Production Management as-a-Service: A Softbot Approach

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Abstract. Production management involves many activities. In order to deal with Industry 4.0 requirements, many systems have developed solutions to gather real-time information from the shopfloor for more reliable decision-making. Empirical studies have been showing that this has created a tremendous overload of information to be handled by managers, causing stress, incorrect analyses and sometimes guessing-based decision-making, especially in SMEs. Using data analytics and maturity models concepts, this work shows *Livia*, a softbot with chatting capabilities. Deployed in a cloud and working on companies' shopfloor information got via a MES system, *Livia* helps managers to identify their main problems, suggests corrective actions, and proactively performs many supporting actions. Results are presented and discussed in the end.

Keywords: Production management · Softbot · Maturity model · Business analytics · MES · Manufacturing Execution System · Software-as-a-Service · SaaS

1 Introduction

Production management (PM) comprehends the sort of activities related to the planning, coordination, supervision, control and decision-making upon resources and business processes' outputs [1]. In Industry 4.0, PM should also consider the increasing digitalization and interconnection of smart products, services, manufacturing systems, value chains and business models in the Internet of Things, Services, and People [2].

This brings up new general technical requirements for enterprise information and operational systems and technologies, such as [3, 4]: distributed and decentralized control; decision autonomy; collaboration of cyber-physical systems (CPS); virtualization; adaptation and plug-and-play capabilities; emergent behavior & self-organization; supervision and resilience; data-driven & real-time control and optimization; and symbiotic interaction of CPSs and humans.

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In order to deal with that, some works have been pursuing the development of environments where managers can be provided with easier, quicker, more systematic and more accurate access to information related to companies' shopfloor, to support more agile and confident decision-making with higher man-machine symbiosis (e.g. [5, 6]).

Implementing such environments is however complex. Regarding its basics – the real-time gathering of information from the shopfloor – some works have been proposing Business Intelligence-based as well as integrated and more interoperable approaches, making easier and more reliable the access to company's information as well as some basic support for decision-making via production dashboards (e.g. [7, 8]).

This is crucial, as information is normally spread over many disparate systems that use different technologies, formats and terminologies, which turns the access, understanding and usage of the right information sometimes even challenging for managers.

Despite the benefits brought up by such environments, they can bring additional complexity to managers. The practice has been showing that they are making managers be increasingly exposed to massive amounts of information about their companies, where lots of checking, analyses and supervision actions as well as critical decision-making need to be more often and rapidly performed [9, 10].

Some approaches have been proposed to handle this, being *software robots* (or just *softbot*) one of them. A softbot can be defined as a virtual system, deployed in a given computing environment, that automates and helps humans in the execution of some tasks with variable levels of intelligence, autonomy and proactivity [11].

In two previous works the authors demonstrated in near-real shopfloor scenarios that softbots can help mitigate some of those problems [6, 10]. Nevertheless, empirical evaluations have been demonstrating that, even though, managers keep being required to check and to do many things, repetitive actions, and without much guidance.

This paper presents a contribution to mitigate these issues. This also includes the consideration of SMEs reality and the coping with some observations came from those two previous works as well as from a MES (Manufacturing Execution System) provider: many SME managers are not used to data-driven philosophies, and they do not have enough or up-to-date theoretical background to more properly manage their companies' production. More specifically, managers are limited: (i) to filter which information from the shopfloor is indeed relevant to consider in the many different situations of analyses; (ii) to properly interpret the actual meaning of the many generated performance indicators and KPIs even though displayed in cute dashboards; and (iii) to reason about them to be more confident on which decisions are suitable for each situation.

These issues are addressed applying the foundations of maturity models and business analytics, employing a *softbot* with chatting properties. It has been developed using Action-Research methodology close to *Harbor*[1], one of the leading software providers of MES in Brazil. Using the Platform-as-a-Service (PaaS) *ARISA NEST* framework to derive particular softbots, this development has been gradually integrated into Harbor's MES and initially used by some of their industrial customers.

[1] https://www.harbor.com.br/.

2 Basic Foundations and Related Work

2.1 Basic Foundations

Production Management (PM) refers to planning, coordinating, and controlling the resources required for fabricating specified products by specified methods [1]. It handles activities like selection of products, production processes, and right production capacity; production planning; inventory control; maintenance of machines; production control; and quality and cost control [1]. Last two activities are the main focus of this work.

