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Conference on Performance Management (COPERMAN)

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Conference on Performance Management (COPERMAN)

The **Conference on Performance Management (COPERMAN)** aims to bring together researchers and practitioners to present and discuss innovative contributions concerning the measurement and management of organizational performance in a modern business environment. COPERMAN maintains an **interdisciplinary and multifaceted approach**, as performance measurement and management are not limited to a specific area of competence. For this reason, scientific contributions addressing the **Performance Measurement and Management Systems field** with ground-breaking theoretical, experimental, and practical models and techniques are welcome, as well as studies on the latest organizational/technological trends. Participation is **free of charge** and the conference is **publicly broadcasted on LinkedIn and other social media**.

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Conference on Performance Management

Discrete Event Simulation as A Remote Decision-Making Tool for Improving Overall Line Effectiveness

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Abstract. Decision-making tools and performance metrics are vital elements in manufacturing process improvement. Due to the growing complexity of manufacturing systems as well as stimulation of computer-based technologies by the global pandemic, remote working is extensively adopted in most of the organizations. Through review of various literature, it is discovered that there is lack of comprehensive framework on integrating simulation software with decision-making in process improvement, particularly for remote working. This paper is about formulating a new decision-making framework that integrates discrete event simulation (DES) software to select the best alternative to improve a manufacturing system. This new framework provides guidelines in goal, objectives and decision criteria setting, constructing simulation models that are precise in reflecting the real system, identifying root causes, generating relevant solutions, experimenting solutions and selecting the best performing solutions with the aid of WITNESS 20 simulation software, analytic hierarchy process (AHP) as well as analysis of variance (ANOVA). The framework was also validated by conducting a case study at a box manufacturing company. This framework can be exploited by practitioners who are driving decision-making events during remote working.

Keywords
Decision-making; Process improvement; Discrete event simulation; Remote decision-making.

1. Introduction

The term decision making implies that there are several alternative options to be scrutinized and it is the study of determining and selecting alternatives [1]. There are tremendous types of analysis tools to evaluate and select alternative. Ultimately, choosing a viable tool is crucial in decision-making process because different tools correspond to different needs and complexity of decision-making.

Due to the growing complexity of manufacturing systems as well as stimulation of computer-based technologies by the global pandemic, software and remote working are extensively adopted in most of the organizations. In manufacturing aspect, recent researches had conducted study pertaining to process improvement and decision-making, but there is lack of comprehensive framework on integrating simulation software with decision-making in process improvement for remote working.

Thus, a new decision-making framework is necessary in order to serve as a guideline for deploying a contemporary decision-making tool to establish remote and effective decision-making process in process improvement. The aim of this research is to test the feasibility of a new decision-making framework for system performance improvement. This can be achieved through an objective which is to develop and validate a new comprehensive decision-making framework.

Throughout the research, WITNESS 20, a DES software, was used as decision-making tool. Minitab software was used to analyze simulation results. In addition, the case study was conducted at a packaging manufacturing company located in Malaysia. This paper is presented in the order described as follows: literature review, development of new framework, case study results, discussion of findings and conclusion.

2. Literature Review

To thoroughly gain insights on decision-making framework, recent researches were reviewed. Multi-criteria decision-making (MCDM) is the main challenge in process improvement. Bayazit (2005) studied the use of AHP in MCDM to determine whether to implement a new system in a factory [2]. It was determined that AHP is suitable to evaluate the applicability of a new system as it is designated to solve multi-criteria decision problems by assigning criteria weights through pairwise comparison. Correspondingly, MCDM was also carried out by Gurumurthy and Kodali (2008) and the model was known as Performance Value Analysis (PVA). A step-by-step algorithm of PVA was formulated. Performance measures that quantify the criteria were also determined and assigned with weight values [3].

Moreover, it is discovered that simulation is extensively used in decision-making. Robinson et al. (2001) developed a methodology for decision making with simulation model by incorporating visual interactive simulation (VIS) [4]. It was deduced that VIS is an effective approach for experimentation of alternatives, and deliberate model building is mandatory to ensure the precision of simulation result. The researcher also revealed that DES can be used to identify problems in the system.

AlDurgham et al. (2008) developed a Simulation Application Framework for Manufacturing that aids in decision making and can be adapted to wide range of simulation software [5]. A general framework and major steps for each decision area were explicitly demonstrated in flowchart, and also validated by conducting case study at a real system. In case study, decision was made based on performance predicted by simulation model.

A framework for improvement project selection and evaluation was formulated by Aqlan et al. (2017) by using simulation and optimization techniques to solve MCDM problem [6]. DES simulation was used to perform scenario experiments for selected projects. This concurs with Kibira et al. (2015) who also used simulation software to experiment different scenarios by varying the input data to obtain a set of input values that achieves optimization in manufacturing process [7]. On the other hand, Sachidananda et al. (2015) developed a DES model construction methodology. DES was used to model a system and estimate performances of existing and proposed manufacturing processes. It was pointed out that DES provides clear visualization of system which facilitates the process of designing improved system [8].

Chan and Spedding (2003) had also composed an integrated multi-dimensional process improvement framework that encompassed productivity, quality and cost dimensions. In addition, they adopted DES software as decision support tool [9]. Furthermore, Jurczyk-Bunkowska (2020) advocated that DES is time-efficient to solve optimization problem. The researcher had conducted a case study to plan productivity improvement and DES was used to evaluate the performance of proposed configurations on the virtual system through simulation-generated statistics [10].

It was ascertained that most of the decision-making procedures involve three crucial steps in decision making, which are determining decision criteria, evaluating alternatives and selecting the best alternative. Decision criterion is a characteristic or variable in a system that is used to evaluate alternatives in decision making events, so it is necessary to identify decision criteria systematically [11]. For MCDM, the relative importance of criteria must be weighted to seek for alternative that has good performances for the main decision criteria, hence contributing a larger impact in the system.

Yet, there is a lack of comprehensive framework that guides practitioners from initiating decision-making event to concluding the selected alternative. There is a scarcity of guidelines to help in identifying problems from existing manufacturing system, defining objective to commence decision-making event and generating alternatives based on the roots of the problems.

Besides, DES software was selected as the decision-making supporting tool in this research as it can visualize the dynamic behaviour of manufacturing system as well as investigate problem and predict effectiveness of an implementation.

3. Methodology

A comprehensive decision-making framework for process improvement was formulated by synthesizing the strengths and addressed gaps of the frameworks reviewed. Subsequently, a case study was conducted by applying the proposed framework in real manufacturing system for validation.

In this section, a new decision-making framework that employs DES software as decision-making tool is illustrated in graphical mean as shown in Figure 1. The representation of framework comprises of three segments: The upper segment consists of keywords that generally signify the tasks of each main stage. The middle segment states the objective of each stage, whereas the bottom segment is a flowchart of precise steps that elaborates on respective keyword to achieve the objective. The name of the new framework is IMAST, the initials of the five main stages of the framework which are initiation, modelling, analysis, selection and termination.

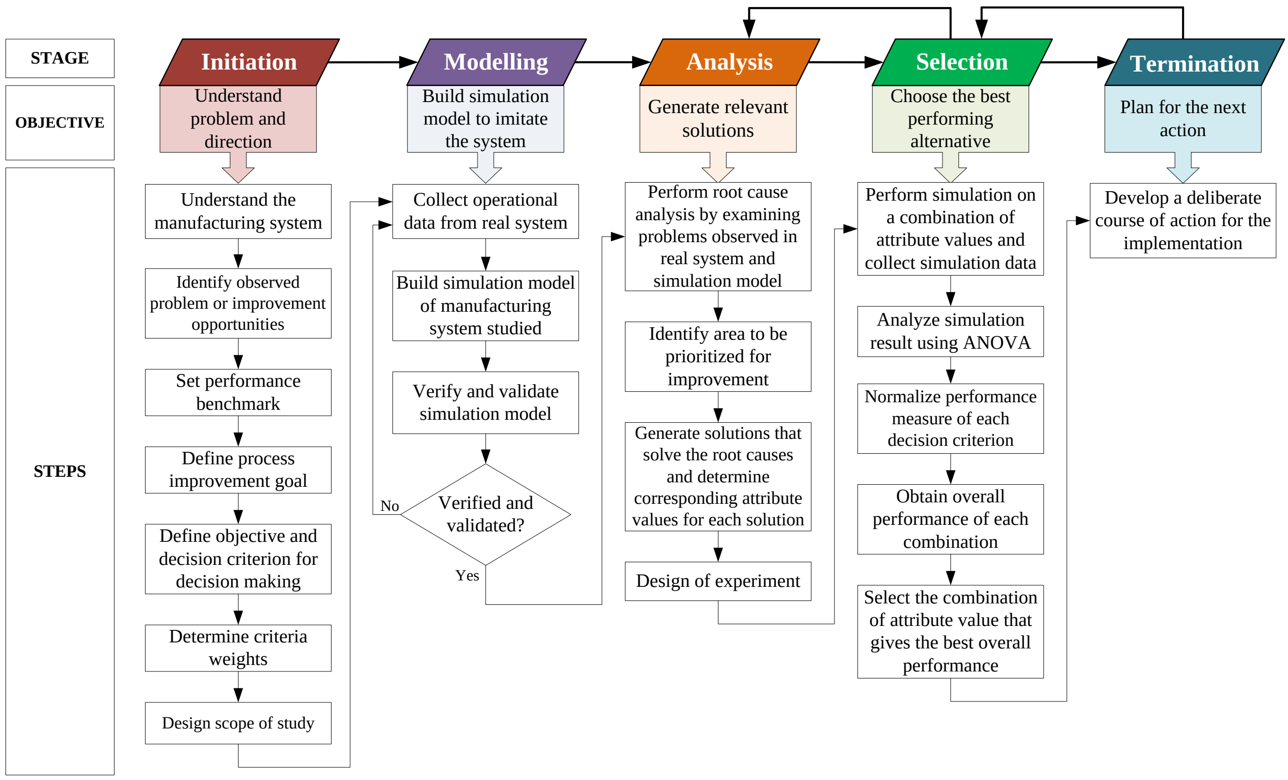

Figure 1: Proposed Decision-Making Framework, IMAST.

In the 'Initiation' stage, the objective of this stage is to understand the nature of manufacturing system and direction of the project. This framework provides guidelines in setting performance benchmark, goal and objectives. Additionally, decision criteria and criteria weights were determined through AHP pairwise comparison based on the goals and objectives of the improvement project to ensure that all alternatives were assessed with reference to the objectives [12].

In 'Modelling' stage, the objective of this stage is to build a simulation model that is precise in imitating real operation. This framework guides practitioners to utilize the collected data to build a comprehensive simulation model by using DES software. Warm-up period is determined to obtain accurate simulation results by performing data collection when the simulation has reached steady-state. A simple technique to determine warm-up period is time-series inspection, which is the time taken for the time-series to achieve steady line [13].

The fourth step is verifying and validating the simulation model. The purpose of model verification is to ensure the program of simulation model is correct by using manual calculations or timelines to identify theoretical outputs of the simulation model [14]. The accuracy of simulation model is validated if a deviation between actual and simulated values is less than 15 % [15].

In 'Analysis' stage, relevant solutions are generated. Root cause analysis and solution brainstorming that exist in conventional framework were adapted into the new framework, in which simulation model is used to facilitate root cause analysis. Then, design of experiment (DOE) is carried out to determine possible combinations of the alternatives [16].

In 'Selection' stage, best performing alternative is selected. The simulation model was used to predict the system performance of new implementation. Then, ANOVA was used to filter out solutions that do not play impact on the system performances [17]. Normalized performance measures of decision criteria are multiplied with corresponding criteria weight to obtain overall performance score. Gurumurthy and Kodali (2008) had described calculation steps of normalizing performance measures [3]. As a result, decision-making is carried out based on the overall performance score of the alternatives.

In 'Termination' stage, blueprint for the new implementation is formulated. The blueprint can include, but not limited to, the implementation steps, mitigating measures for anticipated difficulties, persons-in-charge and plans to achieve targeted parameters distinguished in the simulation model [18].

4. Case Study Results

The case study was carried out in Company X, a packaging supplier in Malaysia to validate the framework.

4.1. Stage 1 – Initiation

A few highlights about the nature of the manufacturing system are described as follows. Firstly, the factory adopts job shop and make-to-order production system. Secondly, there are 6 workstations in the factory that run different processes: corrugating, printing, jaw die-cutting, rotary die-cutting, gluing and packing. Thirdly, there are 6 product types in the manufacturing. The production route and machine setup of each product type were distinct.

Based on observations at production floor and documentations such as financial as well as inventory reports, it was found out that the work-in-process (WIP) area was congested, large amount of waste was generated. Besides, undesired costs, such as overtime allowance and penalty for late delivery as well as poor product quality, were increasing.

The performance benchmark determined to measure the manufacturing system's efficiency was overall line efficiency (OLE). With respect to the administration's requirement, the goal of the process improvement project was to improve OLE by at least 15 %.

The first objective of this improvement project is to find out the root causes of the problems. Secondly, to brainstorm solutions that can resolve or alleviate root causes. Thirdly, to seek for solution(s) that is effective in attaining the goal. Fourthly, to seek for solution(s) that effectively diminishes the company's cost, by reducing production waste as well as late delivery. Fifthly, to seek for solution(s) that incurs minimal cost and time for implementation. Subsequently, decision criteria were determined with the aid of third to fifth objective, which were OLE, line scrap rate (Q), average flow time per order (AFT), equipment cost efficiency (ECE) and level of difficulty (LOD).

Criteria weights were determined for each decision criterion through AHP pairwise comparison. The relative significance (9-point scale) was rated among the decision criteria and criteria weights (ω) were computed as shown in Table 1. For design of scope, key formulas of measurable decision criteria were obtained and a 5-point scale was established for LOD, which is the immeasurable decision criterion. With respect to the relative significance scores, the rated scores are consensual inputs from managers of different departments, which are production, quality control and financial department. Lastly, the elements to be built were also planned in this step.

Table 1 : Determination of criteria weights (ω).

	OLE	ECE	LOD	Q	AFT	Π_i	$\sqrt[5]{\prod_i}$	ω_i
OLE	1	3	5	2	8	**240**	**2.9926**	**0.4254**
ECE	0.3333	1	5	3	8	**40**	**2.0913**	**0.2973**
LOD	0.2	0.2	1	0.5	4	**0.08**	**0.6034**	**0.0858**
Q	0.5	0.3333	2	1	5	**1.66667**	**1.1076**	**0.1575**
AFT	0.125	0.125	0.25	0.2	1	**0.00078**	**0.2391**	**0.0340**
∑							**7.0339**	

4.2. *Stage 2 – Modelling*

Data collection was performed on the elements planned to be modelled in Stage 1. The operational data collected included work element time, cycle time of the machine as well as weight of scrap generated. Time study was performed for 1 working day at each workstation to obtain the work element time.

Next, a simulation model of the manufacturing line was constructed. Elements used to build the model are shift, machines, buffers, parts, attributes and variables. Figure 2 shows the print screen of the simulation model, with the machines labelled. Warm-up period of 6000 hours was determined with respect to a time series graph which showed that the system performance reached steady-state after 6000 hours of simulation run. To obtain performance data, the duration of simulation run was set to 2160 hours, to test the long-term impact of solutions on the system for 3 months.

The simulation model was then verified and validated by using actual and simulated line scrap rate. The actual line scrap rate used for validation was the average of line scrap rate from the last 3 months' production reports. The validation result was acceptable, which was a deviation error of 12.93 %.

4.3. *Stage 3 – Analysis*

After running the simulation model, production reports and simulation results were scrutinized together in order to thoroughly ascertain the problems in the factory as well as their root causes. It can be identified from the statistical report of simulation model that printing workstation was the bottleneck of the manufacturing line. Blockage occurred at the workstation's upstream process and starvation occurred at its downstream processes despite it was fully utilized for production. The root causes of problems identified were inefficient printer setup method, low throughput at printing workstation, as well as poor troubleshooting skills among operators.

It was determined that areas to be improved were printing and corrugating workstations. This is because according to the Theory of Constraints, it would be effective by focusing on improvement at the bottleneck (printers) and its upstream process (corrugator). Potential solutions to solve or mitigate corresponding root causes are enhancing printer efficiency by implementing quality check (QC) form or/and single-minute exchange of die, increase workers for external setup, increase number of printers, revise job dispatching rule and improve troubleshooting skills among operators.

To obtain attribute values of the solutions for new input parameters of the manufacturing line simulation model, supplementary models were built for corrugating and printer setup processes. Full factorial experimental design was performed, which resulted in 288 possible combinations of the attribute values being tested in the simulation model.

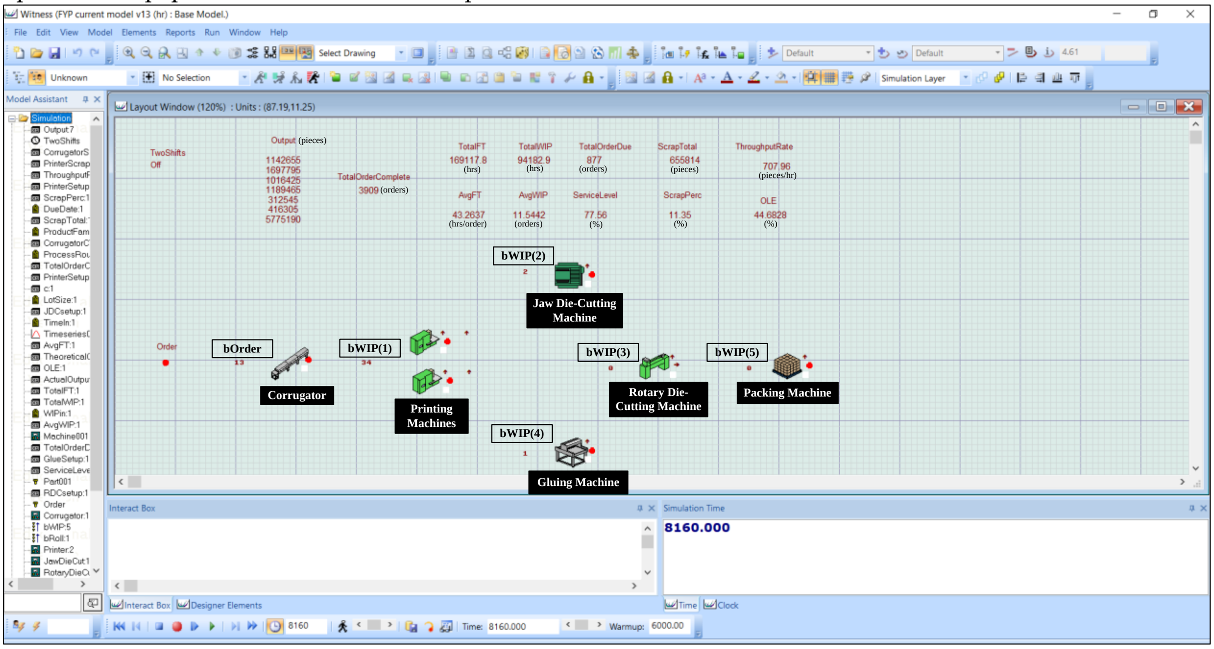

Figure 2: Print Screen of Simulation Model with Performance Measures After 6000-Hour Warm-Up and 2160-Hour Simulation Run.

4.4. Stage 4 – Selection

The experimenter function in WITNESS 20 was used to run simulation for the 288 combinations of attribute values. The simulation data was imported to Minitab software and Microsoft Excel for data analysis. One-way ANOVA was performed through Minitab software to assess the impact of the solutions on system performance. As a result, among the solutions generated in Stage 3, only revising dispatching rule did not play impact on any of those system performances. Therefore, combinations that encompassed new dispatching rules were eradicated, preserving only 71 combinations of alternatives for the next decision-making step.

The performance measures of decision criteria of the 71 combinations were normalized. To compute overall performance score of a combination, the normalized performance measure of the decision criteria was multiplied with the corresponding criteria weight. The overall performance score calculated for the existing system was 0.3906 and the highest overall performance score among the combinations was 0.9219.

Among the proposed solutions, the selected alternatives to improve OLE was enhancing printer setup efficiency by implementing QC form and improving operators' troubleshooting skill. Table 2 shows the comparison of the simulated system performances of the existing situation and selected implementations.

Table 2 : Comparison between Simulation Results of Existing System and Proposed Implementations.

	Existing	Proposed
OLE (%)	44.68	89.61
ECE (RM/pcs)	-2.98×10^{-4}	5.6×10^{-7}
Q (%)	11.35	6.03
AFT (hrs)	43.26	13.23

4.5. Stage 5 – Termination

There are two elements to be improved in the manufacturing line, which involved corrugating and printing workstation. The first solution was enhancing printer's setup efficiency by deploying QC form. The LOD score rated for this alternative was 2, which was an easy implementation because it involved change in working procedure that do not require new technical skill. Therefore, operators can adapt quickly with the changes made in their work elements during setup. It was targeted to achieve at most 3 setup trials through this implementation.

