational design and cyber-physical systems, In: Chiabert, P., Bouras, A., Noël, F., Ríos, J. (eds.), *Product lifecycle management to support Industry 4.0. PLM 2018. IFIP advances in information and communication technology,* Vol. 540, Springer, Cham, Switzerland, 227-237, doi: 10.1007/978-3-030-01614-2_21.
[57] Nesi, P., Pantaleo, G., Paolucci, M., Zaza, I. (2018). Auditing and assessment of data traffic flows in an IoT architecture, In: *Proceedings of 2018 IEEE 4th International Conference on Collaboration and Internet Computing (CIC),* Philadelphia, USA, 388-391, doi: 10.1109/CIC.2018.00058.
[58] Roda, I., Macchi, M., Fumagalli, L. (2018). The future of maintenance within Industry 4.0: An empirical research in manufacturing, In: Moon, I., Lee, G., Park, J., Kiritsis, D., von Cieminski, G. (eds.), *Advances in production management systems. Smart manufacturing for Industry 4.0. APMS 2018. IFIP advances in information and communication technology,* Vol. 536, Springer, Cham, Switzerland, 39-46, doi: 10.1007/978-3-319-99707-0_6.
[59] Cortés Serrano, D., Chavarría-Barrientos, D., Ortega, A., Falcón, B., Mitre, L., Correa, R., Moreno, J., Funes, R., Molina Gutiérrez, A. (2018). A framework to support Industry 4.0: Chemical company case study, In: Camarinha-Matos, L., Afsarmanesh, H., Rezgui, Y. (eds.), *Collaborative networks of cognitive systems. PRO-VE 2018. IFIP advances in information and communication technology,* Vol. 534, Springer, Cham, Switzerland, 387-395, doi: 10.1007/978-3-319-99127-6_33.
[60] Badarinath, R., Prabhu, V.V. (2017). Advances in internet of things (IoT) in manufacturing, In: Lödding, H., Riedel, R., Thoben, K.D., von Cieminski, G., Kiritsis, D. (eds.), *Advances in production management systems. The path to intelligent, collaborative and sustainable manufacturing. APMS 2017. IFIP advances in information and communication technology,* Vol. 513, Springer, Cham, Switzerland, 111-118, doi: 10.1007/978-3-319-66923-6_13.
[61] Dragičević, N., Ullrich, A., Tsui, Y.H.E., Gronau, N. (2017). Modelling knowledge dynamics in Industry 4.0: A smart grid scenario, In: *Proceedings of the 18th European Conference on Knowledge Management, ECKM 2017,* Vol. 1, Academic Conferences Limited, Barcelona, Spain, 267-274.
[62] Durão, L.F.C.S., Haag, S., Anderl, R., Schützer, K., Zancul, E. (2017). Development of a smart assembly data model, In: Ríos, J., Bernard, A., Bouras, A., Foufou, S. (eds.), *Product lifecycle management and the industry of the future. PLM 2017. IFIP advances in information and communication technology,* Vol. 517, Springer, Cham, Switzerland, 655-666, doi: 10.1007/978-3-319-72905-3_58.
[63] Innerbichler, J., Gonul, S., Damjanovic-Behrendt, V., Mandler, B., Strohmeier, F. (2017). NIMBLE collaborative platform: Microservice architectural approach to federated IoT, In: *Proceedings of 2017 Global Internet of Things Summit (GIoTS),* Geneva, Switzerland, 1-6, doi: 10.1109/GIOTS.2017.8016216.
[64] Lall, M., Torvatn, H, Seim, E.A. (2017). Towards Industry 4.0: Increased need for situational awareness on the shop floor, In: Lödding, H., Riedel, R., Thoben, K.D., von Cieminski, G., Kiritsis, D. (eds.), *Advances in production management systems. The path to intelligent, collaborative and sustainable manufacturing. APMS 2017. IFIP advances in information and communication technology,* Vol. 513, Springer, Cham, Switzerland, 322-329, doi: 10.1007/978-3-319-66923-6_38.
[65] Saldivar, A.A.F., Goh, C., Li, Y., Yu, H., Chen, Y. (2016). Attribute identification and predictive customisation using fuzzy clustering and genetic search for Industry 4.0 environments, In: *Proceedings of 2016 10th International Conference on Software, Knowledge, Information Management & Applications (SKIMA),* Chengdu, China, 79-86, doi: 10.1109/SKIMA.2016.7916201.
[66] Sandor, H., Genge, B., Haller, P., Graur, F. (2017). Software defined response and network reconfiguration for industrial control systems, In: Rice, M., Shenoi, S. (eds.), *Critical infrastructure protection XI. ICCIP 2017. IFIP advances in information and communication technology,* Vol. 512, Springer, Cham, Switzerland, 157-173, doi: 10.1007/978-3-319-70395-4_9.
[67] Tedeschi, S., Emmanouilidis, C., Farnsworth, M., Mehnen, J., Roy, R. (2017). New threats for old manufacturing problems: Secure IoT-enabled monitoring of legacy production machinery, In: Lödding, H., Riedel, R., Thoben, K.D., von Cieminski, G., Kiritsis, D. (eds.), *Advances in production management systems. The path to intelligent, collaborative and sustainable manufacturing. APMS 2017. IFIP advances in information and communication technology,* Vol. 513, Springer, Cham, Switzerland, 391-398, doi: 10.1007/978-3-319-66923-6_46.
[68] Adeyeri, M.K., Mpofu, K., Adenuga Olukorede, T. (2015), Integration of agent technology into manufacturing enterprise: A review and platform for industry 4.0, In: *Proceedings of 2015 International Conference on Industrial Engineering and Operations Management (IEOM),* Dubai, United Arab Emirates, 1-10, doi: 10.1109/IEOM.2015.7093910.
[69] Klein, G.A. (2009). *Streetlights and shadows: Searching for the keys to adaptive decision making,* MIT Press, Cambridge, Massachusetts, USA, doi: 10.7551/mitpress/8369.001.0001.