Production Control means ensuring that production is running as planned. If any deviation is found, then corrective actions should be taken. *Quality & Cost Control* means that good quality products should be produced at the lowest possible cost, with minimum possible delay, in a way that the company remains sustainable [1].

Maturity is a measurement of the ability of an organization to continuously improve some of its capabilities. Maturity is typically expressed in levels. The higher the maturity the better the company [12]. One referential model is CMMI[2], which allows assessing software companies based on processes and further assigning a given maturity (from 1 to 5) depending on which set of processes have been properly implemented.

Business Analytics refers to methods and techniques used to measure an organization's performance exploring its data to gain insight and drive business [13]. In general, there are five types of analytics [13]: Planning analytics: *What is our plan?;* Descriptive analytics: *What happened?;* Diagnostic analytics: *Why did it happen?;* Predictive analytics: *What will happen next?;* Prescriptive analytics: *What should be done about it?*

Softbots in an Industry 4.0 scenarios mean 'talking' to operators about their daily workflows, technical problems, and work-related topics [11]. Softbots represent novel human-machine/computer interfaces. In [6] & [14] are listed eleven softbots activities.

2.2 Related Works

Few works have been found in the literature combing *softbots* and *Industry 4.0* with a focus on PM. Schwartz et al. [15] proposed softbots to support hybrid teams to increase collaboration between humans, equipment, and software. Kar et al. [16] proposed a cloud-based system architecture for softbots to handle communication between humans and IIoT environments. Kassner et al. [17] proposed a general architecture for softbots to interact with a single machine to illustrate their benefits in smart factories. Dersingh et al. [18] developed a chatbot to monitor and record issues of a production line, notifying workers for appropriate actions. Longo et al. [19] implemented a framework to support the interaction of humans with physical equipment and their digital twins.

[2] https://cmmiinstitute.com/.

Chen et al. [20] developed an engine that adapts production plans to the skills and experience of workers aiming at improving factory efficiency as well as human satisfaction.

In previous research [6, 10], the authors implemented a scenario where a *single softbot* helped machine operators in some tasks via a high-level and voice-enacted interaction. In the second stage of this work, they implemented a scenario of *collaborative softbots* on top of a group of CPS to enhance operation excellence in a shopfloor.

Despite the important contributions of these works, no work has been found using softbots for the envisaged PM support, combining smart chatting, real-time information and alarms, maturity analysis upon companies' shopfloor status, and some business analytics to guide managers in their final decision-making against identified problems.

3 Production Management as-a-Service

Production Management as-a-Service (*PMaaS*) is a general business term for a system module that works together with a given commercial MES system called as *LiveMES*®.

This module works as a softbot (called *Livia*[3]) with chatting properties that: (i) evaluate companies' shopfloor information, identifying current problems in the production against what was planned (e.g. by the ERP) or what it is expected (e.g. based on operational metrics); (ii) identifies company maturity model so that managers can be aware of its operating excellence level; (iii) helps managers in decision-making thanks to some business analytics; and (iv) can be accessed *as-a-service* from the Internet.

Figure 1 shows the general architecture of the PMaaS environment the developed work – the dashed square – is inserted in. Next sections complement this explanation.

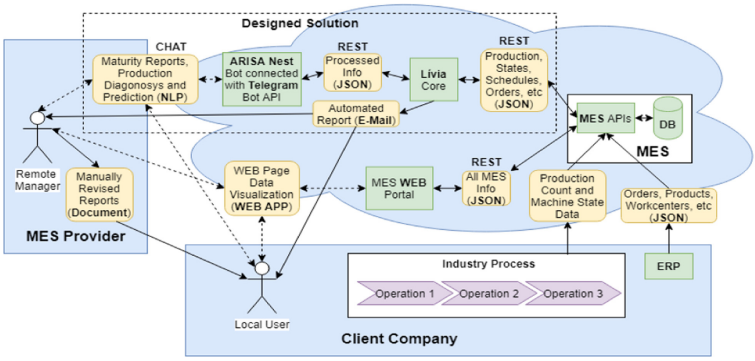


Fig. 1. General systems' architecture

[3] The name *Livia* comes from the union of *Liv*eMES with the *i*ntelligent *a*nalysis words.

The architecture follows the ISA-95 five-layer model. "Industry Process" encompasses layers 0-1-2 (machines, local controllers, industrial networks, sensors, IoT, etc.); "MES" represents layer 3; and "ERP" system the layer 4. The PMaaS approach is implemented via *Livia*, which works as a (new) module of LiveMES. The ERP feeds MES with the production plan.