On the other hand, the second solution was reducing production scrap by improving troubleshooting skills among corrugating operators. The LOD score of this alternative was 5, which indicated that there will be difficulties to overcome in achieving desirable results. The main concern was human factor, in which operators might be unable to meet expectation due to their limitation in regards of their skill, knowledge and personality. It was targeted to reduce the mean time to solve machine issues from 5 minutes to 2 minutes.

5. Discussion

Trial-and-error of potential solutions is the most common traditional way in decision-making for process improvement project. This method is normally carried out at a process that is intended to be improved, during off-shift time or on a selected batch of product type during production time. Nevertheless, solution trials during production time is considered non-value-added because it may affect the process's productivity and manpower is needed to instruct and monitor the operators to temporarily implement the new work pattern. In addition, experimenting possible solutions during off-shift time incurs overtime cost. Not to mention that the solution might fail, time and resources are wasted in conducting multiple attempts to obtain the best parameter for the solution.

Conversely, the new framework enhances the efficiency and effectiveness of decision-making for process improvement by coupling contemporary approaches with the major steps of factory improvement comprised in the conventional method. The purpose of deploying simulation model in the new framework is to visualize system's dynamic behaviour, investigate problems and root cause, predict the long-term effects of the possible solution(s) on the system performance, as well as obtaining targeted values or parameters for actual implementation.

Another main contribution of the new framework is remote decision-making. This is an adaption to the evolving work nature as the global pandemic has stimulated computer-based work environment and many organizations tend to continually deploy this work nature even though the movement restriction has relieved. With the proposed framework, the efficiency in process improvement can be highly enhanced because decision-making can be conducted regardless of location and time, provided that the practitioner has knowledge in using DES software and AHP. This contrasts with the conventional way that encounters resource availability constraints.

In certain circumstances, the entire proposed decision-making framework can be accomplished remotely when the operational data for model construction can be accessed from the production documentations, so on-site data collection is not necessary. Hence, provided that practitioners have the knowledge of using simulation software and AHP, this framework is more relevant than the conventional one because it supports remote decision-making that is presently prevailing, brings convenient due to lesser constraints, and amplifies improvement efficiency as it helps in avoiding non-value-added activities that had incurred in conventional factory improvement.

Apart from that, comparing the conventional way with the new framework, the new framework emphasizes on the quality of the solution selected for implementation. The proposed framework assures the successfulness of the implementations by evaluating alternatives in a measurable way based on the project's goal and objectives. The computed performance score explicitly expresses the extent of the successfulness of a particular alternative in attaining goals and objectives, so that it can be compared with others systematically. This assures the quality of selected solutions by obtaining solutions that fulfil multiple objectives.

Moreover, the new framework differs that it facilitates improvement project involving different aspects or workstations and predicts the long-term effects of the solutions on the manufacturing line. Several exceptional factors that can be assessed through the new framework are the impacts and relationships of a solution for a process, a combination of solutions for a process and a combination of solutions for different processes towards the whole manufacturing system in a long run. Thus, it is a beneficial approach in manufacturing line improvement because improvement of different processes in the factory can be conducted concurrently and long-term effects can be predicted.

6. Conclusion

This paper proposes a new decision-making framework that incorporates DES software as a decision support tool in selecting best alternatives for process improvement project. This is because it was discovered that there is lack of comprehensive framework on integrating simulation software with decision-making in process improvement, particularly for remote working.

Literature pertaining to decision-making frameworks were reviewed. DES software was selected as the decision-making supporting tool in this research as it can visualize the dynamic behaviour of manufacturing system as well as investigate problem and predict effectiveness of an implementation.

A new decision-making framework that comprises of five main stages was formulated. 'Initiation' stage provides guidelines in understanding existing problems and setting direction for the project. 'Modelling' stage is about building a precise simulation model that can imitate the manufacturing system. 'Analysis' stage provides guidelines to generate possible solutions that are relevant in solving root causes. 'Selection' stage provides steps in selecting the best performing solution among various alternatives. Lastly, 'Termination' stage is about planning and recommendation for future implementation.

A case study was carried out at a box factory by applying the new framework to improve its OLE. Based on overall performance scores of the alternatives, the best combination of solutions was enhancing printer setup process by deploying QC form and improving the troubleshooting skill among corrugator operators. As such, OLE of the factory was expected to be improved from 44.68 % to 89.61 %.

All of these had proven the feasibility of simulation software in decision-making because an optimized solution can be sought, in which goals are achieved with minimal resources. Besides, it is deduced that this new framework is more beneficial than the conventional one as it contributes in remote decision-making, exploiting the usefulness of simulation software as well as systematic evaluation of alternatives to assure the success of process improvement projects.

The main limitation of this research work is the proposed framework only comprises of systematic methodology to select the best alternatives for process improvement project, which is an initial stage of entire process improvement project in the factory. Future study can be conducted by integrating successive stages of process improvement project into this framework, such as implementation, benchmarking and sustaining, in order to formulate a comprehensive framework that enhances efficiency of process improvement project in remote environment.

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Conference on Performance Management

The Impact of Green Orientation of Human Resource Management on Employee Green Performance: The Mediating Role of Green Organizational Citizenship Behaviour

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Abstract. The green components of human resource management (HRM) are gaining more attention from academics and practitioners. Still, there is a lack of theoretical and empirical information on how well employees perform in their roles in terms of the environment to increase organization's environmental performance. The main thrust of the present research study examined the role of Green Orientation of Human Resource Management (GOHRM) in improving Employee Green Performance (EGP) by analysing the mediation and direct effects of Green Organizational Citizenship Behaviour (GOCB) on EGP. Participants in this study were selected from a public sector manufacturing organization in West Bengal, India. The results depict that GOHRM has a significant impact on EGP. However, the association between GOHRM and EGP at the individual and team levels is partially mediated by GOCB. This study looks into the mechanism and impact of GOHRM on EGP in Indian organization and attempts to offer theoretical recommendations for organizations to implement green management effectively.

Keywords
Green Orientation of Human Resource Management (GOHRM); Employee Green Performance (EGP); Green Organizational Citizenship Behaviour (GOCB); Public Sector Manufacturing Organization.

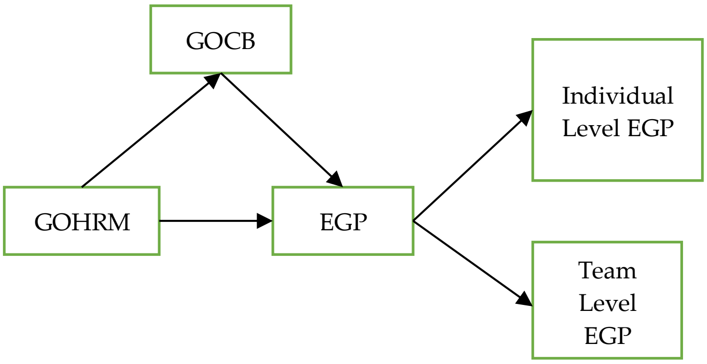
1. Introduction

Over the past few years, the significant issues related to the environment have been global warming, pollution, acid rain, ozone-layer depletion, loss of biodiversity, deforestation, etc. [1]. Avoiding taking precautionary measures regarding these environmental issues can devastate the entire ecosystem [2]. Green sustainable practices can assist manufacturing organizations in reducing carbon emissions and promoting sustainable use of resources [3]. Therefore, the organizations are transitioning from traditional business models to green business models by incorporating green practices into their operations [4].

Therefore, the main objective of incorporating green practices in different functional areas of HRM is to start green programs that necessitate employee behaviors to accomplish their green goals [5]. Green Human Resource Management (GHRM) can be explained as "HRM activities that enhance positive environmental outcomes" [6]. According to [7,2,8,9,10,11], the primary focus of GHRM is about integrating or orienting the environmental aspects on different functional areas of HRM. Therefore, [12], have used the term, preferably, Green Orientation of HRM (GOHRM) instead of GHRM and defined GOHRM "as the extent to which HRM functions in an organization have been made green." Again, Employee Green Performance

(EGP)is defined "as the extent to which a particular employee has engaged in behaviours (actions and activities) and produced results in respect of greening during a particular period" [12]. There are mainly three dimensions of EGP, namely, effective utilization of input resources, innovative employee initiative towards the environment, and employee contribution towards Corporate Environment management (CEM) [12].
The present research gap suggests that there have been few empirical studies on GOHRM practices conducted in the public sector, specially, in the manufacturing industry [3,9].
Hence, the present study has attempted to contribute to the growing body of knowledge on green human resource management by means of providing empirical findings with respect to the relationship between GOHRM and EGP in public sector manufacturing firms.

Furthermore, employees are crucial in improving an organization's environmental performance [13]. GOCB may be defined as "individual and discretionary social behaviours that contribute to organisations' more effective environmental management but are not explicitly recognised by the formal reward system" [14]. GOCB is reshaping the behaviour of individuals and groups of employees by transforming employees into green employees. Research exploring the mediating role of GOCB on GOHRM and EGP has received minimal attention. The GHRM can increase GOCB for a variety of reasons. First, GHRM practices (green hiring, green training and development, green reward, and green performance evaluation) can shape green ideals, knowledge, and abilities, as well as assist individuals in engaging in environmentally friendly activities [15,16] and encourage staff to voluntary participation in environmental activities. Secondly, according to some of the HRM theories, the significance of HRM practices to influence appropriate workplace behaviour depends on employees' understanding of the importance and urgency of implementing such practices [17,2]. GOHRM practices can accentuate the level of organizational commitment to environmental preservation, motivating staff to pursue more environmentally realted activities [2]. Thirdly, Green HRM strategies such as green promotion, green reward, and green evaluation criteria for performance assessment can encourage employees to take proactive steps to safeguard the environment [2]. Lastly, employers who adhere to the GHRM rules make their workers feel valued and respected. As a result, employees are more encouraged to exhibit voluntary green behaviour [2]. Hence, the present research work may be considered as an attempt to reduce this gap by conducting a research study in a public manufacturing firm in India. It may further provide new research insights to researchers and practitioners working in this arena.
Therefore, in order to change the organization into a green organization and employees into green employees, the organization has to focus on the practical implementation of GOHRM and GOCB to increase EGP on the job. Based on this proposition, the following research questions have been formulated.
R1: How does GOHRM can influence GOCB and EGP (individual and team levels) at job?
R2: How does GOCB influence EGP at both (individual and team levels) at job?
R3: Can GOCB mediate the relationship between GOHRM and EGP (individual and team levels) at job?
Using this perspective from the standpoint of contemporary literature review seven resultant hypotheses as well as the conceptual model has been formulated, (See Figure 1).



Source: Compiled by Authors

Figure 1: Conceptual Model of GOHRM

1.1. Theoretical Framework

The present research study focuses on orientating green aspects to different functional areas of HRM to have positive impact in transitioning the employee performance into green performance at both the individual and team levels. This study examines the relationships between how and when green HR practices support EGP at the individual and team levels, using the Conservation of Resources (COR) Theory. The theory of COR is based on the belief that people with many resources are more likely to adopt proactive resource acquisition techniques and invest their present resources in activities that go above and beyond fundamental requirements as a strategy for the sustainable use of resources [18,19]. COR theory is a valuable framework for analysing employee motivation [18]. The philosophy and pattern of GHRM Introduces the concept of "Green" (i.e., preservation and conservation of natural resources and sustainable uses of resources) to attain organizational Corporate Environmental goals [20,21]. As seen through the perspective of this concept, by obtaining green-related resources through green HR practices, employees are more likely to participate in voluntary environmental activities, show citizenship behaviour towards the environment. Consequently, more green-related resources may be acquired, allowing individuals and teams to improve their overall green performance [22].

2. Research Methodology

2.1. Method and Procedure

This exploratory study is an attempt to investigate the relationship between GOHRM, GOCB, and EGP. These variables are correlated to one another, whereas GOCB mediates the relationship between GOHRM and EGP. In this regard, the cross-sectional approach and quantitative methodology have been applied. The data for the present study were collected from employees and their supervisors of a public sector manufacturing organisation in West Bengal. This organization has a functional organizational structure with standard HR practices across the departments.

Stratified random sampling has been applied to collect the data from a sample of 250 employees, by means of administering the standardized questionnaires relevant to the present study.The employees have been divided into different strata according to their current position, such as operational level, executive level, and managerial level. Additionally, participants were made aware that their participation in the surveys was voluntary and that their responses would only be utilised for research purpose. Participants completed their survey questionnaires while taking breaks in order to minimize the detrimental effects of method biases. Although 250 questionnaires were distributed, initially among the employees belonging to the organization, only 223 filled-in questionnaires were analysed for further processing with respect to the current study.

2.2. Measures

The following standardized tools were used in the study :

2.2.1. General Information Schedule

Data were collected with respect to certain demographic variables, like age, gender, experience, designation and income levels of the respondents. The demographic details of the sample (See table 2), presented in appendix section.

2.2.2. The GOHRM Scale

The variable, GOHRM, has been measured by a 16-item scale, as constructed by the researchers, adapting items from conceptual work of Shah (2019). The 16 items [23] are divided into four dimensions: green recruitment and selection, green training and development, green performance management, and green compensation management respectively. The participants rated their level of agreement or disagreement based on a five-point Likert type scale (1= “Strongly Disagree” to 5= “‘Strongly Agree”).

2.2.3. The Green Organizational Citizenship Behaviour Scale

The GOCB was measured by using an adapted 13 itemed questionnaire, as constructed by [13].The 13 items are divided into five dimensions, namely,Helping, Sportsmanship, Organizational loyalty, Individual initiative, and Self-development. The participants rated their level of agreement or disagreement based on a five-point Likert type scaleranging from (1= “Completely Disagree” to 5 “Completely Agree”).

2.2.4 The Employee Green Performance Scale

EGP was measured by a 20 itemed questionnaire, as constructed by the present researchers. Out of these 20 items, ten items were distributed among the Individual level EGP, and the remaining ten items belonged to the Team level EGP. Further, the items are divided into three dimensions namely, Effective utilization of input resources, Innovative employee initiative towards the environment, and Employee contribution towards Corporate Environment. management (CEM).The participants rated their level of agreement or disagreement based on a five-point Likert type scale (1= “Strongly Disagree” to 5= “Strongly Agree”). The summary of the variables is displayed in table1.

Table 1: List of Variables

Sl. No.	Variable Name	No. of items	Source
1	GOHRM	16	Shah, 2019
2	GOCB	13	Boiral & Paillé, 2012
3	Individual level EGP	10	Authors
4	Team level EGP	10	Authors

3. Results

Primarily Exploratory Factor Analysis was conducted, and subsequently, data were analysed using the Cronbach alpha value to check reliability. Furthermore, regression analysis was performed to analyse hypothesized relationships, and Hayes Process Macro was used to analyse the mediation effect.

3.1**.** *Exploratory Factor Analysis*

For results of exploratory factor analysis, refer to table 3 and table 4.

The factor structure was investigated using exploratory factor analysis in SPSS utilizing the principal component method. The varimax rotation approach with Kaiser normalization was used to ascertain the linear combination of variables and their related items. Items were kept based on two standards. The retention cutoff value of 0.5 was first taken into account. Item deletion criteria came in second. Delete any items that loaded on more than one factor. The results for EFA for induvial level EGP on the job were significant. The results show that the factor loadings of the constructs are above .50. The total number of the sample (n-223), the value of Chi-square (X^2) =1264.707 (P<0.001), which indicates suitability for factor analysis, and Kaiser- Meyer-Olkin result is 0.879. The total variance explained is 83.70 percent. The two items, IGEP1 and IGEP7, were removed because these two factors do not have any meaningful relationship with the constructs (See table 3). On the other hand, the results for EFA for team-level EGP on the job were significant. The results show that the factor loadings of the constructs are above .50. The total number of the sample (n-223), the value of Chi-square (X^2) =972.965 (P<0.001), which indicates suitability for factor analysis, and Kaiser- Meyer-Olkin result is 0.844. The total variance explained is 72.48 percent. The one item TGEP1 was removed due to low correlation with the constructs (See table 4).

Table 3: EFA results for Individual Level EGP on job

	Component		
	1	2	3
IEGP5	.850		
IEGP4	.829		
IEGP6	.802		
IEGP10		.838	
IEGP9		.777	
IEGP8		.766	
IEGP2			.902
IEGP3			.859

(IEGP :Individual Level Employee Green Performance)

Table 4: EFA results for Team level EGP on job

	Component		
	1	2	3
TEGP6	.922		
TEGP7	.908		
TEGP5	.891		
TEGP8	.879		
TEGP10		.867	
TEGP9		.741	
TEGP2			.804
TEGP3			.731
TEGP4			.542

(TEGP- Team Level Employee Green Performance

3.2. Reliability

The Cronbach Alpha score was considered while evaluating the internal consistency of the survey instrument. According to the findings of the Cronbach's Alpha test, the reliability of constructs is over .70, and the overall reliability is above 83 percent, which is regarded as excellent (See table 5).

Dimension	No of Items	Cronbach's Alpha
GOCB	13	.910
GOHRM	16	.952
EGP (Individual Level)	8	.904
EGP (Team Level)	9	.835

Table 5: Results of Cronbach's Alpha test

3.3. Hypothesis Testing

Individual Level Employee Green Performance (IEGP) was regressed against the predictive factors GOHRM and GOCB. The independent variables significantly predict IEGP, F (2, 220) =29.772, p <.001. This indicates that two factors under study have a significant impact on IEGP in the job. Moreover, the R^2 = .195 depicts that the model explains 19.5% of the variance. On the other hand, team-level EGP in the job also has a significant relationship between GOHRM and GOCB. The independent variables significantly predict TEGP, F (2, 220) =43.429, p <.001. This indicates that two factors under study significantly impact TLEGP on the job. Moreover, the R^2 = .272 depicts that the model explains 27.2% of the variance. As GOCB is mediating variable so, there is a direct relationship between GOHRM and GOCB. Therefore, GOCB is another dependent variable. The independent variables (GOHRM) significantly predict GOCB, F (1, 221) =20.140, p <.001. Moreover, the R^2 = .527 depicts that the model explains 52.7% of the variance. The regression results have been displayed in the table 5 in appendix section.

3.4. Mediation analysis

This present study assesses the mediating role of GOCB on the relationship between GOHRM and IEGP and TEGP. The results revealed a significant indirect effect (b=0.1587, t=3.246), (b=.2161, t=3.187) on GOHRM and individual and team level employee green performance on the job. Furthermore, the direct effect of GOCB in GOHRM and individual and team level employee green performance in the job was found significant (b=0.3320 P<0.001), (b=.2699, P<0.001). Hence GOCB partially mediates the relationship between GOHRM and individual and team-level employee green performance. The mediation analysis summary was presented in table 6 in the appendix section.

4. Discussion and conclusion

The present study has investigated the relationship between GOHRM and EGP at work and the role of GOCB as a mediator, influencing this relationship.

Overall, the findings indicate a significant impact of GOHRM on increasing the EGP at both individual and team levels on the job. The results showed that GOCB partially mediates the existing relationship between GOHRM and EGP.

Additionally, our study has also highlighted the significance of GOHRM, which may be utilized in changing attitudes and enhancing the voluntary employee participation in different environmental activities, which can further increase organizational environmental performance and environmental sustainability. The results support the underlying theories that have substantially influenced GHRM and EGP [24]. Furthermore, effective implementation of GOHRM practices may increase organizational environmental performance [3].

Furthermore, employees may be thought of being accountable for increasing organization's environmental performance also, thus implicating that may increase its positive environmental impacts, by means of applying the concept of employee green performance of their jobs within the context of their work.

It is crucial to draw attention to the study's limitations as well. Even though this study is cross-sectional, conducting a longitudinal study in the future would be advantageous. Data were collected only from public sector manufacturing organization. So future research studies may be conducted in other sectors like private sector manufacturing sector, service sector, non-profit organizations, etc.

Present study considered four GOHRM parctices namely: green recruitment and selection, green training and development, green performance management, and green compensation management. Other dimensions like, Green job description, Green organizational culture, Green employee empowerment, and Green health and safety management may be considered in future research study. Future studies may consider the inclusion of other different cluster of moderators and mediators such as, Green value, Employee commitment, Proactive personality, and Mindfulness, Workplace happiness etc.

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6. Appendix

Table 2: Demographic details of the samples

Variables	Classification	Frequency	Percentage
Gender	Male	153	68.6
	Female	70	31.4
Age	21-25 Years	147	65.9
	26-30 Years	54	24.2
	31-35 Years	14	6.3
	36-40 Years	3	1.3
	Above 41 Years	5	2.2
Designation	Operational Level	119	53.4
	Executive Level	96	43.0
	Managerial Level	8	3.6
Experience	1-4 years	115	51.6
	5-9 years	74	33.2
	10-14 years	24	10.8
	15-19 years	9	4.0
	Above 20 years	1	0.4
Income	30k-50k	31	13.9
	51k-70k	109	48.9
	71k-90k	55	24.7
	Above 91k	27	12.1

Table 6: Results of Regression analysis

Hypothesis	Regression Weight	R square	B	Std. Error	t	P value	Hypothesis Supported
H1a	GOHRM-IEGP	.195	.332	.102	3.246	.001	Yes
H1b	GOHRM-TEGP	.272	.270	.085	3.187	.002	Yes
H2	GOHRM-GOCB	.527	.750	.048	15.690	.000	Yes
H3a	GOCB-IEGP	.195	.212	.099	2.137	.034	Yes
H3b	GOCB-TEGP	.272	.288	.082	3.516	.001	Yes

Table 7: Results of mediation analysis

Relationship	Total Effect	Direct Effect	Indirect effect	Confidence Interval		t- Statistics	Conclusion
				Lower Bound	Upper Bound		
GOHRM->GOCB->IEGP	.4907	.3320	.1587	0.130	0.533	3.246	Partially mediated
	(0.000)	(0.0014)					
GOHRM->GOCB->TEGP	.4860	.2699	.2161	0.1030	0.1267	3.187	Partially mediated
	(0.000)	(0.0016)					

Conference on Performance Management

A methodological framework to assess investments in automatic storage systems for light-weight load units

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Abstract. Given the 4.0 Industrial Revolution and the current transition toward technologies that enable effectiveness and efficiency of industrial operations, one element that could determine the success of warehouse logistics is to replace Manual Storage and Retrieval Systems (MS/RSs) with the Automated ones (AS/RSs). This possibility offers great opportunities for the storage of Lightweight Load Units (LLUs), since a high number of small items could be stocked by AS/RSs, allowing high turnover rates along with faster and accurate logistics operations. However, evaluating the convenience of replacing MS/RSs with AS/RSs is not an easy task. Indeed, both operational and economic key performance indicators (KPIs) should be considered. Moreover, several types of AS/RSs should be assessed, identifying the technologies for the storage of LLUs compliant with the company's requirements and constraints. Finally, appropriate methodologies should be adopted for sizing AS/RSs, analyzing their performance based on their functioning modalities and constituent characteristics. To minimize evaluation efforts, not all the possible AS/RSs for storing LLUs should be assessed. Instead, practical decision-making guidelines should be adopted to narrow down the design space, directing company managers towards comparing the current MS/RSs with the sole AS/RS alternatives compatible with the company's requirements. Moreover, guidelines should be provided to select the most convenient sizing models among the existing ones, considering that designing a novel storage system is a strategic process. This paper proposes a framework based on the analysis of warehouse KPIs which, first, allows identifying AS/RSs for the storage of LLUs compatible with the company's requirements. Then, provides rules for comparing the selected AS/RSs with the existing MS/RS, evaluating the convenience of investing in such solutions at both operational and economic levels. The proposed framework is applied to the case study of an electrical material distribution company, considering the replacement of a picker-to-parts warehouse system with an Aisle-Based Shuttle one. Results prove the convenience of investing in the Aisle-Based Shuttle system.

Keywords
Automated Storage and Retrieval Systems; Investments Evaluation; Warehouse Performance; Light Load Units.

1. Introduction

In the context of the 4.0 industrial revolution, to improve warehouse logistics operations, it has been suggested to work on two fundamental factors [1]: the inventory management software and the handling and storage procedures (which are strongly dependent on the adopted storage and retrieval systems). Regarding inventory management software, the existing alternatives have been described in detail, also proposing structured procedures to choose the optimal control system based on business requirements and constraints [2]. On the other hand, regarding the inventory procedures, a transition from Manual Storage Systems (MS/RSs) to Automatic Storage Systems (AS/RSs) has been strongly urged [3], but without describing how to choose the optimal AS/RS. Specifically, AS/RSs have shown to produce advantages over MS/RSs in terms of savings in labor costs, increased inventory accuracy (due to the reduction of storage errors), higher flexibility in managing demand variations, and cost-effective utilization of time, space, and equipment (being also able to work 24/7) [4]. Focusing on AS/RSs, different warehouse solutions have been developed for the storage of products of different size, weight, and quality level (even unconventional loading units, which are bulky, heavy, or with special sizes) [5]. The best candidates for automation have been considered to be the warehouses for the storage of conventional Load Units, especially those for Lightweight Load Units (LLUs) with large and variable daily order volumes [6]. Indeed, in the case of LLUs, AS/RSs ensure faster loading and unloading stock procedures, higher reliability, and better utilization of space and resources. Moreover, they do not necessarily require the adaptation of the storage shelves to the geometric and quality characteristics of individual stock-keeping units. As a result, literature has reported that, by installing AS/RSs, the performance of LLU warehouses can be maximized so that the obtained profits justify the high investment cost of AS/RS. Given the advantages achievable by automating LLU storage and retrieval procedures, many companies have recently considered replacing MS/RSs (e.g., the classic Picker-to-Parts) with the AS/RSs counterparts [7]. However, evaluating the convenience of a switch from MS/RSs to AS/RSs is not an easy task. In fact, many warehouse key performance indicators (KPIs) should be analyzed, to improve both the economical and operational performance of the plant. Moreover, several types of AS/RSs have been provided for the storage of LLUs, with different operating characteristics and advantages (e.g., mini-loads, vertical or horizontal carousels, and shuttle systems). Therefore, an investment evaluation would require companies to identify all existing AS/RSs alternatives, analyze them from both an operational and economic perspective through proper KPIs, and finally compare their performance with those of the current MS/RSs. Furthermore, evaluating the investment in AS/RSs would require determining which of the existing alternatives are compatible with the needs and constraints of companies in terms of storage space, cost, and average quantity of items to be handled. In fact, the high economic investment usually associated with the installation of AS/RSs could only be justified by identifying facilities that are compatible with space constraints, capable of guaranteeing the company's target performance in terms of capacity and throughput, and able to improve the performance of the current MS/RSs [4]. Despite the increasing interest of companies in AS/RSs, most of the warehouse research still focuses on MS/RSs and the classical picker-to-parts methods, while studies on AS/RSs have been overlooked [8]. To the best of the authors' knowledge, the literature is lacking practical guidelines to support companies in choosing the most appropriate AS/RS according to performance targets and constraints. Moreover, guidelines are missing to design AS/RSs, selecting optimal sizing models among those existing in the literature. Based on this, a company interested in AS/RSs cannot focus its investment evaluation efforts on the AS/RSs that are likely to be successful. On the contrary, it should make investment evaluations considering all existing alternatives (such as mini-loads, carousels, and shuttle). Additionally, the company should select AS/RS sizing models based on empirical considerations and experience, adopting specific configuration algorithms for each AS/RS alternative, thus resulting in a complex and time-consuming evaluation procedure. Consequently, the lack of practical guidelines to choose and size AS/RSs discourage companies from investing in new storage systems. As a result, the transition from traditional to 4.0 warehouses is strongly hampered [6]. To fill the identified gap, the goal of this paper is to propose a methodological framework, which guides companies in evaluating investments in AS/RSs for LLUs, thus taking strategic warehouse decisions. The provided methodological framework is composed of six sequential steps , which, based on the evaluation of both operational and economic KPIs, allow companies to perform three activities: (i) determine the most promising AS/RS solutions (narrowing down the design space); (ii) select the optimal AS/RS sizing model; (iii) focus investment evaluation efforts on AS/RSs that are likely to respect company targets and constraints, also improving the performance of the current MS/RS. The remainder of the present paper is as follows: Section 2 presents the relevant background literature on AS/RSs for LLUs. Section 3 proposes the methodological framework. Section 4 shows the application of the methodological framework to a case study. Finally, Section 5 offers some conclusions on this work.

2. Literature review

An automated storage and retrieval system (AS/RS) is a type of warehouse automation technology first introduced in 1950s [7]. This technology is designed to buffer, store, and retrieve inventory on demand, being usually integrated with warehouse execution software (WES), or other management controls. AS/RS technology varies significantly, but six primary types of AS/RSs can be identified, whose functioning characteristics have been described by [6]: (i) Unit-Load AS/RS Cranes (Fixed-Aisle & Moveable-Aisle); (ii) Mini-Load AS/RS Cranes; (iii) Shuttle- and Bot-based AS/RS; (iv) Carousel-based AS/RSs (Vertical, Horizontal, and Robotic); (v) Vertical Lift Module (VLM) AS/RSs; (vi) Micro-Load (Stocker). Each type of AS/RS fills its own niche, and the optimal choice for a specific company depends on many factors, including floor space, current operations and procedures, the kind of items being managed, the available economic budget, and the required capacity and throughput.

The existing literature on AS/RSs can be traced back to two main research streams. The first research stream relates to reviews and qualitative discussions on AS/RS alternatives, describing the advantages and disadvantages of individual AS/RS types [6]. The second research stream refers to studies proposing simulation-based or analytical-based models to optimize the design of specific AS/RS types, eventually applying the proposed sizing procedures on example case studies [8]. This last category of papers usually does not compare AS/RS alternatives, but rather focuses on optimizing the performance of a single AS/RS type. For this reason, according to Rouwenhorst et al. [9], papers belonging to the second research stream are better for taking short term decisions on a specific AS/RS type, rather than strategic (long term) decisions such as the convenience in investing in AS/RSs, or the selection of the optimal AS/RS sizing model. According to Darmawan et al. [7], given the benefits of AS/RSs and the increasingly advanced technological developments, the growth of AS/RSs for LLUs is expected to enter a golden age. Despite this, the use of AS/RSs is still limited to a small number of companies for two reasons. First, installing AS/RSs requires a significant capital investment to get up and run the new equipment, but companies lack literature methodologies to select the right AS/RS type, avoiding investment mistakes. Second, for each AS/RS type, several simulation-based and analytical-based models are available for sizing the system, but companies lack methodologies to select the optimal one. To confirm these literature gaps, Darmawan et al. have shown that researchers have mainly discussed AS/RSs from a technical point of view, but few studies have been provided to capture the critical points in selecting AS/RSs from a strategic perspective. Indeed, Rouwenhorst et al. [9] have listed the main KPIs to be considered when evaluating AS/RSs, dividing such criteria into operational and economic ones. Based on the operational KPIs, Azadeh et al. [6] have evaluated the available AS/RS types, suggesting as more appropriate for LLUs the mini-load systems, shuttle-based systems, and carousel-based systems. Moreover, Azadeh et al. have summarized the simulation-based and analytical-based models available for sizing each AS/RS type, but without indicating how to select the optimal one. Since, Azadeh et al. has only assessed the performance of AS/RS types from an operational point of view, Zaerpour et al. [10] have continued the investigation by comparing AS/RSs based on economic KPIs. As an outcome, insights in the investment and operational costs of AS/RS types have been provided, but without indicating how to select the most promising AS/RS investment. Subsequently, Manzini [11] and Darmawan et al. [7] have reported that is not time nor cost effective to evaluate investments in all the AS/RS types, but rather is preferable to skim the most promising solutions, limiting the design space and focusing on the remaining ones. Therefore, indications have been provided to define the most promising AS/RS types based on company's requirements (in terms of capacity and throughput). However, no indications on how to size the most promising solutions have been provided. Moreover, no sequence of practical and structured guidelines has been suggested to prioritize the evaluations of the most promising AS/RS types according to operational and economic KPIs, despite it is known that many interrelated decisions affect the warehouse design. As a result, to the best of the authors' knowledge, a comprehensive methodological framework is missing, which brings together considerations from multiple literature studies, then providing decision-making rules to support companies in comparing AS/RS types, selecting the most promising ones, defining the optimal sizing model, and evaluating the convenience of the final investment. To fill this gap, such a methodological framework is provided in this work, which is described in the next Section.

3. Methodological framework

The proposed methodological framework for evaluating investments in AS/RSs for LLUs is composed of six sequential steps. In step 1, the plethora of existing AS/RS technologies for LLSs is identified. Indeed, knowing the body of AS/RS alternatives is a prerequisite for optimizing any investment [12]. The available AS/RS alternatives for LLUs were defined based on [6], being listed in Figure 1. It should be noted that Figure 1 refers only to automatic storage and retrieval systems, without considering the picking ones (e.g., Automated Guided Vehicles - AGVs) [12], which are beyond the scope of this study.

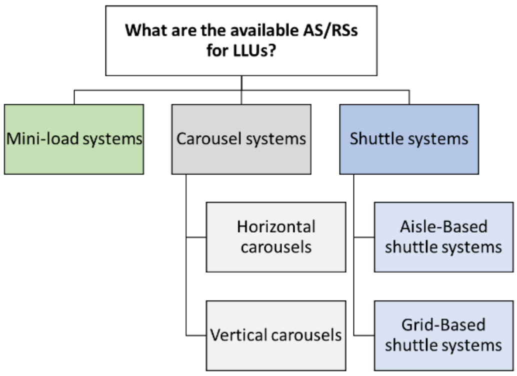

Figure 1. Existing AS/RSs for LLUs.

In step 2, considering the available AS/RSs, the design space is narrowed down in an early stage to save costs and time efforts in the rest of the evaluation process. To this end, the most promising AS/RS alternatives are selected based on two operational KPIs: the number of references managed by the company and the number of average rows (transactions) carried out in the warehouse in an hour. Indeed, these two KPIs depend on the range of stock keeping units managed by the company and inventory turnover. Consequently, these KPIs are directly related to the required storage capacity and throughput, which are considered the two main input KPIs to be evaluated when selecting an AS/RS [13], [14]. With this in mind, the suitability of AS/RS can be chosen based on Figure 2, which was obtained by readapting several literature studies [10]–[12], but focusing on LLUs. The ovals of Figure 2 were positioned in the graphical map after evaluating the average AS/RS speed and the variety of products that they allow storing.

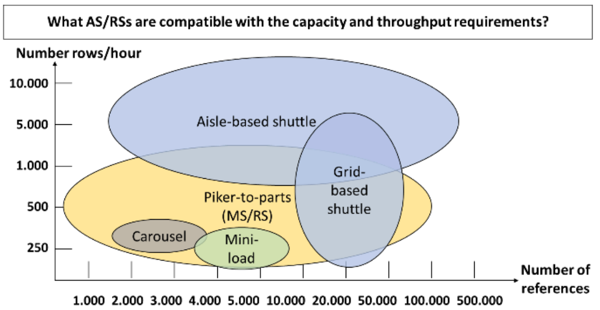

Figure 2. Graphical map for selecting AS/RSs for LLUs, which provide sufficient capacity and throughput based on current (or future) needs.

In step 3, issues related to company constraints are investigated, gathering information on space limitations (e.g., maximum volume or height of the facility in which the AS/RS has to be installed) and cost limitations (e.g., maximum investment budget). According to [15], the constraints imposed by the company should not be considered from the very beginning of the investment evaluation, but rather in step 3. Indeed, the first skimming of the most promising AS/RS solutions should be as general as possible, while space and cost constraints enable or inhibit AS/RSs based on specific company contexts.

In step 4, for each AS/RS (among the most promising ones selected in step 2), the technological equipment is sized. In fact, according to [12], only a specific sizing of each AS/RS allows for an accurate assessment of operational KPIs, such as the speed of product retrieval operations, the average waiting time before retrieval, and the throughput rate. However, among the available sizing models, it should be selected the one constituting a trade-off between the level of detail reached in designing the AS/RS and the time and computational costs required for the design phase. The aim of this study is to take strategic (not tactical or operational) decisions on investing in AS/RSs. Hence, an excessive level of detail in sizing AS/RSs results in a high design effort, without any benefit in taking long-term investment evaluations. Based on this, Figure 3 is provided to support companies in selecting the most appropriate sizing model, listing the existing alternatives, and defining a preference order (numbers 1-6) for their selection. Specifically, the preference order was established based on [6], [16], and [17], suggesting to prefer semi-open queueing network models (number 1) for the following reasons.

Azadeh et al. [6] stated that analytical sizing models should be preferred to simulation-based ones. Indeed, generating a detailed and accurate simulation model is time intensive, while rough evaluations are sufficient to take strategic decisions on AS/RSs. Azadeh et al. [6] also specified that errors made when estimating AS/RS performance through analytical models are usually acceptable during a conceptualization phase. Concerning analytical sizing models, the travel time and queuing network ones are indicated as preferable over the linear and mixing-integer programming models. Indeed, as reported in [6] and [16], the latter do not consider any stochasticity related to AS/RSs. Hence, their use is more convenient for performing other evaluations, such as choosing the right storage policy, and sequencing order transactions, and establishing optimal order batching rules. Finally, according to [6] and [17], travel time models are not capable of capturing several factors such as interactions between multiple resources, parallel processing by multiple resources, or queueing within the AS/RS. For this reason, queuing network models should be preferred, with a specific recommendation towards the semi-open ones. Indeed, open and closed queueing network models do not consider resource constraints and customer waiting times, respectively.

In step 5, an operational evaluation of each sized AS/RS (emerged in step 4) is performed according to Figure 4. Indeed, it is necessary to check if the achieved solutions (according to their sizing) meet the company operational targets and space constraints (emerged in step 3). Moreover, it is necessary to exclude from the next step of the investment evaluation the AS/RSs that do not improve the AS-IS warehouse, performing worse than the current MS/RS. Finally, in step 6, an economic evaluation of the remaining AS/RSs is carried out to check if the remaining solutions (filtered in step 5) respect the cost constraints emerged in step 3. To this end, Rouwenhorst et al. [9] and Darmawan et al. [7] suggested assessing Capex and Opex costs (including purchase and installation, maintenance, consulting, and future scalability costs), then performing the economic evaluation based on three KPIs: return on investment (ROI), net present value (NPV), and payback period (PBP). Zaerpour et al. [10] confirmed this, also showing the investment costs of different AS/RS solutions in a case study, thus enabling companies to get an idea of

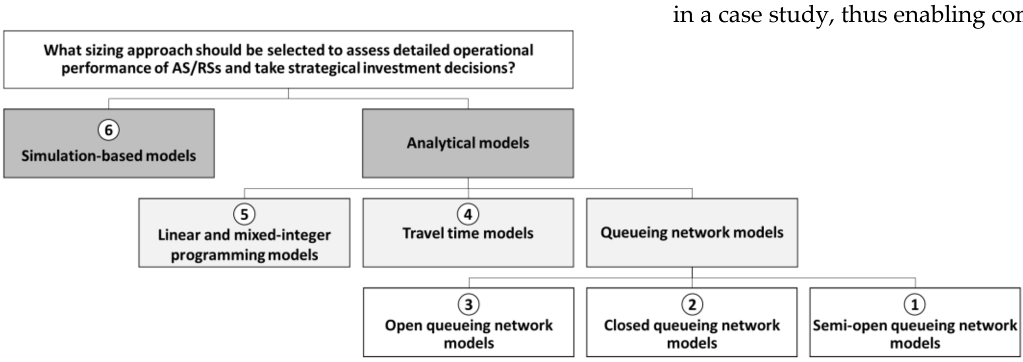

Figure 3. AS/RS sizing models, with their preference order (numbers 1-6).

the economic expenses that they generally require. Figure 5 shows how to develop the economic evaluation. Once completed step 6, only the AS/RS solutions associated with advantageous investments are achieved. As a result of this methodological framework, investment evaluation efforts are minimized, and detailed AS/RS analyses are reduced to the only AS/RS solutions with a strong potential for success. For these solutions, it is worth developing detailed and complex design and evaluation analyses to validate the obtained results before investing any money.

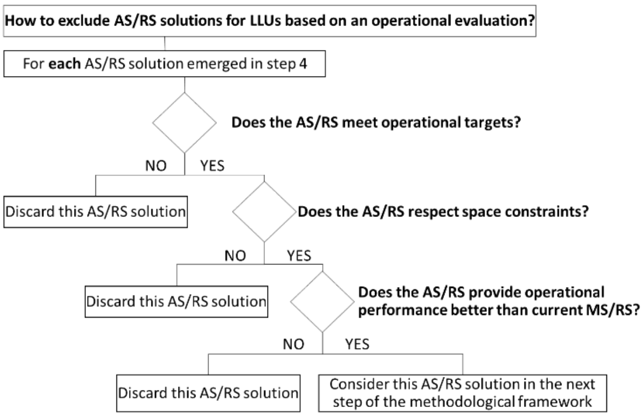

Figure 4. Operational evaluation of AS/RSs for LLUs.