LiveMES is a fully cloud-based system, deployed at *Amazon*, also proving mobile access via a Web app, from anywhere, anytime. Although companies' machines can be equipped with controllers, industrial networks, etc., LiveMES only requires an Internet connection and that given (simple and low cost) IoT-based data collectors are installed in the machines under supervision in the different production processes.

Data collectors grab every change in the (predefined) information about each machine (e.g. production counting and machine status) and keep it in memory. The information is sent to the cloud in batches every ten seconds, where they are properly handled and stored in a database (DB), per company. Some manual data entry is complementarily supported, regarding companies' possibilities and needs.

LiveMES has the sort of functionalities (exposed via an API implemented as *REST/JSON*-based microservices), being their invocation and results (including dashboards and emails) mostly performed via GUIs. There are different permissions, granting access to allowed system's functionalities, information filters and reports.

3.1 The ARISA NEST Tool and the *Livia* Softbot

ARISA NEST[4] is a PaaS-based-academic tool that allows the derivation of ("instances-of") both single and groups of service-oriented softbots [6], which can be accessed via Web or mobile phones. ARISA (which is deployed in another cloud/server) supports the communication between it and the derived softbots in different ways and protocols.

User communicates with *Livia* via *Telegram* – *Livia* communicates with LiveMES and its DB by invoking their API. It has been specialized via coding the envisaged functionalities (in *Python* language), whereas some functionalities are provided by the own ARISA tool (like chatting via *Telegram*, messages modeling and their processing).

Livia, via ARISA, supports three types of softbot's behavior modes in its communication with end-users: (i) *reactive*, when the softbot acts in response to direct users requests via chatting (e.g. to ask about more detailed information from a given machine); (ii) *planned*, when the softbot acts in response to predefined scheduled tasks (of different types and complexities), bringing their results to users after their execution (e.g. to generate consolidated performance reports weekly); and (iii) *pro-active*, when the softbot performs predefined tasks autonomously on behalf of users or of LiveMES, bringing their results to users if needed (e.g. to continuously checking communication problems between data collectors and LiveMES and promptly take measures to solve them, or sending warnings and alarms).

[4] ARISA NEST tool for softbots derivation – https://arisa.com.br/ [in Portuguese].

In Arisa, all dialogues between a softbot and users were inspired by AIML[5] concept, where key elements are the contexts. *Contexts* mean domain's subjects (and the related key terms in a dialogue) users are supposed to express when asking things or ordering actions to the softbot. A dialogue is modeled as a flow of inter-related contexts in a tree. Users can write (or say) whatever they want since the expected keywords are provided. New contexts, keywords and communication flows can be added, removed, or modified anytime during the softbot's lifecycle.

3.2 The "Real-Time" Maturity Model

In this work, the concept of maturity models has been adapted to the envisaged PMaaS environment. However, instead of checking if given very formal processes are or aren't implemented in the companies, *Livia* checks if some expected actions have been performed. Once this is assessed then the company's maturity level is identified and a set of improvement actions are suggested to its managers (see next section).

Another difference is that *Livia* assesses maturity in "real-time". Given the required time to do that, managers usually do wider analyses once a week based on what happened in the production during this time horizon. With the real-time mode, managers can be permanently aware of the most important problems in the shopfloor.

Applying the descriptive and bottom-up approaches, four maturity levels have been conceived: the "4R". Roughly, level 1, *Resources*, assesses if the shopfloor's supporting instrumentations are properly running and measuring the expected information. Level 2, *Rigor*, assesses if the set of expected assets and production entities are properly registered and communicating with the MES system. Level 3, *Routine*, assesses if the set of predefined management and supervision actions and processes have been executed. The highest level, 4, *Run*, assesses if a high-level set of production data is being used to manage the production. The calculated assessment level is displayed in a *Radar*-like interface. This creates the so-called *RA-RE-RI-RO-RU* measurement cycle of the company's maturity evolution.

Besides identifying the maturity level, *Livia* computes a grade within it. Grades range from 1 to 4, indicating how much of the expected actions, information, processes, etc., have been performed within the given maturity level. This computation basically considers if each action, etc., has been done ("OK"), hasn't been done ("NOK") or it is not supported/non-available ("NA"). For example, a company can be measured as Level 3, but has a grade "2.75", indicating that some aspects need to be improved towards reaching Level 4. Section 4 shows some *Livia* interactions related to this.