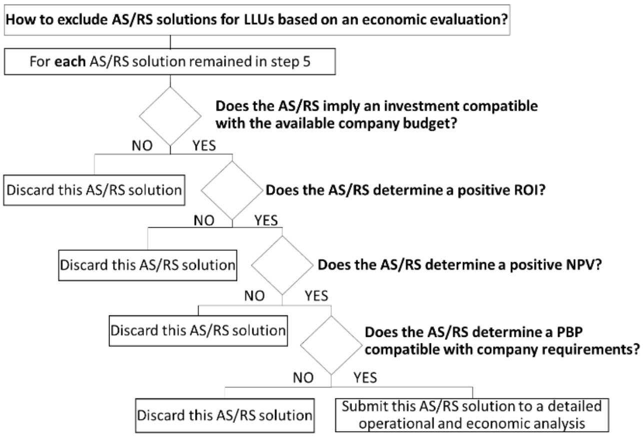

Figure 5. Economic evaluation of AS/RSs for LLUs.

4. Results: application of the methodology

The methodological framework was applied to the case study of an electrical material distribution company. The aim was to focus on a specific distribution center, improving its storage performance by evaluating investments in AS/RSs for LLUs (i.e., replacing the existing traditional racking MS/RS with a new 4.0 AS/RS). Before evaluating investments in AS/RSs, the company established two operational targets: the number of references to be managed by the AS/RS (60,000) and the number of hourly transactions (1,000 rows/hour). The second target was obtained by calculating the average hourly transactions on the day corresponding to the 95th percentile and doubling this number to cope with future demand growths. Moreover, the company applied the linear regression technique to forecast the demand, defining future warehouse occupation trends in the years 2022-2027. Annual occupation levels were compared with the storage capacity of the current MS/RS, determining the annual levels of storage saturation (i.e., the ratio between the annual occupation and the static capacity). Table 1 summarizes the results, confirming the need to replace the current MS/RS, whose capacity cannot cope with future needs (saturation levels of 2024-2027 exceed 100%).

Table 1 : Saturation level of the analyzed distribution center.

Year	Storage capacity [units]	Occupation level [units]	Saturation level [-]
2022	66,558	60,810	91.36%
2023		63,705	95.71%
2024		66,601	**100.06%**
2025		69,497	**104.42%**
2026		72,393	**108.77%**
2027		75,288	**113.12%**

After defining the operational targets and the existing AS/RS alternatives for LLUs (step 1, see Figure 1), in step 2 the most promising AS/RS solution was identified based on Figure 2, resulting in the aisle-based shuttle. This result immediately proves the importance of adopting the proposed methodological framework. In fact, by consulting Figure 2, the company was allowed to exclude, from the earliest stages of the analysis, types of AS/RSs such as mini-loads, carousels, or grid-based shuttles (for which the literature indicates inability to guarantee the required capacity and throughput). Conversely, not excluding such types of AS/RSs would have involved applying complex and time-consuming mathematical models for sizing and evaluating solutions, which result in disadvantageous investments. Subsequently, in step 3, the company imposed some space and cost constraints for the new AS/RS, resulting in a budget limit of 400,000 € and in the two space constraints listed at the beginning of Table 2. Next, the structure of the AS/RS was assumed, opting for a tier-captive aisle-based shuttle (see Figure 6) and assuming the following simplifying hypotheses (usually adopted by AS/RS suppliers [18]: (i) two lifts (for the input and output storage cycle, respectively) move in a vertical direction, transporting bins of products to the storage shelves. The lifts perform single-cycle transactions according to the First Come First Served (FCFS) rule; (ii) a shuttle is located at each level of the rack (tier-captive), which places the stock in compartments, handling only one bin at a time. Each shuttle can perform both single and double storage cycles, following the FCFS rule; (iii) the stock input/output points are located in the lowest level of the rack, facing the input and output lifts, respectively; (iv) lifts and shuttles accelerate and decelerate constantly; (v) the transfer time of bins to/from shuttles varies depending on the rack depth. Whereas the transfer time of bins from the input lift to the input buffer is equal to same time from the output buffer to the output lift; (vi) an input bin is always waiting to be stored in in the rack. This assumption is imposed to cautiously assess the maximum throughput achievable by the AS/RS; (vii) bins are uniformly distributed within the racks and picking orders are distributed throughout all bins; (viii) finally, in the case of multiple depth racks, a "filling degree" is considered, which allows relocating cycles if the bin to be stored/picked is not in the position adjacent to the aisle. At this point, in step 4, based on Figure 3, the optimal sizing model was selected by consulting the scientific literature. No semi-open or closed queueing models were found in the literature for sizing aisle-based shuttle systems. Therefore, open queueing network models were searched, opting for the one with capacity-constraints (M/G/1/K in Kendall's notation) proposed by [18]. The mathematical formulas that make up the queueing model are not reported here for brevity reasons. However, the input parameters on which it relies are listed in Table 2. Moreover, the imposed objective functions and boundary conditions are summarized in Eq. 1, referring to the decision variables described in Table 3. According to [15] and [18], two linear programming problems were solved, searching the AS/RS solutions which minimize F and $Ctot$, respectively.

$$\begin{cases} o.f._1 \min(Area) \\ o.f._2 \min(Cost) \\ s.t. \\ T \leq \left[\frac{H_{max}}{\Delta y}\right]^+ \\ C \leq \left[\frac{L_{max}}{\Delta x}\right]^+ \\ A_{min} \cdot T \cdot C \cdot 2 \cdot D \geq n_{bins} \\ T, C \in int \end{cases} \quad (1)$$

Table 2. Input parameters for sizing the AS/RS.

Input parameter	Value	Input parameter	Value
Maximum warehouse height	$H_{max} = 10\ m$	Lift speed	$v_{lift} = 5\ m/s$
Maximum warehouse length	$L_{max} = 80\ m$	Lift acceleration	$a_{lift} = 7\ m/s^2$
Rack depth	$D \in \{2,3\}$	Transfer time of a bin from/to the lift	$t_{tL} = 2.8\ s$
Number of buffers on each side of the aisle	$n_{buff} = 1$	Shuttle speed	$v_{shutle} = 2\ m/s$
Filling degree	$f = 0.9$	Shuttle acceleration	$a_{shuttle} = 2\ m/s^2$
Distance between two storage locations	$\Delta x = 0.5\ m$	Transfer time of a bin from the shuttle to a generic (n) storage location or vice versa	$t_{tn} \in \{12.7\ s; 16.8\ s\}$
Distance between two rack levels	$\Delta y = 0.4\ m$		

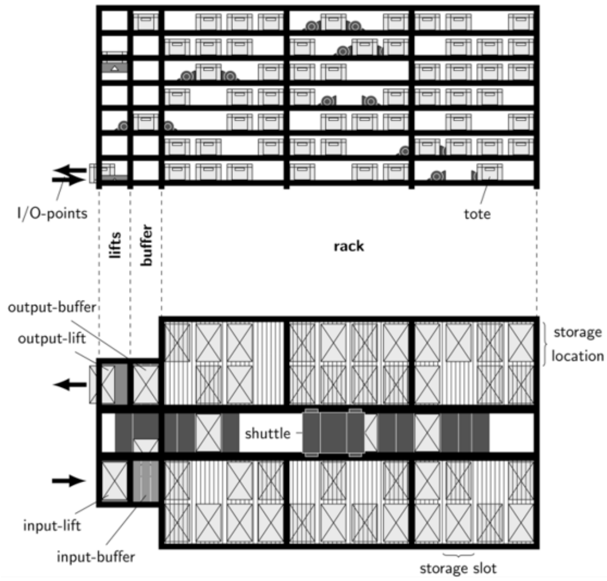

Figure 6. Scheme of a tier-captive aisle-based shuttle (readapted from [18]).

Table 3. Sizing model variables. Refer to [18] and [15] for their calculation.

Variable name	Description
F	AS/RS footprint (ground area) [m^2]
$Ctot$	AS/RS annualized cost [€/year]
T	Optimal number of rack levels [-]
C	Optimal number of rack columns [-]
n_{bins}	Optimal number of bins
A_{min}	Minimum number of isles required to stock the bins [-]
A	Optimal number of aisles [-]
D	Rack dept [-]

Table 4 shows the results of the sizing model, describing four AS/RS solutions achieved by minimizing different objective functions (columns) and varying the input parameters of Table 2.

Table 4. Four optimal solutions achieved through the AS/RS sizing model.

Sizing characteristics	$Min\ F$	$Min\ Ctot$	$Min\ F$	$Min\ Ctot$
D	2	2	**3**	3
A	2	2	**2**	2
T	25	21	**25**	20
C	131	156	**87**	109
n_{bins}	26,200	26,208	**26,100**	26,160
FP	497.8 m^2	592.8 m^2	**452.4 m^2**	566.8 m^2
$Ctot$	259,024 €	250,039 €	**264,110 €**	251,331 €
θ_{SC} (system throughput in case of single cycles)	2068.5 $rows/h$	1953.2 $rows/h$	**1545.6 $rows/h$**	1447.0 $rows/h$
θ_{DC} (system throughput in case of double cycles)	2179.6 $rows/h$	2158.1 $rows/h$	**1620.7 $rows/h$**	1586.8 $rows/h$

In step 5, the four solutions were filtered according to Figure 4, excluding those not meeting spatial constraints and capacity and throughput targets. Among the remaining, in agreement with company experts, the bold solution was considered optimal, determining the lowest F and the second lowest $Ctot$. Finally, in step 6, the selected AS/RS solution (bold in Table 4) was submitted for an economic analysis, producing an NPV of 2,733.319 €, a PBP of 5 years, and an ROI equal to 16%. Based on Figure 5, the investment on the selected AS/RS solution was considered advantageous, producing improvements over the current MS/RS. The AS/RS solution also respected the available economic budget. Therefore, detailed design and evaluation analyses were performed, which validated the results achieved. Specifically, a discrete event simulation model was developed to realistically represent the AS/RS. Results proved the effectiveness of the methodological framework, confirming the convenience of the investment and great performance improvement opportunities. A comparison between the results of the sizing queueing model and the simulation one produced a mean square error of 0.98%, validating the accuracy of the analyses.

5. Conclusion

This paper proposes a methodological framework to support companies in investing in AS/RSs. The methodological framework points out successful AS/RS solutions, for which an investment is worthwhile. Both operational and economic KPI targets and constraints are achieved, and an improvement over MS/RSs is ensured. The contribution of this paper is to promote the transition of warehouses towards the 4.0 paradigm. The proposed methodological framework provides practical guidelines to systematize and streamline the AS/RS evaluation procedure, encouraging companies in investing in AS/RS. By applying six procedural steps, companies can minimize the complexity and time-consumption of AS/RS analyses, restricting the detailed evaluations only to promising AS/RS solutions, which are likely to improve the warehouse performance. The methodological framework was applied to a case study company, identifying (in only 2 days of work) an aisle-based shuttle system, which overcomes the limitations of the current MS/RS and face future company developments. Future developments of this work could be twofold. First, to apply the methodological framework to another case study, further validating its effectiveness. Second, to compare (in terms of working time, computational efforts, and operational and economic KPIs) the AS/RS solutions achieved by leveraging the methodological framework (i.e., narrowing down the design space from the early stages of the analysis) with the ones achieved by not restricting the design space. Consequently, it will be confirmed that the methodological framework does not exclude valuable AS/RS solutions when restricting the design space.

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Conference on Performance Management

A New Approach to Evaluate Human Error Probability (HEP)

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Abstract. The aim of the present research is to propose a hybrid model to evaluate Human Error Probability (HEP) called Logit Human Reliability (LHR). The new approach is based on logit normal distribution, Nuclear Action Reliability Assessment (NARA), and Performance Shaping Factors (PSFs) relationship. The present paper analyzed some shortcomings related to literature approaches, especially the limitations of the working time. We estimated PSFs after 8 hours (work standard) during emergency conditions. Therefore, the correlation between the advantages of these three methodologies allows proposing a HEP analysis during accident scenario and emergencies. The proposed approach considers internal and external factors that affect the operator's ability. LHR has been applied in a pharmaceutical accident scenario, considering 24 hours of working time (more than 8 working hours).

Keywords
Human Factors; Environmental Factors; HRA; HEP; PSFs; Pharmaceutical Plant; Logit Normal Distribution

1. Introduction

The complexity of technological evolution has increased the risks related to the management of industrial machines [1]. Lately, after many accident situations, the emergency management in production systems has assumed an important role [2]. According to Sheridan and Ferrell [3], the emergency management evaluates two fundamental parameters: system reliability and human reliability. In particular, it is necessary to monitor the safety of critical infrastructures [4] because their failure could generate serious consequences on the surrounding environment and drastic emergency [5]. It is necessary to study human behavior during emergency conditions. An operator wrong choice could worsen emergency conditions. It is necessary to identify all factors that affect the operator's behavior [6]. Definitively, the emergencies are complex and dynamic; therefore, operators must recognize, prevent, and solve problems that can generate accidents [7]. It is important to analyze and manage external and internal factors relating to human [8]. The risk management studies all factors to limit emergency conditions and to reduce the consequences of human errors [9]. HRA is a systemic approach, which evaluates HEP during the working time, analyzing external and internal factors, which could influence workers' performance [10]. The "external" factors depend on the work environment. The "internal" factors are related to the individual's characteristics [11]. The paper analyses the most important HRA approaches. LHR method starts from the NARA model proposed by Kirwan et al. [12], the SPAR- H model proposed by Gertman et al. [13] and the Performance Shaping Factors (PSFs) dependence proposed by Boring [14]. The "external" factors depend on work environment; they modify the working conditions and thus leading to errors. The "internal" factors are related to the individual's characteristics, and individual psychophysical conditions of the operator

However, NARA and SPAR-H models do not analyze the dependencies between the external environmental factors. Using PSFs it is possible to value the influence of many external environmental factors, coming from the analysis of 82 real case studies.

The aim of this study is to propose a hybrid model, called Logit Human Reliability (LHR) for evaluating human error probability in the industrial plants during an emergency condition.

The proposed approach combines three methods of HRA: the NARA methodology, Logit Normal Distribution, and Boring's PSFs dependency. The fusion among these three methodologies allows to develop a reliable simulator for human error probability analysis during the emergency conditions.

The human (internal) and environmental (external) factors

that influence the operator's ability are both evaluated in the proposed approach. The Boring's PSFs dependency considers the external factors, while the NARA methods consider the internal factors. The Logit Normal Distribution can be evaluated through basic HEP that will be corrected by PSFs. The proposed method uses Logit function because it represents the "wear-out" condition of the human operator. Using Logit distribution, HEP increase vs. time can be calculated.
LHR model is validated in a pharmaceutical plant. In particular, the operator's behavior in a control room is analyzed. The paper is organized as follows: Section 2 analyses the state of the art of HRA (human reliability analysis). In Section 3, the methodological research approach is presented. In Section 4, the case study is analyzed, while in Section 5, the results are presented and discussed. Finally, in Section 6, the conclusions and future developments are described.

2. Literature Review

Any Human Reliability Analysis (HRA) analyses the human reliability, in a similar way to the analysis of system reliability [15]. According to Swain and Guttman [16], HRA methodologies have motivated many activities in research and development [17].HRA influences the maintenance system [18]. The availability of a production system depends on the performance and connections of the machines and operators [19-20]. In general, the causes that lead to an accident are three: system failures, natural events, and human errors [21]. Several authors analyzed human behavior in emergency conditions. For example, Jung et al. [22] analyze the performance of the operator in a pharmaceutical plant. Houshyar and Imel [23] developed a simulation model of human behavior in a nuclear plant.
Literature analysis divides HRA methodology in three different generations:
a) First generation (1970 - 1990) focus on the skills and rules of human factors without considering social interest, management factors and communication errors. Some first generation approaches are:
Systematic Human Action Reliability (SHARP): it considers the integration of man and machines [24] and it calculates HEP in seven steps [25,26].
The Empirical Technique to Estimate the Operator's Error (TESEO): considering five factors, it calculates the HEP of operator [27-28].
Accident Sequence Evaluation Program (ASEP): it has been applied to nuclear plants. ASEP uses the correlation between time and reliability to obtain HEP [29,30].
Human Cognitive Reliability Correlation (HCR): it used SLIM factors to estimate HEP. SLIM Equations have been revised to evaluate PSFs effect on human reliability [31].
Technique for Human Error Rate Prediction (THERP): it analyzes some PSFs but not their effects on HEP [32]
Success Likelihood Index Method (SLIM): It has been used in nuclear plants, but it can be easily applied to other plants. [33-34].
Human error assessment and reduction technique (HEART): it has been developed in the early 1990's [35] in the United Kingdom nuclear plants. Identifying "generic tasks" (GTTs), the analyst can determinate the HEP basic [36].
b) Second generation methodologies (1990-2005), which integrate internal and external factors affecting human reliability. In second-generation models, the factors that determine PSFs are derived by focusing on the environmental impact on the cognitive level. Some methodologies below to the second generation are:
Cognitive Reliability and Error Analysis Method (CREAM): it is based on the Contextual Control Model (COCOM) [37]. Konstandinidou et al. [38] used this approach to construction a fuzzy model for HRA. The approach is developed to determine the HEP with PSFs values.
A Technique for Human Event Analysis (ATHEANA): it was designed to be a full scope HRA method including the capability for performing predictive task analysis and retrospective event analysis. [39].
Standardized Plant Analysis Risk - Human RA (SPAR-H): it was a revised version of ASP approach. Rasmussen et al. [40] applied this approach to estimate HRA to the pharmaceutical industry. SPAR-H is based on eight PSFs.
c) In the last ten years, the shortcomings of the second-generation HRA have been overcame by third-generation methods:
Nuclear Action Reliability Assessment (NARA): it is an upgrade of the HEART method to (a) have better fit to nuclear context, (b) consider errors of commission, (c) have substantial data support, (d) consider long time scale scenarios, and (e) have better guidance on usage [41-42].
Boring [14] proposes a dependence model between the PSFs. Rauschert et al. [43] using GIS a geographic interface to manage emergencies. The research takes into account the external environment and its characteristics . Even Schafer, Ganoe and Carroll [44] manage the planning of emergency management through geographical software. Currion Silva and Van de Walle [45] developed a simulation tool to manage the coordination during an emergency. Levi et al. [46] describe the experience with developing and implementing the use of simulation software as a drilling technique used by Israeli hospitals. Cowan and Cloutier [47] describe a required, role-intensive leadership simulation in emergency and disaster medicine management for fourth- year medical students. Christie and Levary [48], which use the simulation model, "what-if" analyses to predict the consequences of conceivable scenarios.
The present study starts from several shortcomings of literature HRA models. The proposed model, called Logit Human Reliability (LHR), overcomes the limitations of the most conventional HRA methodologies, merging the advantages of NARA, PSFs, and SPAR-H models.

Furthermore, the present research analyzed three limitations related to the NARA model: 1) HEP is limited to the first 8 hours of work; 2) no dependency between the relationships of PSFs; 3) the failure rate is constant.

3. Logit Human Reliability (LHR)

In this section, the proposed LHR model is described. The new approach combines three methods of HRA: the NARA methodology, Logit Normal Distribution, and Boring's PSFs dependency. The human (internal) and environmental (external) factors that influence the operator's ability are both evaluated in the new approach. We estimated HEP after 8 hours (work standard) during emergency conditions. The model will be applied during a simulated emergency in a pharmaceutical plant, considering 24 hours of working time. LHR method is structured in the following steps:

Step 1: Preliminary Analysis.
An identification of the activities to be simulated. It lists all activities performed by the decision makers while working in nominal conditions and during an emergency. HEP will be associated with each of these activities, where HEP represents the unreliability of the operator. For example, Di Pasquale et al. [49] and Gertman, and Blackman [50] simulated the HEP with the Weibull function, while Chiodo et al. [51] uses a random function to evaluate human performance. Usually, Logit Normal function is selected during "wear out" phase of components. This phase can be compared to the stress phase of an operator during an accident scenario. Starting from the above analysis, we have selected Logit distribution to link HEP and operating time. The human unreliability has been evaluated by the Logit function of failure probability (Eq.1).

$$g(t) = 1 - \frac{e^{\left(\frac{t-\mu}{\sigma}\right)}}{1+e^{\left(\frac{t-\mu}{\sigma}\right)}} \tag{1}$$

Where μ is the average value and σ is the standard deviation.

Step 2: Identification of Internal Factors
In this phase, we defined Gric Tasks (GTTs), that represent the internal factors of the operators. Each GTT follows the Logit function. Using Logit distribution, HEP will be calculated. The HEP increase vs. time. Table 2 describes the NARA GTTs, while k is the human unreliability value to the 8th hour of working time, λ is the constant value of failure rate, μ is the Mean Time to Failure and σ is the standard deviation. Assuming λ=constant, we obtain:

$$\lambda = -\frac{ln(1-k_{24})}{8} \tag{2}$$

$$MTTF = \mu = \int_0^{\infty} t \cdot f(t) = \frac{1}{\lambda} \tag{3}$$

$$\sigma = \sqrt{\int_0^{\infty}(t - MTTF)^2 \cdot f(t)dt} = \sqrt{\int_0^{\infty}\left(t - \frac{1}{\lambda}\right)^2 \cdot \lambda \cdot e^{-\lambda t}dt} \tag{4}$$

Table 1 : Generic Tasks

GGT	k (t=8h)	λ [1/h]	μ [h]	σ [h]
A1Carry out simple single manual action with feedback. Skill-based and therefore not necessarily with procedure.	0.0050	$6.266{\cdot}10^{-4}$	1596.00	618
A2 Start or reconfigure a system from the Main Control Room following procedures. with feedback.	0.0010	$4.169{\cdot}10^{-5}$	23988.00	6010
A3Start or reconfigure a system from a local control panel following procedures. with feedback.	0.0030	$1.252{\cdot}10^{-4}$	7987.99	2800
A4 Reconfigure a system locally using special equipment. with feedback; e.g. Closing stuck open boiler SRV using gagging equipment. Full or partial assembly may be required.	0.0300	$1.269{\cdot}10^{-3}$	787.94	413
A5 Judgment needed appropriate	0.0100	$4.188{\cdot}10^{-4}$	2387.98	1004
A6 Completely familiar well designed highly practiced. Routine task performed to highest possible standards by highly motivated. Highly trained and experienced person. Very aware of implications of failure with time to correct potential error.	0.0001	$4.167{\cdot}10^{-6}$	239988.0	59995
B1 Routine check of plant status	0.03	$1.269{\cdot}10^{-3}$	787.94	413
B2 Restore a single train of a system to	0.007	$2.927{\cdot}10^{-4}$	3416.56	1316

correct operational status after test following procedures.				
B3 Set system status as part of routine operations using strict administratively controlled procedures	0.0007	$2.918\cdot 10^{-5}$	34273.71	8566
B4 Calibrate plant equipment using procedures; e.g. adjust set Point	0.003	$1.252\cdot 10^{-4}$	7987.99	2800
Carry out analysis	0.03	1.269·10-4	787.94	413
C1 Simple response to a key alarm within a range of alarms/indications providing clear indication of situation (simple diagnosis required). Response might be direct execution of simple actions or initiating other actions separately assessed.	0.0004	1.667·10-5	59988	14995
C2 Identification of situation requiring interpretation of complex pattern of alarms/indications. (Note that the response component should be evaluated as a separate GTT)	0.2	9.298·10-3	107.5	117

Step 3: Basic Human Error Probability (HEPbasic)

The calculation of the basic error probability (influenced by GTTs) follows the Logit distribution (eq. 1). The nominal distribution is theoretical and does not take into account the external environment factors. HEPbasic takes into account only the k value (table 2). The human unreliability value (Table 2) is the input value for equation (1), where μ and σ

$$[HEP_{basic}]_{t1}^{t2} = \int_{t1}^{t2} 1 - \frac{e^{\left(\frac{t-\mu}{\sigma}\right)}}{1+e^{\left(\frac{t-\mu}{\sigma}\right)}} dt = \frac{1}{t2-t1}\left[t - \sigma ln\left(1 + e^{\left(\frac{t-\mu}{\sigma}\right)}\right)\right]_{t1}^{t2} \quad (5)$$

are calculated using equations (3) and (4). The basic HEPbasic is determined as:

Equation (5) considers a working time greater than eight hours, because in several emergencies some operators could work even 24 hours consecutive.

Step 4: Identification of External Factors

The environmental influences are modelled with the use of Performance Shaping Factors (PSFs). The PSFs increase the HEP values. The PSFs analyzed are: Available time; Stress/Stressor; Complexity; Experience and training; Procedures; Ergonomics and Human machine interface; Fitness for duty; Work processes. However, PSFs dependencies are not considered in the NARA model. Boring (2010) proposes a table of PSFs dependencies (Table 2).

Table 2 : PSFs dependence

	Available Time	Stress	Complexity	Experience Training	Procedures	Ergonomics HMI	Fitness for Duty	Work Process
Available Time	1							
Stress Stressors	0.50*	1						
Complexity	0.38*	0.35*	1					
Experience Training	0.31*	0.21*	0.32*	1				
Procedures	0.05	-0.01	0.12*	0.08*	1			
Ergonomics HMI	0.10*	0.04	0.08*	0.08*	0.29*	1		
Fitness for Duty	0.20*	0.29*	0.22*	0.17*	0.12*	0.27*	1	
Work Process	0	0.13*	0.16*	0.20*	0.35*	0.12*	0.15*	1

Step 5: PSFs Correlation (PSFcor)

The PSFcor value is evaluated from the product of all PSFs and their value of independence. The PSFcor represents the external environmental conditions as the following Equation 6:

$PSF_{cor} = \prod_{i=1}^{n}[PSF_i(1 - \sum dependence\_indexes) \cdot State(PSF_i)]$ (6)

where "n" is the total number of PSFS that are considered in the approach. The state of each PSF has been assessed by an Expert Judgment (0<State(PSFi)<1).

Step 6: PSFs correct by time (PSFtime)

The results obtained from Eq.6 are corrected by time factors where 1≤ t ≤24

Applying the following equation 8, we obtained the PSFs corrected by time:

$$PSF_{time} = PSF_{cor} \cdot T \quad (8)$$

Eq.8 is able to increase PSFs after the 8th of work. In this condition, the influence of external factors is more several to operators.

Step 7: LHR Model (HEPLHR)

Starting from NARA formulations the real HEP is calculated. The combination of human factors and environmental factors returns the HEPLHR value:

$$HEP_{SHRA} = HEP_{basic} \cdot [PSF_{time} + 1] \quad (9)$$

The HEPSHRA is the unreliability value of the operator during an accident scenario, depending of the influencing factors.

4. Case Study: LHR Application in a pharmaceutical plant

A pharmaceutical plant is considered to validate our model. To develop LHR approach, we used NARA and SPAR-H methods (designed for nuclear plants) because the consequences of disaster in a pharmaceutical plant are very several for environmental and operators. In particular, the HEP in a control room is analyzed.

Step 1: Preliminary Analysis

The emergency activities of the decision makers in the control room of a pharmaceutical plant during a fire are summarized in nine steps: emergency alarm activation, activate the emergency signal, activate of the protection system, evacuation of personnel, system block, activate the external alarm, insolation damaged area, internal Emergency Team activation and request for external aid.

Step 2: Identification on Human Activities

The choice of four GTTs was carried out through interviews with an Expert Judgments. Applying eq. (2), (3), and (4) the four GTTs are related to the activities managed by the decision maker described in step 1 (Table 3).

Table 3 : GTTs of the control room operator

N°	GGT	K24 (t=24h)	λ [1/h]	μ [h]	σ [h]
A5	Judgment needed for appropriate procedure to be followed. based on interpretation of alarms/indications. situation covered by training at appropriate intervals.	0.0100	4,19E-04	2388	1004
A6	Completely familiar. well designed highly practiced. routine task performed to highest possible standards by highly motivated. highly trained. and experienced person. totally aware of implications of failure. with time to correct potential error. Note that this is a special case.	0.0001	4,17E-06	239988	59995
B5	Carry out analysis.	0.0300	1,27E-03	787,94	413
C2	Identification of situation requiring interpretation of complex pattern of alarms/indications. (Note that the response component should be evaluated as a separate GTT)	0.2000	9,30E-03	107,55	117

Step 3: Basic Human Error Probability (HEPbasic)

Using Equation (5), HEPbasic for four GTTs is calculated. Table 4 describes HEPbasic values during 24 working hours.

Step 4: External Factors Definition

According to an Expert Judgment, PSFs values have been selected:

Table 4 : HEP basic

	GTT-A5	GTT-A6	GTT-B5	GTT-C2
t=2h	4.17·10-2	6.15·10-2	1.01·10-1	1.17·10-2
t=4h	7.10·10-2	7.18·10-2	1.25·10-1	3.10·10-2
t=6h	9.23·10-2	1.33·10-1	1.93·10-1	6.23·10-2
t=8h	1.26·10-1	2.28·10-1	2.98·10-1	8.26·10-2
t=12h	1.51·10-1	2.81·10-1	3.11·10-1	1.11·10-1
t=10h	2.26·10-1	3.36·10-1	3.86·10-1	1.25·10-1
t=14h	2.89·10-1	3.81·10-1	3.99·10-1	1.99·10-1
t=16h	3.41·10-1	4.10·10-1	4.45·10-1	2.31·10-1
t=18h	3.91·10-1	4.61·10-1	5.23·10-1	2.56·10-1
t=20h	4.25·10-1	4.99·10-1	5.99·10-1	3.05·10-1
t=22h	5.15·10-1	5.91·10-1	6.02·10-1	3.99·10-1
t=24h	5.98·10-1	6.17·10-1	6.19·10-1	4.21·10-1

Available time: the time needed to make the decision;
Stress: the degree to which you feel overwhelmed;
Complexity: the complexity of task performing;
5 of 6
Experience: the competence of the decision maker;
Procedures: risk management of nuclear plants.
Table 5 describes the PSFs values and Table 6 reports the PSFs correlation (Boring. 2010).

Table 5 : PSFs values

PSF	Low Hazard	Medium Hazard	High Hazard
Available time	0.1	1	10

Stress	0.2	2	20
Complexity	0.1	1	10
Experience	0.1	1	10
Procedures	0.3	3	30

Table 6 : PSFs dependence

	Available Time	Stress Stressors	Complexity	Experience Training	Procedures
Available Time	1				
Stress Stressors	0.50*	1			
Complexity	0.38*	0.35*	1		
Experience Training	0.31*	0.21*	0.32*	1	
Procedures	0.05	-0.01	0.12*	0.08*	1

Step 5: PSFs Correlation (PSFcor)
According to equation 6 and considering State (PSF)=0.2 for each Performance Shaping Factor, PSFcor index was calculated:
PSFcor=0.192

Step 6: PSFs corrected by time (PSFtime)
According to equation 7 and 8, we obtained the PSFs corrected by time (table 7). PSFtime value is equal to PSFcor value at the 8th working hour but is a triple value at 24th working hour.

Step 7: LHR Human Error Probability (HEPLHR)
Applying equation 9, HEPLHR has been evaluated combining internal operating conditions (HEPbasic) with external environment conditions corrected by T factor (PSFtime).

Table 7: Time Factor

	T	PSFtime
t=2h	0.25	0.048
t=4h	0.50	0.096
t=6h	0.75	0.144
t=8h	1.00	0.192
t=10h	1.25	0.240
t=12h	1.50	0.288
t=14h	1.75	0.336
t=16h	2.00	0.384
t=18h	2.25	0.432
t=20h	2.50	0.480
t=22h	2.75	0.528
t=24h	3.00	0.576

Table 8 shows the HEPLHR values for four GTTs during the high hazardous scenario and Figure 1 describes the HEPLHR trends.

Table 7: HEPLHR

	GTT-A5	GTT-A6	GTT-B5	GTT-C2
t=2h	4.37%	6.45%	10.58%	1.23%
t=4h	7.78%	7.87%	13.70%	3.40%
t=6h	10.56%	15.22%	22.08%	7.13%
t=8h	15.02%	27.18%	35.52%	9.85%
t=10h	18.72%	34.84%	38.56%	13.76%
t=12h	29.11%	43.28%	49.72%	16.10%
t=14h	38.61%	50.90%	53.31%	26.59%
t=16h	47.19%	56.74%	61.59%	31.97%
t=18h	55.99%	66.02%	74.89%	36.66%
t=20h	62.90%	73.85%	88.65%	45.14%
t=22h	78.69%	90.30%	91.99%	60.97%
t=24h	94.24%	97.24%	97.55%	66.35%

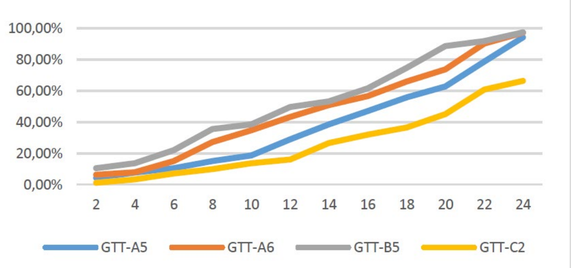

Figure 1: HEPLHR

5. Discussion

The operator's choices in emergency conditions depend on many factors. In this condition, HEP is influenced by human factors, the environmental factors (PSFs) and working time.
The proposed model HEPLHR increases with operating time due to human factors, because the decision maker will be tired during the working time. HEPLHR for GTT-A5 in the 2th hour it is 4.37%, while at the 24th hour it is 94.24%. However, the human unreliability depends also on the GTTs. The results highlight that GTT-B5 is the most relevant task – HEPLHR(t=24h)=97.55% while GTT-C2 is the less relevant task HEPLHR(t=24h)=66.35%.
The HEPLHR output highlighted the following improves: improve the work processes (e.g.: work breaks, ergonomics, statistical process control, logistic quality, etc.); improve of reliability system; improve of safety system; improve of maintenance system; improve by training on the job.

6. Conclusion

The aim of the present paper is to propose a hybrid method to evaluate HEP, called Logit Human Reliability (LHR). This study was done for identifying and evaluating of the human error in control rooms in a pharmaceutical plant. The proposed approach considers all factors that influence the decisions and actions of the operator: internal, external factors and time indexes. GTTS represent internal factors. PSFs represent external factors. T represent the time index. HEP is the output. Starting from Logit Normal distribution, the new approach is based on NARA model and on PSFs dependence. HEPLHR increases with operating time due to human factors, because the decision maker will be tired during the working time. In the other hand, the human unreliability depends also on the GTTs.

However, we find some disadvantages for applying this method. They include ambiguity and overlap in definitions of the PSFs. Future research aims to develop a statistic function on evaluate States (PSFs), using multi-decisions model (e.g., AHP/ANP or Fuzzy Logic).

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Conference on Performance Management

The impact of the complexity of information systems on user performance

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Abstract. The literature review highlights that the complexity of information systems increases with the increase in size and with the decrease in the percentage of family actions within the company, as well as having a highly trained leader. An analysis of previous works shows that several researchers have used the criterion of the degree of complexity to characterize information systems.

The first objective of our research is to assess the influence of the degree of complexity of information systems on the frequency of their use. We will then examine the impact of this frequency on the overall work performance of information system users. However, we conducted a questionnaire survey and we were able to analyze just the responses of 49 companies.

Given that the objective of our research is to examine the influence of the degree of complexity of information systems on the frequency of use and to assess the impact of this frequency on the performance of users, and in order to confirm or refute our research hypotheses, we conducted a data analysis using IBM SPSS Statistics 25.0 software, which allows us to perform the chi-square independence test to determine the existence of a relationship between the qualitative variables.

Our results prove the significant impact of the degree of complexity of information systems - defined by the quality of its functionalities, its outputs and its flexibility - on the frequency of use. They also highlight the influence of this frequency on user performance defined by speed, productivity and response to work needs.

Our study has limitations that open research perspectives in the future. Taking into account the national aspect of our study, it would be interesting to understand our results in different cultural areas with more qualitative devices and with a larger sample.

Keywords

Complexity of information systems; User performance; Frequency of use of information systems.

1. Introduction

Work aimed at determining the factors of adoption of information systems emerged in the 1970s, trying to find the answer to the following question: - To what degree the specificities of the structure and context of organizations are able to influence the adoption and complexity of information systems? In this regard, we can cite the pioneering work [1,2].

In the current context, the business environment is known by an increasing complexity, under the influence of technical, economic and institutional conditions. In this context, the emergence of information systems seems to have a major impact on the development and success of organizations [3,4].

The objective of our research is to assess the influence of the degree of complexity of information systems on the frequency of their use, and to examine the impact of this frequency on the work performance of system users' information. However, we conducted a questionnaire survey sent and from which we were able to analyse just 49 responses.

Given the objective of our study and in order to confirm or refute our research hypotheses, we relied on IBM SPSS Statistics 25.0 software to analyse the existence of relationships between our qualitative variables.

After presenting the literature review and the research hypotheses, we will present the methodology adopted and then we will present the results obtained. We will discuss in conclusion the results and we will highlight the contributions and limitations of this study and avenues for future research.

2. Literature review

2.1. *Degree of complexity of information systems and frequency of use*

Several studies prove the existence of a relationship between the structure of organizations and the traits characterizing the situations in which they operate. It must adapt to a set of contingent variables such as the size of the organization [5], the age of the organization [6] and the environment in which it operates [7]. Indeed, not all companies have the same information needs. Some more than others need the timely, reliable information to make decisions. However, the integration of information systems in the company can raise organizational problems likely to jeopardize its successful implementation [8].

According to the life cycle theory of the firm, organizations passing through different stages of development have different conceptions of information systems [9]. Many studies have shown that the more the size of the company grows, the more resources and skills it will have to make its information system more complex. Thus, having a management controller who masters management accounting impacts the degree of complexity of the information system [10,11].

In the same way, and according to the growth phase model [12], the age of the organization impacts its management practices. Thus, the past and the history of events that have marked the management practices of the company provides time for the organization to learn, improve and make its information system more complex [13].

In addition, the ownership structure impacts the information system which shows the complexity of the accounting information system increases with the decrease in the percentage of family shares [14].

From the above, we formulate our first hypothesis:

H1: ***The degree of complexity of information systems influences the frequency of their use.***

2.2. *Frequency of use and user performance*

Competitive pressure requires greater responsiveness, which relies on decentralization and timely dissemination of information. Information systems are one of the factors of this decentralization thanks to the potential offered in terms of capturing, processing and communicating information. They thus offer managers the possibility of monitoring in real time the management of their business and the management of their activities. But massive investments in information technology (IT) infrastructure alone cannot have an impact on work performance without strengthening the degree of connection between Human – Technology – Organization [15].

The adoption of the information system allows operational managers, who have become complete managers of responsibility centers, to be more efficient by collecting and processing, more frequently and in a short time, data in order to be able to analyse and ensure an adequate link between local objectives and the overall performance of the company. This allows information asymmetry in large groups that have adopted an external growth strategy [16].

To assess the impact of the frequency of use of information systems on the performance of users, we considered it relevant to rely on subjective measures that call on the evaluation of users of the information system adopted. In this sense we were inspired by the Technology Acceptance Model (TAM) which is considered one of the most widely used theoretical models in information system research and innovation adoption studies. The TAM identifies two determinants of the attitude and intention of users to accept the technology: perceived usefulness defines as the degree of belief that the user has that the technology increases its effectiveness and ease of use; perception defines as the degree to which a person believes that using a system will save them a great deal of effort [17].

We have therefore proposed three items to assess the influence of information systems on user performance, namely: the speed of work, work productivity and the ease of meeting business needs.

From the above, we formulate our second hypothesis:

H2: ***The frequency of use of information systems impacts the performance of their users.***

Thus, we can design our research model, deduced from our literature review and hypotheses, as follows:

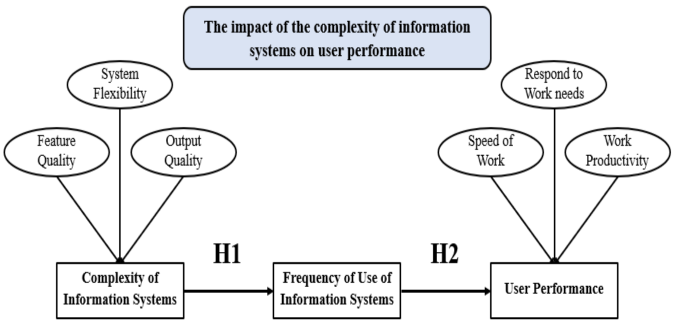

Figure 1: Theoretical research model

3. Research methodology

3.1. *Data gathering*

To test the hypotheses of our research, we conducted a questionnaire survey that includes a variety of questions and is organized mainly into two question forms: closed and multiple-choice. This questionnaire was sent to management controllers and accounting managers. It was sent by post and e-mail to the region of Rabat-Salé-Kénitra in the Kingdom of Morocco.

Of the 108 questionnaires administered, 59 questionnaires were returned initially. After a second e-mail reminder, we received 13 more responses. With a total of 72 returned questionnaires representing a response rate of 66.67%, only 49 of them ultimately proved usable.