3.3 The Business Analytics and Decision-Making Support

One of the most relevant goals of the PMaaS approach is helping managers in better, less stressing and more agile decision-making.

[5] https://web.archive.org/web/20070715113602/http://www.alicebot.org/press_releases/2001/aiml10.html.

Making use of those three softbot's behaviors (see Sect. 3.1) and via interacting with *Livia*, four types of business analytics are provided: *description, diagnostic, prediction* and *prescription*. They can be triggered either sequentially or independently one from another, depending on the situation in place. For example, when a given problem happens, it is identified (*description*) and its cause(s) named (*diagnostics*). Possibilities to solve it can be generated and evaluated (*prediction*), and straightforward measure(s) are suggested (*prescription*). However, depending on the problem, the solution is so simple or clearly known that there is no need to generate predictions.

Considering that each maturity model addresses very different production and MES related aspects, that four types of analytics are executed per level, and not globally.

Business analytics can be extremely complex and can use sophisticated software tools, AI-based methods and big data, for example. In this initial version of PMaaS, it is however relatively simple, also considering the envisaged market niche of SMEs. On the other hand, the algorithms of each type of analytics are implemented as loosely-coupled services, following that general sequential logic, meaning that different and more powerful algorithms (or even external tools) can be added in the future replacing current services by the new ones.

That inter-related logic is modeled as a forward rule-based decision-tree, similar to some expert systems. Starting from the set of predefined problems to be detected from the information received by the data collectors, the system is prepared to identify the one(s) that can indeed take place. For each problem there is a direct relation to the prediction method to be used. Finally, predefined management measures to face the identified problems (within the previously identified maturity level) are suggested.

Applying again the descriptive and bottom-up approaches, these suggestions were conceived based on good practices and managerial foundations, combined with the solid empirical knowledge from the MES provider's professionals got along years.

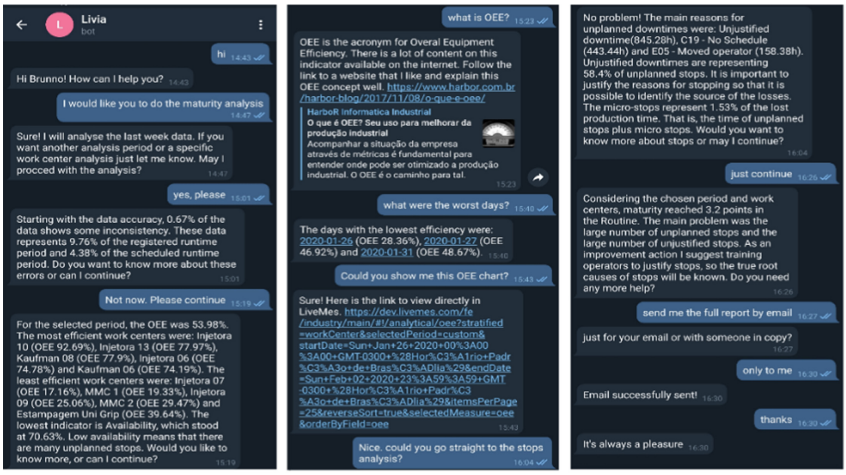
4 Experimental Setup and Preliminary Results

This section provides a broader view of the main steps of one example scenario of *Livia* execution[6] under the *reactive* mode, which is based on a real case.

In this example, *Livia* is running in stand-by waiting for some requests from the manager (called *Brunno*). The conversation style tried to let the interaction the most symbiotic/user-friendly as possible. *Brunno* is interested to make the maturity analysis of his company (see Fig. 2a). *Livia* asks *Brunno* if he wants to run the weekly-basis general analysis (which is set up by *default*), or if he wants to apply a different time frame or to focus on some specific shopfloor's work centers[7].

[6] All the conversations and figures' texts were translated *ipsis litteris* to English only for the purpose of this paper. All the *liveMES* and *Livia* user interfaces are written in Portuguese.

[7] A work center can embrace one or more machines, depending on local installations.



(a) **(b)** **(c)**

Fig. 2. Chatting between *Livia* and the Manager

Following the maturity model, one level of analysis (*Routine*, in this example) refers to data integrity and consistency. For example, due to some reasons, some operators forgot to register some information or did it wrongly; or the data collected is actually an outlier; or the observed production rate of a given work center was higher than its standard rate. All this is informed to *Brunno* by *Livia*. If this analysis is not done, then the quality of other higher-level analyses and further decisions will be impacted by those problems. It is important to also highlight that the softbot does this analysis over hundreds of data, which would be not feasible at all for humans to do.