3.2. *Statistical tool*

To analyze the influence of structural contingency factors on the degree of complexity of the information system and its contribution to the performance of management controllers, we proceeded by an analysis of descriptive data by the IBM SPSS Statistics 25.0 software.
The objective of our research is to determine the relationships of independence between the qualitative variables. To confirm or refute our research hypotheses, we relied on the chi-square independence test. This test, which is used to determine the existence of a relationship between two categorical variables, assumes that the variables are not related. It measures the overall difference between the cell numbers observed and the numbers expected if the proportions were identical [18,19].

4. Results

The objective of this section is to present the analysis of the results obtained from our research.

4.1. *Degree of complexity of information systems and frequency of use*

Table 1 shows the distribution of the frequency of use according to the perception of the flexibility of the system.

Table 1 : System Flexibility * Frequency of use Crosstabulation

	System Flexibility			
Frequency of use	Very good	Good	Moderately good	Total
Very frequented	12	4	6	22
Frequented	3	6	4	13
Moderately frequented	1	4	9	14
Total	16	14	19	49

The analysis of the data aimed at studying the influence of the users' perception of the degree of flexibility of the system on the frequency of their use, shows that 75% of the users who perceive a very good flexibility of the system use very frequently the information system, 42.86% who perceive a good flexibility of the system use it frequently. While 47.37% who perceive average flexibility have an average frequency of use of the information system.
Table 2 presents the result of the Chi-square test measuring the relationship between the perception of the degree of flexibility of the system and the frequency of its use.

Table 2 : System Flexibility * Frequency of use Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	11,937	4	,018
Likelihood Ratio	12,358	4	,015
Linear-by-Linear Association	8,343	1	,004
N of Valid Cases	49		

With a Chi-square value = 11.937, a degree of freedom df = 4 and a significance p = 0.018 the relationship between the perception of the degree of flexibility of the information system and the frequency of its use is very significant.
Table 3 shows the distribution of the frequency of use according to the perception of the feature quality of the system.

Table 3 : Feature Quality * Frequency of use Crosstabulation

	Feature Quality		
Frequency of use	Very good	Good	Total
Very frequented	28	0	28
Frequented	5	1	6
Moderately frequented	3	12	15
Total	36	13	49

The analysis of the data aimed at studying the influence of the users' perception of the feature quality of the system on the frequency of their use, shows that 77.78% of the users who perceive a very good feature quality use the information system very frequently and 13.89% of them use it frequently. While 92.31% who perceive a good feature quality use the information system with an average frequency.
Table 4 presents the result of the Chi-square test measuring the relationship between the perception of the feature quality of the system and the frequency of its use.

Table 4 : Feature Quality * Frequency of use Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	32,412	2	,000
Likelihood Ratio	36,278	2	,000
Linear-by-Linear Association	30,327	1	,000
N of Valid Cases	49		

With a Chi-square value = 32.412, a degree of freedom df = 2 and a significance p = 0.000, the influence of the perception at the level of feature quality of the information system on the frequency of their use turns out to be very significant.
Table 5 shows the distribution of the frequency of use according to the perception of the quality of the outputs of the system.

Table 5 : Output Quality * Frequency of use Crosstabulation

	Feature Quality		
Frequency of use	Very good	Good	Total
Very frequented	28	0	28
Frequented	5	1	6
Moderately frequented	3	12	15
Total	36	13	49

The analysis of the data aiming to study the influence of the users' perception on the quality of the output of the information system on the frequency of their use, shows that 77.78% of the users who perceive a very good quality outputs show very frequent use of the system and 13.89% of them have frequent use. While 92.31% who perceive a good quality of output have an average frequency of use of the information system.

Table 6 presents the result of the Chi-square test measuring the relationship between the perception of the outputs quality of the system and the frequency of its use.

Table 6 : Output Quality * Frequency of use Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	32,412	2	,000
Likelihood Ratio	36,278	2	,000
Linear-by-Linear Association	30,327	1	,000
N of Valid Cases	49		

With a Chi-square value = 32.412, a degree of freedom df = 2 and a significance p = 0.000, the influence of the perception at the level of output quality of the information system on the frequency of their use turns out to be very significant.

From this analysis we underline the significant impact of the flexibility of the system, the quality of its functionalities and the quality of its output on the frequency of use of the information system. Thus, we can deduce, while basing ourselves on the results of the chi-square tests, that the perception of the degree of complexity of the information systems impacts the frequency of use. And we can then confirm our first research hypothesis.

4.2. Frequency of use of information systems and user performance

Table 7 shows the distribution of the frequency of use according to the perception of the improvement of the speed of work.

Table 7 : Frequency of use * Speed of work Crosstabulation

	Speed of work			
Frequency of use	Very good	Good	Moderately good	Total
Very frequented	20	2	0	22
Frequented	5	6	2	13
Moderately frequented	0	0	14	14
Total	25	8	16	49

The analysis of the data aimed at studying the influence of the frequency of use of the information system on the improvement of the degree of speed of work, shows that 90.91% of the users who use the information system very frequently affirm its very good contribution in improving the speed of their work, 46,15% who frequently use the system claim a good contribution. While 100% of users with an average frequency affirm an average contribution of the information system in improving the speed of their work.

Table 8 presents the result of the Chi-square test measuring the relationship between the frequency of use of the system and its contribution to improving the speed of work.

Table 8 : Frequency of use * Speed of work Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	52,298	4	,000
Likelihood Ratio	58,736	4	,000
Linear-by-Linear Association	37,210	1	,000
N of Valid Cases	49		

With a Chi-square value = 52.298, a degree of freedom df = 4 and a significance p = 0.000 the relationship between the frequency of use of the information system on the improvement in the degree of speed of work turns out to be very significant.

Table 9 shows the distribution of the frequency of use according to the perception of the improvement of the work productivity.

Table 9 : Frequency of use * Work productivity Crosstabulation

	Work Productivity			
Frequency of use	Very good	Good	Moderately good	Total
Very frequented	15	7	0	22
Frequented	3	9	1	13
Moderately frequented	0	3	11	14
Total	18	19	12	49

The analysis of the data aimed at studying the influence of the frequency of use of the information system on the improvement of the degree of work productivity, shows that 68.18% of the users who use the information system very frequently affirm its very good contribution in improving their productivity at work and 69.23% who frequently use the system affirm its good contribution. While 78.57% of users with an average frequency affirm an average contribution of the information system in improving their productivity at work.

Table 10 presents the result of the Chi-square test measuring the relationship between the frequency of use of the system and its contribution to improving the work productivity.

Table 10 : Frequency of use * Work productivity Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	39,802	4	,000
Likelihood Ratio	43,202	4	,000
Linear-by-Linear Association	29,595	1	,000
N of Valid Cases	49		

With a Chi-square value = 39.802, a degree of freedom df = 4 and a significance p = 0.000 the influence of the frequency of use of the information system on the improvement of work productivity turns out to be very significant.

Table 11 shows the distribution of the frequency of use according to the perception of the system's ability to respond to work needs.

Table 11 : Frequency of use * Respond to work needs Crosstabulation

	Respond to work needs			
Frequency of use	Very good	Good	Moderately good	Total
Very frequented	6	12	4	22
Frequented	4	6	3	13
Moderately frequented	2	4	8	14
Total	12	22	15	49

The analysis of the data aimed at studying the influence of the frequency of use of the information system on its ease of responding the users' work needs, shows that 27.27% of them who use the system very frequently of information affirm its very good contribution in the ease of responding to their work needs and 46.15% who frequently use the system affirm its good contribution. While 57.14% of users with an average frequency affirm an average contribution of the information system in its ease of responding the needs of their work.

Table 12 presents the result of the Chi-square test measuring the relationship between the frequency of use of the system and its degree of responding to work needs.

Table 12 : Frequency of use * Respond to work needs Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	6,737	4	,150
Likelihood Ratio	6,471	4	,167
Linear-by-Linear Association	3,719	1	,054
N of Valid Cases	49		

With a Chi-square value = 6.737, a degree of freedom df = 4 and a significance p = 0.150 the relationship between the perception of the improvement in the ease of responding to work needs and the frequency of use does not prove to be significant.

From this analysis we underline the significant impact of the frequency of use of information systems on the speed of the work of the users and on the improvement of their productivity at work. Except that this impact has no influence on improving the ease of responding to work needs of users. Thus, while basing ourselves on the results of the chi-square tests, we deduce that the frequency of use of information systems influences, in a limited way, the performance of their users. And we can then partially confirm our second research hypothesis.

5. Discussion

Information systems now assist men in their professional tasks and can even replace them in some of them. They ensure, however, the collection, storage, processing and dissemination of information provided by management control and which is crucial to making the right decision. The information system is at the heart of value creation. Any organization is therefore required to monitor and converge its impacts to ensure the performance of the company. The adoption of information technology is thus a strategic tool that allows men to improve their performance at work.

[20] point out that the coronavirus epidemic is considered one of the most critical disruptions of recent decades, as it ravages a large part of businesses around the world. [21], for their part, show that supply chains are directly influenced by epidemics such as COVID-19, since they constitute sources of external risks that can harm the functioning of chains of supply and therefore negatively impact the satisfaction of customer needs. Thus, the manufacturing and service sectors may need more new information and communication technologies (NTIC), which may lead to an increase in demand on information systems [22].

Our results highlight the impact of perceived usefulness and perceived ease on the use and acceptance of information systems by management controllers, which reinforces the TAM model chosen in this study, and joins the set of works whose objective is to understand the behavior of the individual with regard to ICT since users seek to maximize their satisfaction by using information systems, as well as [23] with their theory that usage and satisfaction influence each other and are jointly determined by the quality of the information and the quality of the system.

The modifications at the level of the individual appear in relation to those of organizational efficiency and vice versa, our research thus shows the impact of the degree of complexity of the information system, on the quality of its functionalities, the quality of its output and the degree of improvement in the work performance of management controllers. Use and satisfaction generate their own impacts, and can have an individual (user behavior) or organizational (work performance) form [24].

6. Conclusion

Information systems ensure the collection, storage, processing and dissemination of information provided by management control and which is crucial to making the right decision. The information system is at the heart of value creation, its implementation is a strategic choice and it is conditioned by technological developments. Any organization is therefore required to monitor and converge its impacts to ensure the performance of the company's users.

The objective of our research was to assess the influence of the degree of complexity of information systems on the frequency of their use, and to examine the impact of this frequency on the work performance of users of the information system. information. Among the most popular theoretical models for studying the adoption of

innovations, we have chosen the technology acceptance model "TAM Model".
To test the hypotheses of our research, we conducted 16 interviews with management controllers and accounting managers before distributing a questionnaire to 108 people and only 49 of the responses were usable. And to test the validity of our research hypotheses, we used a descriptive data analysis by IBM SPSS Statistics 25.0 software to perform the Chi-square test.
The results of our study prove the significant impact of the flexibility of the system, the quality of the functionalities and the quality of the outputs, like our items defining the degree of complexity of the information system, on the frequency of use. of the information system. It also highlights the influence of this frequency of use of the information system on the improvement of the degree of speed of work, the ease of meeting the needs of the trade and the improvement of the degree of productivity at work, as our items defining user performance.
Beyond these contributions, our study has limitations that open research perspectives and that can be removed by future research. First, our study presents a sample of (49 observations analyzed) and only captures structural contingency factors. It would therefore be interesting to understand the behavioral and/or cultural contingency factors in future studies with a larger sample. Secondly, taking into account the national aspect of our study, it would be appropriate in future research on the subject to verify the relevance of our results by carrying out the same study in different cultural areas with more qualitative devices and which can be inspired by works sociologists or anthropologists to help understand how managers manage to adapt the information system to their needs, their skills, the structural context and the culture of their country, thus benefiting from effective management of their company .

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Conference on Performance Management

On the relationship between Human Factor and Overall Equipment Effectiveness (OEE): evidences from an application of the Analytic Hierarchy Process

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Abstract. The Overall Equipment Effectiveness (OEE) is one of the leading Key Performance Indicators (KPIs) for manufacturing operations management, which is aimed at identifying and measuring the inefficiencies of industrial equipment. Along the years, the OEE indicator, first introduced by Seiichi Nakajima within the Total Productive Maintenance (TPM) theory, has become a pillar for continuous improvement and productivity measurement in the operations context, and is largely adopted by many manufacturing organizations. However, despite the wide adoption and implementation of OEE, the influence of the "human factor" on its outcomes has only begun to receive attention during the last decades. Indeed, in recent years few scientific contributions have investigated their relationship, showing that the link between manufacturing performances and human aspects appears relevant, though not clearly identified yet. For this reason, the objective of our study is to investigate the relationship between the Overall Equipment Effectiveness and the human factor, with the aim of identifying the human activities that exert an influence upon reaching high levels of OEE. To reach this goal, the paper first proposes a framework to clarify the relationship between human factors, OEE parameters, industrial sector and degree of automation, and then validates it through the application of the Analytic Hierarchy Process methodology, with a set of experts with relevant experience in the manufacturing industrial setting. As a result, 13 aspects related to the human factor have been identified and their degree of influence on the OEE indicator has been analysed and described. Lastly, the paper provides practical guidance and implications for leveraging the outcomes of this investigation, with the objective of improving an organization's overall manufacturing performance.

Keywords

Overall Equipment Effectiveness, OEE, ISO22400, KPI, Human Factor

1. Introduction

Overall Equipment Effectiveness (OEE) is a key performance indicator widely adopted in the manufacturing environment, developed and introduced for the first time by Nakajima in 1988 within the "Total Productive Maintenance" (TPM) theory [1]. Its broad diffusion can be traced back to the easy interpretation of the indicator values and to the capability to summarize several metrics typically monitored by companies [2, 3], which allow for the continuous improvement of production activities and, in turn, for the achievement of competitive advantage in the market. The OEE adoption both in the industrial and scientific context is confirmed by the number of research articles published within the last decades. Indeed, it has been possible to observe a constant increase in the number of scientific publications related to the Overall Equipment Effectiveness, concerning the improvement of the indicator itself or its usage as a key indicator for improving business performance.

In this context, although Nakajima recognizes the primary role of manpower in the achievement of a high rate of OEE [1], by analysing the existing literature on the subject it is possible to note how the relationship between the performance indicator and human factor has not been deepened. In conclusion, the ways in which people carry out operational activities that are relevant to the achievement of high OEE values – and therefore to the achievement of a high level of corporate effectiveness – have not been appropriately discussed in the literature [4, 5]. For this reason, the objective of our study is to investigate the relationship between the Overall Equipment Effectiveness and the human factor, with the aim of identifying the human activities that exert an influence on reaching high levels of OEE. To our knowledge, no other scientific contribution has discussed, proposed, and validated a model for the identification of the aspects related to the human factor that influence OEE. The rest of the paper is organized as follows. Section 2 reports the OEE definition and describes the background concerning the relationship between OEE and the human factor. Section 3 introduces the adopted methodology for the research work, while Section 4 identifies the main aspects related to the human factor impacting OEE and proposes a framework to clarify the relationship between those aspects and the indicator. Lastly, Section 5 presents and discusses the results of the Analytic Hierarchy Process (AHP) analysis, and Section 6 shows the conclusions of the article.

2. Background

Starting from the definition provided by [1], the Overall Equipment Effectiveness can be defined as a Key Performance Indicator (KPI) which involves the aggregation of three different indicators: Availability, Performance Efficiency, and Quality. The indicator is described as follows:

$$OEE = Availability \cdot Performance\ Efficiency \cdot Quality \qquad (1)$$

Where, as reported by [6]:

- *Availability* represents the percentage of scheduled time actually capitalized once all the time losses due to macro-stops of the machinery have been removed, thus removing the losses due to failures, downtime, and setup losses;
- *Performance Efficiency* represents the percentage of operating time actually capitalized once all the time losses due to micro-stops of machinery or speed reductions have been removed, including idling and minor stoppages, reduced speed, and reduced yield;
- *Quality Rate* represents the percentage of net operating time actually capitalized once all the time losses due to work activities for the processing of non-sellable units (i.e. production waste, or for the rework of defective units) have been removed.

In addition, as reported in Table 1, Nakajima [1] defined the values of the different indicators to set as a target for the evaluation of good manufacturing performance, establishing a target level for OEE known as the "World-Class Level" (85%).

Availability	Performance Efficiency	Quality	OEE
90%	95%	99%	85%

Table 1: World-Class Level target values

However, these values are not always shared by the scientific literature: Kotze [7] argues that, unlike Nakajima, an OEE equal to or less than 50% is more realistic due to the different industrial realities; Ericsson [8], on the other hand, argues that an OEE between values of 30% and 80% can be a good reference benchmark. This difference of views may be due to the difficulties that may occur in the evaluation and comparison of the OEE between the different production processes and related industries [9].

Due to the abovementioned differences, over the years several authors have introduced different ways of calculating the OEE indicator strictly dependent on the specific industry/production process, thus creating ambiguity in the implementation of the indicator within the manufacturing settings. For this reason, the International Organization for Standardization (ISO) introduced the ISO22400 standard (*"Key performance indicators (KPIs) for manufacturing operations management"*), with the aim of providing a definition of the KPIs in such a way that they can be as more independent as possible from the production and operational context in which the single company lives and operates [10, 11]. Within the ISO22400 standard, two different definitions of the Overall Equipment Effectiveness are provided, which are referred as to "Model A" and "Model B". Schiraldi and Varisco in 2020 [2] discussed in detail the two models and analyses their consistency with respect to the original definition provided by Nakajima [1]. Having said that, it is possible to state that a large effort has been placed towards the development of thorough definitions and frameworks for the implementation of OEE since it allows to pave the way for a path of continuous improvement. Indeed, the evaluation of the elements impacting OEE represents an opportunity for manufacturing organizations to re-engineer, standardize and streamline their production processes and performances [12].

In this context, while the attention has originally been paid mainly to the assessment of equipment, machinery and other tangible factors concerning the manufacturing processes, the investigation of the relationship between human factors and Overall Equipment Effectiveness has been recognised as a crucial step for the achievement of a competitive advantage [4]. Indeed, as originally stated by Nakajima [1], even if it is possible to reach a configuration of a plant characterized by a high degree of automation, it will not be possible to eliminate the need – and consequently the impact, both positive and negative – that manpower can generate on the manufacturing outcomes. For instance, by carrying out manual maintenance and retooling activities on machineries, the human factor could influence the execution times of activities and have an impact on Performance Efficiency or it could influence the Quality Rate in case of visual inspection. Within the scientific literature, [13] discusses this influence and proposes a classification of operational losses due to human actions defined below:

- *Certain influence of operators on wasted time*, losses in which the duration of downtime, from when a fault occurs to the point where the machinery is back in operation, depends on the activities carried out by the operators;

- *Uncertain influence of operators on wasted time*, losses in which the duration of downtime may depend on the activities carried out by the operators;
- *No influence of operators on wasted time*, losses in which the duration of downtime is independent of the activities carried out by the operators.

A similar approach is adopted by [14], which classifies human errors affecting plant performance into six categories: 1) operating errors; 2) assembly errors; 3) design errors; 4) inspection errors; 5) installation errors; 6) maintenance errors.

On the other hand, the relationship between the skills, competences, and attitudes of workers and OEE has also started to gain increasing importance [15, 16]: indeed, the human element should be considered a source of competitiveness [17] due to the intangible characteristics of human nature, such as organizational knowledge, skills, attitudes and knowledge [18]. For instance, the scientific research conducted by Chen et al. [19] focuses mainly on the attitudes of human resources belonging to large manufacturing companies, identifying the main elements and factors to be leveraged to enhance operational productivity.

Alternatively, other publications either propose performance improvement through the implementation of approaches where the central role of the human factor is recognised (such as TPM), without however discussing in detail the human elements that influence performance – see the contribution of Sun et al. [20] – or describe very specific cases in which manpower has dramatically influenced the operational activities – see the contribution of Pinto et al. [21].

Hence, from the analysis of the existing literature, it is possible to state that the existence of a link between business performance and human activities clearly appears. Nevertheless, this relationship is not exhaustively detailed regarding the influence that the human factor could have on the Overall Equipment Effectiveness. For this reason, the objective of our study is represented by the investigation of the relationship between the Overall Equipment Effectiveness and the human factor, with the aim of providing a comprehensive framework and organizational guidance for the improvement of the manufacturing performance.

3. Method

To identify the human activities that exert an influence on the Overall Equipment Effectiveness, a general procedure was developed as represented by Figure 1.

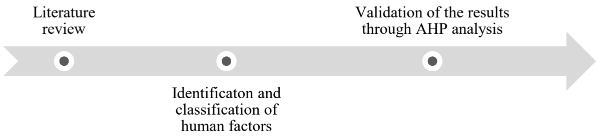

Figure 1: methodology process flow

The starting point is represented by a thorough literature review. Indeed, the objective is to evaluate the state-of-the-art concerning the relationships between the human factors and OEE, according to the scientific background. Hence, the first phase of the study involved the revision of articles proposed by major databases (e.g., Scopus, Web of Science, etc.). After defining the bibliographic portfolio, the identified human elements were grouped by macro-categories following a hierarchical structure, which has been required for the subsequent step of the described procedure.

Successively, an analysis to either confirm or reject the defined relationships was carried out as a second phase of the study. To this end, the opinions of experts within a Think Tank in Operations Excellence[1] have been collected, with the aim of defining the relevance and hierarchy of importance of the identified human elements concerning OEE performance. Those judgments were collected with a dedicated questionnaire and analysed through the Analytic Hierarchy Process (AHP) methodology. Indeed, the Analytic Hierarchy Process is a multi-criteria method mainly adopted to obtain pairwise comparison scales for both continuous and discrete factors [22] and developed at the Wharton School of Business by Thomas Saaty. It provides decision support in situations of difficult problem structuring, limited rationality, and a plurality of decision-making criteria, even in contrast with each other. It also allows factors, both tangible and intangible, to be included in the choice among the solution alternatives, such as, for example, the experiences and values of the decision maker. It can also overcome deficiencies, both descriptive and evaluative, in the description of the problem or of the criteria and can accept contributions from different decision-makers (e.g., situations involving different areas) [23].

For this reason, the categorization of human factors influencing OEE allowed to determine the AHP questionnaire that was compiled by experts, with the aim of firstly defining a comparison of the human macro-factors importance in influencing the OEE values and secondly a comparison between the sub-factors belonging to the same macro-category. The experts' answers were then used for the validation of the human factors and for the identification of the factors that can most affect the achievement of a high degree of OEE.

[1] The Think Tank in Operations Excellence was founded in 2019 in 'Tor Vergata' University of Rome to provide a platform for information sharing, exchange of ideas, knowledge creation, and dissemination of Operations Excellence best practices in industries. Currently, it is composed of 13 experts at managerial or executive positions, with 10 to 30+ years of proven qualification in Operations Excellence themes, on behalf of 6 multinational companies operating in different sectors: consumer goods, food, beverage, pharmaceutical, textile manufacturing, robotics, and automation technologies.

4. Analysis of the OEE and human factor in the scientific literature

As reported in the previous paragraph, the starting point of the procedure is represented by the state-of-the art review, with the objective of identifying the main human factors influencing OEE values. The analysis therefore focused on articles that, both on a theoretical and a practical basis, consider OEE in specific production contexts. For this reason, the keyword "OEE" joint with other specific words related to improvement activities – thus referring also to the typical tools of Lean Manufacturing and Six Sigma (e.g., "Improvement", "SMED", "TPM", "Fishbone diagram", "WCM" and "Performance measurement management") – have been adopted for the article search phases within the major scientific databases.

Level 1	Level 2	Level 3
Organization and planning of manual activities	Proper execution of production activities	Personal features
		Human interaction with the environment
	Proper execution of setup interventions	Personal features
		Human interaction with the environment
	Proper execution of maintenance interventions	Personal features
		Human interaction with the environment
	Proper execution of logistics activities	Personal features
		Human interaction with the environment
Definition and execution of standards, quality, and procedures	Proper execution of procedures	Personal features
	Expertise for conducting operational activities	Personal features
	Order and cleanliness in the management of equipment within the workplace	Personal features
Design of production and logistics systems	Proper design and sizing of machinery	Personal features
		Human interaction with the environment
	Proper design of the production department layout	Personal features
		Human interaction with the environment
	Proper ergonomics of the operators' workstations	Personal features
		Human interaction with the environment
	Proper design of material handling systems	Personal features
		Human interaction with the environment
Information management	Accuracy of manual data management	Personal features
	Correct communication and sharing of information within the team	Personal features

Table 1: hierarchical structure of the human factors impacting OEE

The identified publications, then, were evaluated with the aim of establishing whether they could be useful for the identification of human activities that affect the OEE. The reference dataset, therefore, consists exclusively of scientific articles that identify the human impact on plant/ machine/line performance at the OEE level. In conclusion, the analysed dataset is composed of 34 scientific articles, reported as in Appendix A. Subsequently, the bibliographic portfolio analysis allowed to identify and classify the human factors impacting OEE with a hierarchical structure described in Table 1. Moreover, the different levels of the model are defined as follows:

- *1° Hierarchical level*: within the first hierarchical level it is possible to identify the macro-categories of human factors that influence the achievement of high OEE values. Therefore, this level corresponds to the family of human factors grouped by impact area;
- *2° Hierarchical level*: within the second hierarchical level it is possible to identify the human factors identified that influence the values of the performance indicator classified according to the reference category;
- *3° Hierarchical level*: within the third hierarchical level it is possible to identify the factors that can influence the correct execution of manual activities, and which can therefore lead to high levels of the OEE. Those factors are identified either with "Personal features" (i.e., Personal abilities; Experience; Training) or with "Human interaction with the environment" (i.e., Low noise intensity; Proper Illumination; Proper temperature and humidity conditions; Low exposure to vibrations, electromagnetic fields, artificial optical radiation, infrasound and ultrasound, hyperbaric atmospheres).

5. AHP analysis, results and discussions

According to the proposed hierarchical structure of the human factors, an AHP questionnaire was developed to determine the weights of level 1-2 factors, and to determine the relative importance of level 3 elements. For this reason, the survey – that has been compiled by the Operations Excellence Think Tank members – required to perform the:

1. pairwise comparisons between the level 1 criteria;
2. pairwise comparisons between the level 2 criteria;
3. hierarchical ranking of the level 3 criteria.

Note that while the pairwise comparisons were performed adopting Saaty's AHP semantic scale [24], the evaluation of level 3 factors simply required experts to rank the criteria from the most to the lowest relevant (where position 1 represented the greatest ranking) considering its impact on the specific level 2 factor. In the latter case, results were then analysed by averaging the answers provided by decision-makers for each human factor in order to identify the personal features and environmental conditions that are most relevant for the decision-makers. Additionally, each respondent to the questionnaire was associated with a specific Consistency Ratio (CR), thus allowing to perform a detailed analysis of the different level 1-2 factors' weights according to the CR values. The results for the level 1 factors are reported below:

Level 1 factors	CR<0.1	CR<0.2	CR<0.3	*Overall*
Organization and planning of manual activities	0.36	0.29	0.22	***0.18***
Definition and execution of standards, quality and procedures	0.22	0.38	0.34	***0.38***
Design of production and logistics systems	0.32	0.22	0.34	***0.32***
Information management	0.1	0.1	0.01	***0.12***

Table 2: weights of the level 1 factors

As a result of Table 2, it is possible to observe that the factors that play a main role in leading to high values of OEE are represented by the "Definition and execution of standards, qualities and procedures" and the "Design of production and logistics systems". Hence, this allows to observe that organizations should pay attention towards the development of accurate Standard Operating Procedures (SOP) and in the phase of systems design, since they exert a great impact on the achievement of high OEE values. Successively, the results for the level 2 factors are reported as follows:

Level 2 factors	CR<0.1	CR<0.2	CR<0.3	*Overall*
Proper execution of production activities	0.43	0.47	0.39	***0.33***
Proper execution of setup interventions	0.36	0.33	0.36	***0.41***
Proper execution of maintenance interventions	0.08	0.09	0.15	***0.15***
Proper execution of logistics activities	0.15	0.11	0.11	***0.11***

Table 3: weights of the level 2 factors (for level 1 factor "Organization and planning of manual activities")

Level 2 factors	CR<0.1	CR<0.2	CR<0.3	*Overall*
Proper execution of procedures	0.25	/	/	***0.25***
Expertise for conducting operational activities	0.41	/	/	***0.41***
Order and cleanliness in the management of equipment in the workplace	0.34	/	/	***0.34***

Table 4: weights of the level 2 factors (for level 1 factor "Definition and execution of standards, quality, and procedures")

Level 2 factors	CR<0.1	CR<0.2	CR<0.3	*Overall*
Proper design and sizing of machinery	0.16	0.12	0.24	***0.24***
Proper design of the production department layout	0.31	0.28	0.27	***0.25***
Proper ergonomics of the operators' workstations	0.3	0.4	0.33	***0.35***
Proper design of material handling systems	0.23	0.2	0.17	***0.16***

Table 5: weights of the level 2 factors (for level 1 factor "Design of production and logistics systems")

Note that for the level 2 factors belonging to the "Information management" macro-category the pairwise comparison reported – reasonably – only one question. Hence, CR = 0 and the related weights are given as follows:

- Accuracy of manual data management: 0.78;
- Correct communication and sharing of information within the team: 0.22.

According to the above described results, the most relevant level 2 factors are given by the "Proper execution of production activities", the "Proper execution of setup interventions", the "Expertise for conducting operational activities" and the "Proper ergonomics of the operators' workstations". These weights allow to observe that while reasonably the organization and planning of production and setup activities are essential elements for obtaining streamlined operations, the ergonomics, working conditions and expertise of operators are crucial factors to reach great values of OEE. Indeed, overall the level 2 factor concerning the expertise of operators resulted to be the most relevant factor.

Lastly, the results for the level 3 factors are shown as in Table 6 and Table 7.

Level 2 factors	Personal abilities	Experience	Training
Proper execution of production activities	2.58	1.65	1.77
Proper execution of setup interventions	2.64	2.18	1.18
Proper execution of maintenance interventions	2.45	1.82	1.73
Proper execution of logistics activities	2.27	1.91	1.82
Proper execution of procedures	2.18	2.36	1.45
Expertise for conducting operational activities	2.00	3.00	1.00
Order and cleanliness in the management of equipment in the workplace	2.00	2.36	1.64
Proper design and sizing of machinery	1.91	1.64	2.45
Proper design of the production department layout	2.00	1.82	2.18

Level 2 factors	Personal abilities	Experience	Training
Proper ergonomics of the operators' workstations	2.09	1.64	2.27
Proper design of material handling systems	2.18	1.91	1.91
Accuracy in manual data management	2.00	2.45	1.55
Correct communication and sharing of information within the team	2.18	2.18	1.64

Table 6: average ranking of the level 3 factor "Personal features" (for each of the impacted level 2 factor)

Level 2 factors	Low noise intensity	Proper illumination	Proper temperature and humidity conditions	Low exposure to vibrations, etc.
Proper execution of production activities	2.18	1.64	2.55	3.64
Proper execution of setup interventions	2.09	1.36	2.64	3.91
Proper execution of maintenance interventions	2.00	1.45	2.73	3.82
Proper execution of logistics activities	2.27	1.36	2.55	3.82
Proper execution of procedures	2.36	1.36	2.27	4.00
Expertise for conducting operational activities	2.27	1.45	2.27	4.00
Order and cleanliness in the management of equipment in the workplace	2.45	1.27	2.45	3.82

Table 7: average ranking of the level 3 factor "Human interaction with the environment" (for each of the impacted level 2 factor)

It is possible to observe that for the majority of the level 2 factors, "Training" and "Proper illumination" are evaluated as the most important elements for improving the Overall Equipment Effectiveness. Hence, this result allows to state that personal features and the soft side of people are considered by decision-makers as very relevant towards the achievement of excellent operations performances, supporting the considerations of the shift from Operational Excellence to Human Excellence paradigm [25] and showing the need for an individualized Human Resource Management [16].

6. Conclusions

The aim of this paper is the identification of the relationship between the Overall Equipment Effectiveness (OEE) indicator and the human factors exerting the greatest influence on the mentioned KPI. Specifically, the purpose of the study consists in identifying the activities or elements linked to the manpower that affect the OEE performance indicator and which, consequently, if properly controlled and managed, allow the achievement of high values of OEE.

Although this relationship is not sufficiently investigated at an industrial and academic level, it has been possible to identify four different macro-categories of human factors that directly affect OEE values and two categories of factors that indirectly affect the indicator, starting from an extensive review of the literature. The first four categories identify thirteen human factors and the next two categories of factors identify seven different factors which, albeit indirectly, influence the achievement of high OEE values. Overall, twenty human factors have been identified, and they have been organized in a hierarchical structure to better clarify their impact on the OEE indicator. This allows concluding that a strong relationship between the performance indicator and the human factors exists and clearly appears.

The identified relationships have then been validated through the adoption of the Analytic Hierarchy Process (AHP) methodology. A specific questionnaire has been developed and filled out by experts belonging to a primary Think Tank in Operations Excellence. The analysis allowed to determine the weight of importance of the different human factors, and to draw up several conclusions and guidelines for the improvement of the Overall Equipment Effectiveness. Indeed, the main areas of attention stemming from the study are represented by the "Definition and execution of standards, qualities and procedures" and the "Design of production and logistics systems", with specific reference to the expertise and training of operators.

The research area, however, appears to be newly explored and the paper could represent a starting point for a deeper analysis of the relationship between OEE and the human factors. In the future, it may seem appropriate to expand the research for this relationship through studies of production settings that could allow the identification of additional human factors. Lastly, it is possible to carry out the same analysis with a wider audience of respondents from both an industrial and academic background, with the objective of performing a further validation of the obtained results.

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Appendix A

ID	Reference	Title	Journal	Year
1	(Xiang & Feng, 2021)	Implementing Total Productive Maintenance in a Manufacturing Small or Medium-Sized Enterprise	Journal of Industrial Engineering and Management	2021
2	(Di Luozzo, et al., 2021)	The Human Performance Impact on OEE in the Adoption of New Production Technologies	Applied Sciences	2021
3	(Heng, et al., 2019)	Automatic estimate of OEE considering uncertainty	52nd CIRP Conference on Manufacturing Systems	2019
4	(Dal, et al., 2000)	Overall equipment effectiveness as a measure of operational improvement- a practical analysis	International Journal of Operations & Production Management	2000
5	(Fakhri, et al., 2019)	Overall equipment effectiveness (OEE) analysis to improve the effectiveness of vannamei (Litopenaeus vannamei) shrimp freezing machine performance at PT. XY, Situbondo-East Java	IOP Conference Series: Earth and Environmental Science	2019
6	(Tsarouhas, 2018)	Improving operation of the croissant production line through overall equipment effectiveness (OEE)	International Journal of Productivity and Performance Management	2018
7	(Huang, et al., 2010)	Manufacturing productivity improvement using effectiveness metrics and simulation analysis	International Journal of Production Response	2010
8	(Zuashkiani, et al., 2011)	Mapping the dynamics of overall equipment effectiveness to enhance asset management practices	Journal of Quality in Maintenance Engineering	2011
9	(Zennaro, et al., 2018)	Micro Downtime - Data Collection, Analysis and Impact on OEE in Bottling Lines The San Benedetto Case study	International Journal of Quality & Reliability Management	2018
10	(Tsarouhas, 2020)	Overall equipment effectiveness (OEE) evaluation for an automated ice cream production line	International Journal of Productivity and Performance Management	2020
11	(Soltanali, et al., 2021)	Measuring the production performance indicators for food processing industry	Measurement	2021
12	(Castro & Oliveira de Arujo, 2012)	Proposal for OEE (Overall Equipment Effectiveness) Indicator Deployment in a Beverage Plant	Brazilian Journal of Operations & Production Management	2012
13	(Muchiri & Pintelon, 2008)	Performance measurement using overall equipment effectiveness (OEE): literature review and practical application discussion	International Journal of Production Research	2008
14	(Hansson & Lycke, 2003)	Managing commitment: increasing the odds for successful implementation of TQM, TPM or RCM	International Journal of Quality & Reliability Management	2003
15	(Phogat & Gupta, 2017)	Identification of problems in maintenance operations and comparison with manufacturing operations: A review	Journal of Quality in Maintenance Engineering	2017
16	(Mansour, et al., 2013)	Evaluation of operational performance of workover rigs activities in oilfield	International Journal of Productivity and Performance Management	2013
17	(Gupta & Vardhan, 2016)	Optimizing OEE, productivity and production cost for improving sales volume in an automobile industry through TPM: a case study	International Journal of Production Research	2016
18	(Kshantra, et al., 2020)	Calculation and improving the overall equipment effectiveness for textile industry machine	International Journal of Emerging Trends in Engineering Research	2020
19	(Ohunakin & Leramo, 2012)	Total Productive Implementation in a Beverage Industry: A Case Study	Journal of Engineering and Applied Science	2012
20	(Rasib, et al., 2021)	Non-Conformance Time As The Component Of Time Loss Measures In Assembly Processes	Journal of Physics: Conference Series	2021
21	(Li & Rong, 2009)	The reliable design of one-piece flow production system using fuzzy ant colony optimization	Computers & Operations Research	2009
22	(Hedman, et al., 2016)	Analysis of critical factors for automatic measurement of OEE	Procedia CIRP	2016
23	(Martomo & Laksono, 2018)	Analysis of total productive maintenance (TPM) implementation using overall equipment effectiveness (OEE) and six big losses: A case study	3rd International Conference on Industrial Mechanical, Electrical, and Chemical Engineering, ICIMECE 2017	2018
24	(Nayak, et al., 2013)	Evaluation of OEE in a continuous process industry on an insulation line in a cable manufacturing unit	International Journal of Innovative Research in Science, Engineering and Technology	2013
25	(Sousa, et al., 2018)	Applying SMED methodology in cork stoppers production	Procedia Manufacturing	2018
26	(Tsarouhas, 2007)	Implementation of total productive maintenance in food industry: a case study	Journal of Quality in Maintenance Engineering	2007
27	(Trattner, et al., 2020)	Why slow down? Factors affecting speed loss in process manufacturing	The International Journal of Advanced Manufacturing Technology	2020
28	(Hopp & Spearman, 2008)	Factory Physics: Foundations of Manufacturing Management	McGraw-Hill	2008
29	(Strauch, 2002)	Investigating Human Error: Incidents, Accidents, and Complex Systems	CRC Press	2002
30	(Nakajima, 1988)	Introduction to TPM	Productivity Press	1988
31	(Benjamin, et al., 2010)	Scrap loss reduction using the 5-whys analysis	International Journal of Quality & Reliability Management	2010
32	(Dhillon, 2014)	Human error in maintenance: An investigative study for the future	IOP Conf. Series: Materials Science and Engineering	2014
33	(Dhillon & Liu, 2007)	Evaluation of operational performance of workover rigs activities in oil field	Journal of Quality in Maintenance Engineering	2007
34	(Aboutaleb, 2015)	Empirical study of the effect of stochastic variability on the performance of human-dependent flexible flow lines	Published PhD thesis	2015

Table A.1: selected bibliographic portfolio

Conference on Performance Management

Development of a sustainable performance measurement system for human-robot collaborative systems

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Abstract. The study proposes a framework for measuring and evaluating the sustainability of human-robot productive systems. Collaborative robots are actively participating in the digital transition, but their impact on manufacturing sustainability is an open issue. In the proposed approach, sustainability is achieved by incorporating economic, environmental, and social aspects into business management. The performance of the resources involved in the case study was evaluated through *Key Performance Indicators* divided into three categories of sustainability: KPIs obtained from literature research were defined in detail and adapted to the purpose. Each performance indicator considers a specific aspect of the business and, all together, KPIs are able to provide a technique for measuring their progress toward strategic sustainability goals of the companies. Particular attention has been given to the social aspect, less investigated in the literature compared to the other two: it is important to evaluate feelings generated in the human resource that collaborates and shares the space with an anthropomorphized object.

Keywords
Human Robot Collaboration, performance measurement system, framework, literature review.

1. Introduction

Human Robot Collaboration (HRC) is a new emerging trend in the field of industrial and service robotics. The main objective of this innovative strategy is to create a safe environment for collaboration between humans and robots [1]. Collaborative work is described as "the mutualistic engagement of participants in a coordinated effort to solve a problem together" [1]. Successful collaboration, therefore, requires participants to share the process of knowledge creation [2]. The prospect of seeing a machine, a computer or even a robot no longer as a servant, but as a 'collaborator' in solving problems is, in fact, one of the most promising frontiers involving the world of IT (Information Technology) and robotics, both from an academic and entrepreneurial point of view. The main idea of HRC is to combine the capabilities of humans with those of robots. On the one hand, humans have innate flexibility, intelligence, dexterity, vision processing and problem-solving skills; on the other hand, robots provide precision, power, repeatability, and indifference to danger. Today, the technical standard ISO 10218-1 2011 [3] defines a collaborative robot as 'a robot intended to physically interact with humans in a shared workspace'.

The standard de facto ascribes collaborative robots to the more general family of industrial robots, defined as 'reprogrammable multifunctional manipulators, with three or more rotational axes, which may be fixed or mobile for use in industrial automation applications'.

Collaborative activity can be seen as a social interaction in which individuals cooperate to perform individual acts in pursuit of a shared goal that requires coordination [4]. The coexistence of humans and robots poses new challenges to designers and managers of production and logistics operations, who must consider not only traditional economic and environmental aspects in their decision-making processes, but also social ones.