In the example, the *descriptive* analytics for the Routine level has started, checking lots of related data. It has detected that only 0.67% of all the considered data has some inconsistency. However, it is important to check the data related to production time. Livia detects that 9.76% of the time that work centers are at runtime state and 4.38% of the time that work centers should be at runtime state (i.e. planned production time) have some kind of inconsistency detected. Given that none of these values were greater than the accepted default tolerance (10%), the manager decides to continue the analysis.

The analysis goes on and gets into the *diagnostics* analytics. The machines' OEE (*Overall Equipment Effectiveness*) are shown, and *Livia* also provides references to *Brunno*, indicating the best and the worst cases. She also tells that the main reason for the low mean OEE (a low *availability*, of 70.63% in the case) was the too many unplanned stops in the work centers.

Brunno can ask for complementary information about the calculated OEEs, for more detailed information about given work centers, etc. In the case (see Fig. 2b), he is not so sure about what OEE is, for which an answer is provided, including a deeper explanation about it via a suggested Internet URL. Yet, he gets interested to know more about the calculated OEEs and asks about the worst days.

As this information/functionality is casually already provided by LiveMES, *Livia* indicates the URL through which *Brunno* can directly have access to this. Figure 3 shows the OEE analysis for the evaluated period for all the work centers. Several filters can be applied to this afterwards. Many other equivalent graphics are provided by LiveMES, which *Brunno* can just request to *Livia* to have access to.

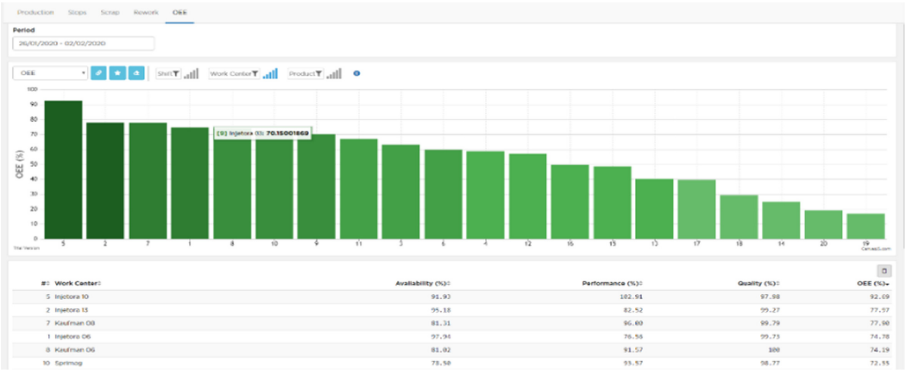


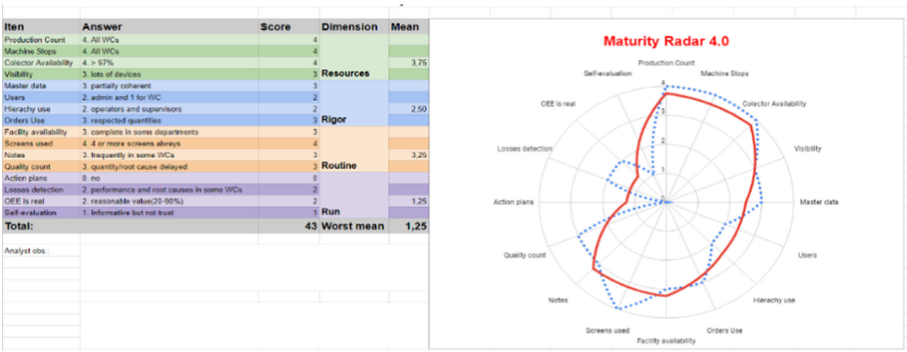
Fig. 3. General OEE dashboard

Some *predictive analytics* might be done in the case *Brunno* requested that (e.g., *Livia* could predict the OEE for the next week considering that the issue would be half-solved – *feature in development). *Livia* then goes directly to the *prescriptive* analytics phase (see Fig. 2c), suggesting a good practices-based measure to tackle the cause(s) of the problem. In the case, the real cause may be related to how operators handle stops in the work centers, for which some training activities are initially recommended.

This example showed how the whole analysis can be done in a "step-by-step" basis, with lots of interactions, intermediate analyses, and requests from *Brunno* to *Livia* being made in her *reactive* mode. In the case *Brunno* wants to have a complete executive report about the whole production (within a given period) or some work center(s), he can just request *Livia* to send it via an email (see Fig. 2c).

Likewise the reactive mode, equivalent actions can be carried out in the *planned* or *pro-active* modes. For example, *Livia* can autonomously start conversations with the manager during the execution of scheduled tasks to ask for some confirmations; or when she detects some serious problem during its supervision activities and decides to inform the manager about it; or to ask him to decide out of given possible solutions.

Figure 4 shows the final Radar view of maturity, also helping managers in having wider perspectives of analysis. It is so far manually generated via LiveMES. However, most of this will be automatically done by *Livia* when it gets fully operational.



Item	Answer	Score	Dimension	Mean
Production Count	4. All WCs	4		
Machine Stops	4. All WCs	4		
Colector Availability	4. > 97%	4		3,75
Visibility	3. lots of devices	3	Resources	
Master data	3. partially coherent	3		
Users	2. admin and 1 for WC	2		
Hierachy use	2. operators and supervisors	2		2,50
Orders Use	3. respected quantities	3	Rigor	
Facility availability	3. complete in some departments	3		
Screens used	4. 4 or more screens always	4		
Notes	3. frequently in some WCs	3		3,25
Quality count	3. quantity/root cause delayed	3	Routine	
Action plans	0. no	0		
Losses detection	2. performance and root causes in some WCs	2		
OEE is real	2. reasonable value(20-90%)	2		1,25
Self-evaluation	1. Informative but not trust	1	Run	
Total:		**43**	**Worst mean**	**1,25**

Analyst obs.:

Fig. 4. The *RA-RE-RI-RO-RU* maturity assessment

On average, a rough weekly manual analysis upon the most important work centers. (normally four) of each company took 2.5 h. Now, it takes from 7 to 16 s for doing a complete analysis of all production issues for all work centers (in general, it spends about 15 s to completely evaluate 2 months of operation of 20 work centers). To be pointed out that this comparison only refers to maturity analysis, without considering the many actions that now the softbot does automatically and more accurately in the background on behalf of the managers in the *planned* and *proactive* modes.

5 Final Considerations

This paper has presented an approach on how softbots can help managers in their daily management of production, called as *Production Management as-a-Service (PMaaS).*

Differently from larger companies, many SMEs are very limited to permanently check their shopfloors, to reason about hundreds of information and of many KPIs usually displayed in managerial dashboards, and to further take decisions based on that.

Livia is a SaaS softbot that has been developed to offer some help and guidance in that, attending companies' managers' requests and performing some actions automatically. It was created to work as a module of a cloud-based MES system (called *LiveMES*), using the real-time data gathered from the shopfloor. To be highlighted a dedicated maturity model, allowing managers to be aware of their data, production and MES issues, and that is the basis for suggesting appropriate decisions.

Livia and *LiveMES* provide an integrated environment. Managers can work without having to spend their time looking for relevant information in the companies' different systems, in a more reliable and less stressing "habitat" for better, agile decisions.

Before the utilization of the softbot, the average time for just doing a rough assessment of the main production issues of a single company was about 2.5 h. Now the complete assessment of all the involved issues of a company is automatically done in few seconds. However, deeper and complementary analyses on top of this can take much longer. Training is also essential to properly to interact with *Livia*; to understand the terminologies' meaning; and to correctly implement the suggested actions.

The developed softbot does not intend to replace managers, but to help them instead. If on one hand it could be observed that the softbot aids managers in faster and more comprehensive analyses, on the other hand, the practice has also shown that managers' experience and insights keep being as essential to interpret the provided analyses and the suggested actions to their companies.

Both Harbor's users and the early company adopters have evaluated this beta-like solution very positively, confirming its claimed benefits. It has also made Harbor and companies strengthen their partnerships, better understanding companies' effective production problems and so helping them in more assertive improvement measures.

Livia implementation has shown very promising results so far. However, being an initial work, some limitations were identified and represent the main next steps of this work: (i) improvements in the messages modeling and handling for more complex interactions; (ii) more clever algorithms for data analytics are very simple, deterministic, and based on a previously known small set of problems; and (iii) expansion of the problems to be considered in the different maturity levels.

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