In recent decades, the concepts of sustainability and sustainable development have emerged as humanity has become more aware of its growing impact on the world [5] Sustainable development, i.e., 'development that meets the needs of the present without compromising the ability of future generations to meet their own needs' [6], is increasingly relevant to industry and supply chains. Today, it is recognised that sustainable development should embrace three main perspectives, namely economic, environmental, and social sustainability [7]. Seuring and Müller [8] introduced the concept of sustainable supply chain management (SSCM) to describe the situation in which a company should embrace the three perspectives of sustainability while maintaining its competitiveness. SSCM describes 'the management of material, information and capital flows as well as cooperation between companies along the supply chain considering the objectives of all three dimensions of sustainable development.

For a proper implementation of the sustainability concept, it is typically necessary to identify and assess critical KPIs for a production system to have more possibilities for self-assessment and improvement along the three perspectives, which could be achieved by developing an appropriate performance measurement system (PMS). A PMS is defined as a system that enables managers to monitor performance indicators relevant to the products, services, and processes inherent in the manufacturing system over a given period [9]. Performance indicators are defined as the criteria against which the performance of products, services and processes can be evaluated. According to Parker [10], the use of PMSs makes it possible to show the capabilities of a supply chain to determine whether customer needs are being met, to detect the occurrence of problems and find ways to solve them, to ensure that decisions are made based on facts rather than intuitions, emotions, or assumptions and, finally, to identify reality and possible deviations from what was planned. These systems could then reveal to the managers whether they are achieving their goals or improvements are needed. The study aims to provide a basic understanding of the issues briefly outlined above and propose the development of a new PMS useful for measuring and evaluating the performance of a collaborative system. This aim is achieved by following these steps:

1. An initial analysis of PMS and their application to various industrial fields, with a specific focus on the HRC and of the related KPIs.

2. The mapping of the relevant perspectives (among economic, environmental, and social) that could be privileged in the creation of the PMS for the HRI and of the KPIs.

3. The final proposal of the framework for the measurement and evaluation of sustainability performance in the HRC.

The methodology used for arriving at the declared result is essentially a literature review on the topics listed above. Specifically, after this introduction, section 2 reviews the literature related to the above topics, starting from the general problem of evaluating the performance of a manufacturing system, then examining the available PMS for HRC and those focusing on the sustainability perspectives. Based on the findings from the literature, the proposed framework is illustrated in Section 3. Discussion and conclusions are outlined in Section 4.

2. Literature analysis

2.1. Performance evaluation in collaborative systems

Several recent studies have shown that cooperative robotics can offer various economic advantages to industries [11]. Various models have been proposed to perform an economic evaluation of cooperative systems, and the use of the cobot appears to be advantageous compared to manual solutions. Fager et al [12] designed a cost model to make a comparison between a manual picking system and one with a cobot. Other authors have proposed mathematical models to make comparisons of production time and costs between cooperative and conventional robotic assembly lines [13], or to estimate time savings due to the introduction of robots in assembly lines [14]. In the evaluation of cooperative systems, ecological factors have not been explored in depth. However, the design of ecological solutions has become a business requirement and production processes must be geared towards minimising negative environmental impacts. In this regard, Ojstersek and Buchmeister [15] developed a simulation model to study the impact of introducing collaborative workstations on sustainability by combining economic and environmental factors. Some previous research has evaluated the performance of various human-robot configurations [16; 17], but none has focused on the role of the worker and its impact on sustainability, providing an overall assessment. The focus on social aspects and the implications of the implementation of the industry 4.0 paradigm on human factors (HF) have not been sufficiently discussed [18; 19]. New technologies seem to pay more attention to economic factors and thus the impact of HR co-operative systems on social sustainability remains an open question. Most studies provide a qualitative analysis and define the main evaluation factors of cooperative HR systems [20; 21]. It is evident that past research has mainly focused on economic aspects. Only very few researchers have extended the analysis to multi-criteria evaluation and explored the entire sustainability of cooperative HR systems. Searcy [22] pointed out that measuring sustainability performance requires a systematic, structured, and integrated approach that considers all the aspects of enterprise sustainability. However, there are some main challenges associated with this approach. Firstly, before an assessment can be made, all key aspects of sustainability need to be identified [23]. Secondly, even if all relevant aspects are considered in the assessment, it is not always possible to measure them all in a meaningful unit. This is particularly true for the social sustainability perspective, which still lacks specific quantitative indices. Finally, to be meaningful, indicators often must be compared with a reference value, such as a threshold or a benchmark, due to the need to assess how far a company is from a target [24]. Götze et al. [17] proposed a theoretical approach to sustainability. A framework for evaluating different alternatives that includes economic (net present value), environmental (CO_2 emissions) and social (ergonomic load and worker acceptance of the robot) criteria. An aggregate index was calculated to measure the overall sustainability of each solution; both quantitative and qualitative criteria were considered but, in this case, the calculation procedure used was not detailed and therefore its impact on industry is very limited. There is a lack of theoretical and empirical studies on sustainability, especially in social terms [25], on the definition support procedure useful to help practitioners to define the best configuration to adopt based on economic, environmental, and social variables. Colim et al. [26] introduced KPIs to evaluate collaborative technologies in manufacturing. In conclusion, many factors must be considered when evaluating collaborative systems and predicting the benefits of their implementation.

2.2. Economic, Environmental and Social perspectives for manufacturing systems

A good sustainability assessment provides decision makers (DMs) with an assessment of the global (or local) outlook of a system to help them determining what actions to take to make the system more sustainable [27].

Economic sustainability' is the ability of an economic system to generate income and employment on a sustainable basis. Economic sustainability indicators aim to measure the historical evolution of the company from an economic-financial point of view to project it towards future objectives (profit maximisation, total cost maximisation, company survival, etc.). In line with these considerations, typical metrics for assessing a company's economic sustainability include return on investment, R&D investments, customer satisfaction, sales growth, the company's share of total market sales, cost of sales and turnover [28]; Helleno et al, [29] proposed a broad set of indices that include metrics related to the costs incurred by the company and their efficiency by measuring operating costs, actual costs, storage costs, process target cost, and the percentage of total costs incurred for production efficiency to total storage costs. Ojstersek et al. (2020) [20] take a similar approach in their study. In fact, the authors propose a series of metrics to measure the costs incurred to produce the Human Robot station in the unit of time, the good maintenance of the station when it is not productive, the average total cost per order and the Time required to produce a part. Ibatova et al., [30] proposed KPIs that include an evaluation of the cost of retraining and upgrading an employee's qualification, the amount of funds allocated by the company for organising an environmentally safe production operation and investments in environmental protection items. Lindberg et al., (2015) [31] focused primarily not so much on the costs incurred by the company as on the speed of production and the quality of the products, assessing the quantity produced in the unit of time, the number of compliant products out of the total number of products, and the total maintenance costs (ordinary and extraordinary) incurred in a year.

Environmental sustainability' is the set of all good practices aimed at protecting the ecosystem and renewing natural resources. Srivastava et al. (2007) [32] argued that environmental sustainability in SCM, in terms of reducing the ecological impacts of industrial activity without sacrificing quality, cost, performance, reliability or efficient use of energy through compliance with environmental regulations, could also lead to an overall increase in corporate profit. In line with this, Helleno et al, [29] defined a number of indices to assess the green performance of a system, such as the calculation of electricity consumption (EPC), water consumption (WCo), harmful gas release (HGR), electricity consumption for rework, the percentage of recyclable waste compared to the amount of total waste generated in production, the percentage of waste that can be treated traceably compared to the amount of total waste generated in production, the percentage of 'green' raw materials purchased compared to the total, the level of environmental-operational sustainability (LESo) and the level of environmental-process sustainability. Other studies have focused on emissions produced in the manufacturing industry. In this regard, Bottani et al., [28] proposed a set of indicators to estimate the amount of greenhouse gas emissions of the products manufactured by the company, the number of pollutants released into the atmosphere in the unit of time, while Götze et al., (2020) [17] focused on the amount of CO_2 released into the atmosphere in the unit of time. Another important aspect is highlighted by Ojstersek et al., [20] who focused on the supply of energy from renewable and non-renewable sources to the production in operational and non-operational mode.

“Social Sustainability” is the ability to ensure that the human welfare conditions are equitably shared. Bottani et al, [28] proposed as metrics for assessing social sustainability the average number of hours worked by an employee per week, the average annual cost per employee, the percentage of female workers compared to male workers, the percentage of workers who have attended training courses, the ratio of full-time workers to total employees, the ratio of the number of new workers hired to the number of layoffs (and retirements) in a working year, the ratio of the number of days on which occupational accidents occurred to the total number of working days, the time of exposure to potentially hazardous agents in a work shift (radiation, noise, vibration, toxic materials, hazardous activities) and the percentage of workers attending training courses on safety and emergency procedures.

Ibatova et al, [30], also addressed the issue of sustainability by focusing on the importance of worker training. In particular, they propose as indicators the measurement of the number of hours devoted to training and the proportion of employees who have undergone retraining and qualification updating.
It is also essential to assess the protection of the worker within the company. For this reason, a series of indices have been proposed that assess employee turnover between in- and outgoing shifts, the number of accidents compared to the total number of employees in a year, the average time spent in a noisy environment during a shift, the relative wage level, benefits, commissions and profits of employees assessed against the reference wage level, the Level of Social Operational Sustainability (LSSo) compared to the number of operations to be performed to realise a unit of product, and the hours of absence compared to the total number of working hours planned [29].
Götze et al., (2020) [17] also went along these lines, proposing indices that evaluate the time spent on (rest) breaks scheduled in a shift, set-up time and non-productive time in a shift, and the number of works shifts per day.
About the social sustainability inherent to the human-robot collaborative environment, Olsen et al., [33] designate the measurement of the amount of attention required by a robot, the working time in which the operator does not need to pay attention to the robot, and the estimation of the number of robots that an operator effectively uses at the same time. Lindberg et al., [31] moving on the same wavelength proposes as an indicator the assessment of the degree of coexistence of the human-robot work pair.
Of utmost importance is also the evaluation of the average metabolic energy expenditure, equal to the sum of the energy demands of the activity and the maintenance of body posture, weighed over time [34] and the ergonomic index that evaluates the workload by analysing the postures assumed by the operator [35].

3. The proposed framework

By combining the findings from the literature about PMS, HRC and metrics for the economic, environmental, and social perspective, a sustainable framework has been derived. The framework considers the relevant indexes for evaluating the sustainable capabilities of a manufacturing system, according to the perspectives below.

3.1. Economic indexes

The following indexes were proposed for evaluating the economic sustainability of HRC:

1. Production rate (PR)= quantity of product / work shifts.
2. Robot utilisation efficiency (RE) defined as the ratio between the actual production time (or active robot time) and the resource occupation time.
3. Operator allocation efficiency (OE) where a comparison is made between the operator's active working time and the work shift.
4. Incidence of operating costs (OC) per unit and Maintenance costs (MC) per year.
5. Processing quality (PQ) = number of conforming products / total number of products.
6. Return On Investment (ROI) = (production value-production cost)/ capital invested.

3.2. Environment indexes

Improving environmental sustainability means reducing the ecological supply chain footprint.
Helleno et al. (2017) highlighted the importance of understanding the limits of natural resources when evaluating the production system [29]. However, until now companies have only sought environmental certification center environmental performance to facilitate business relationships. These considerations led to the following metrics:

1. Electricity consumption (EC) and Electricity consumption for rework (ECR) per unit produced.

3.3. Social indexes

The definition of a set of social indicators is based on the parameters of the production process that interacts directly with employees and the community in which the sector is located. The social dimension of sustainability refers to the human capital of the supply chain: improving sustainability with respect to the social dimension involves developing and maintaining business practices that favour the labour, community, and regional aspects of the supply chain. The indexes below have been proposed to evaluate the social sustainability of HRC:

1. The percentage of hours dedicated to the Training relating to knowledge of the robot, in terms of robot use and control (Tr).
2. The rate of Accidents at work (AW) and Exposure to danger (ED).
3. The amount of time devoted to Coworking (Cow) and to Robot attention demand (RAD).
4. Work distribution (WD) = total number of operations in a shift/ (total number of operations in a shift + number of breaks or waits in a shift).
5. Amount of energy expended by the worker in carrying out the work activity (E_{work}).
6. OWAS index.

4. Discussion and conclusions

Sustainability is a long-term strategy whose objectives (efficiency, performance, and corporate competitiveness) achieved by incorporating economic, environmental, and social aspects into corporate management. Improvements in all three areas can significantly contribute to integrating sustainable development concepts into business practice. If the performance of companies and their competitiveness in today's demanding markets is to be increased, it is necessary to develop a comprehensive indicator evaluation system based on cooperation between interdepartmental teams. The system of evaluating environmental, social, and economic performance obviously offers much greater dynamics of development than hitherto, and at the same time, KPIs provide companies with a technique to measure their progress towards strategic sustainability goals. Key performance indicators can help companies plan and manage their environmental, social, and economic priorities, especially if these indicators focus on the company's main strategies through operational plans that incorporate performance targets. In line with these considerations, this study proposed a framework of 12 indices designed to assess the sustainability of the manufacturing system with respect to the three key perspectives, i.e., economic, environmental, and social within a collaborative human-robot context.

The framework is theoretical in nature, as it was derived from a literature review on the perspectives and was designed for performance measurement in HRC. From a scientific point of view, what has emerged from the literature is that some perspectives have been significantly more explored than others; this is the case, for example, of the economic perspective, whose logic, in fact, could be applied to virtually any context. The environmental perspective, on the other hand, has become widely studied in the last decade, in response to the growing need to preserve increasingly depleting environmental resources. The social perspective, on the other hand, remains an open question.

Similar considerations apply to the available metrics, which are more complete for some perspectives and less complete for others. The performance of the resources at stake has been assessed through several indicators divided into the three sustainability categories. However, each performance indicator looks at a certain characteristic aspect of the company and so many KPIs provide a fragmented assessment. Hence, as a future development, we suggest the creation of a composite indicator to move from a fragmented description of the state of the enterprise to a comprehensive and total assessment of the sustainability of the production cycle. The composite index would allow us to make a direct comparison between the different production cycle proposals to choose the one that is most sustainable overall.

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Conference on Performance Management

Developing a framework to improve the production performance in a small or medium enterprise through the introduction of Lean practices

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Abstract. Small and Medium Enterprises (SMEs) operating within the luxury fashion industry represent an important sector in many countries. Most of the literature on luxury SMEs deals with sociological, marketing, or brand aspects, which are of prominent importance for the luxury industry. By contrast, little attention has been dedicated to operation and production management. However, directing efforts towards the innovation of the production environments could generate competitive advantages for the companies. In this perspective, this paper proposes a framework to implement Lean practices in the production line of a luxury SME. Within this context, a spaghetti chart is used, at first, to track the movements of the operators in the production plant. Furthermore, a set of relevant Key Performance Indicators (KPIs) is defined and measured to identify the AS IS condition in terms of operation efficiency and space occupation. To improve the daily production planning, the heijunka box is introduced, while brainstorming and expert elicitation are exploited to develop a group of Lean solutions along with proposing a new layout. Finally, the relevant KPIs are measured once again to compare the production performance before (AS IS) and after (TO BE) the implementation of the detected amendments. The results proved that the proposed framework is effective to improve the performance of a luxury SME through the introduction of Lean procedures. The present work could assist both researchers and managers to adopt Lean solutions in a luxury SME plant.

Keywords
Small and Medium Enterprises, Luxury, Lean practices, Performance improvement

1. Introduction

The luxury fashion industry is mainly made up of Small and Medium Enterprises (SMEs), which are usually suppliers of process phases. The luxury fashion sector plays a pivotal role in several national economies, as depicted by the worldwide revenue of 97 billion dollars in 2022 [1]. Moreover, the luxury fashion field is one of the few sectors characterised by steady growth, representing a huge opportunity for many brands [2]. As an example, the renowned luxury fashion niche denoted as “Made in Italy” has seen an annual growth between 4% and 6%, along with a ROA (Return On Assets) equal to 7.4% before the pandemic (i.e., before 2020) [3].

A luxury product could be defined as a good with distinguishable characteristics [4], usually associated with excellence [5]. Based on these definitions, many authors have tried to identify the fashion critical success factors, among which premium quality, desirability, craftsmanship, exclusivity, unique elements, and recognisable design are worth mentioning [6]. Thus, fashion companies direct their efforts towards the aforementioned aspects, neglecting cost minimisation, production optimisation, and productivity maximisation.

However, companies operating in the luxury fashion industry face numerous challenges due to market characteristics, such as short life cycles, high volatility, low predictability, and high impulse purchases [7]. Furthermore, luxury fashion enterprises must manage the trade-off between the performance required by customers and the complex stylistic process [8]. Since most luxury companies can be regarded as SMEs, in addition to

previous challenges, fashion companies are subjected to several threats such as the increase in customer needs [9], the overwhelming globalisation [10], and the birth of e-commerce and new organization [11]. Indeed, small businesses, which are often family-owned, usually stick to traditional approaches, failing to pursue innovation [12]. For all these reasons, one of the major issues characterising luxury fashion companies is the inability to meet delivery dates [13]. It follows that a luxury fashion company should also focus on operations management aspects such as production efficiency and flexibility to maintain advantages over its competitors.
To accomplish this task, a possible practical solution could be the implementation of Lean practices. Indeed, the main objective of Lean is meeting the customer needs through a resilient manufacturing process subjected to a progressive and constant removal of waste (muda) [3]. Therefore, it is evident how Lean paradigms can assist in improving the efficiency and reducing costs. In fact, the benefits arising from Lean implementation are well documented in several fields [5], which have experienced a reduction of lead time and inventories, along with stronger processes and improved knowledge [14].
Despite the clear advantages introduced by the Lean approach, the transition to a Lean factory is not straightforward [15], and it could be regarded as a tough task. Furthermore, the Lean paradigms are widespread for high-volume low-variety industrial sectors, while the literature regarding Lean applications in the luxury fashion field is still scarce and mainly related to big companies since there are more entry barriers and obstacles to overcome for SMEs [16]. Indeed, the luxury fashion industry is characterised by low-volume high variety, which is the opposite compared to the industrial sectors where lean is very popular. As a result, this paper aims to define a possible framework to gently introduce Lean practices in a SME operating in the luxury fashion industry, and concurrently investigate the obtained benefits. The presented framework is composed of three stages and nine steps; moreover, it is based on the adoption of different approaches such as heijunka box, spaghetti chart, and 5s. The developed methodology is verified on a real company, which falls within the medium enterprise category.
The remainder of this paper is organised as follows; Section 2 summarises the literature on Lean practices within the luxury industry and SME, while Section 3 describes the developed methodology. Next, Section 4 presents the application of the methodology to a case study, while Section 5 and Section 6 illustrate the discussion and conclusions, respectively.

2. Literature review

As stated by Caniato et al. [6], there are few examples of Lean implementation in luxury companies. This is also confirmed by the more recent literature survey presented by Bhamu and Sangwan [17], who studied the successful application of Lean paradigms reported in 209 papers, none of which is related to the luxury fashion industry. Moreover, a quite recent study by Yadav et al. [18] reports that most Lean implementations are related to large companies, while SMEs are usually neglected. For instance, Carmignani and Zammori [3] investigated the adoption of Lean concepts in a warehouse of an important Italian fashion brand, finding out that the main obstacle is represented by the resistance to change of the managers, who prefer maintaining the traditional methods. In another work by Carmignani [19], an example of successful application of Lean practices in a big Italian enterprise operating in the fashion luxury industry was presented. It emerged that the introduction of Lean paradigms led to a reduction of the production defects and lead time, along with improving the plant management.
Despite the several difficulties and obstacles, the adoption of the Lean approach in a SME should not be discouraged or limited. This statement is supported by the paper presented by Belhadi et al. [20], who developed a framework to facilitate the adoption of Lean practices in an SME, proving the effectiveness of the Lean approach. It is worth mentioning that the previous work does not refer to a fashion company. Considering the fashion industry, the work by Ferdousi and Ahmed [21] investigated the outcomes arising from the exploitation of Lean techniques in nine SMEs operating in Bangladesh. From the investigation, it emerged that the Lean transition could allow significant improvements in operative performance. The study of Durand-Sotelo et al. [22] also highlighted the benefits that the Lean approach can bring for a fashion SME. In fact, the authors report that Lean practices have led to a reduction in the working cycle and the backlog, while increasing the productivity of the plant. In another recent article by Cantini et al. [23], the Lean paradigms are employed to optimise plant layout and tool disposal, leading to a reduction in operational costs.
Based on the previous considerations, it is possible to state that the Lean paradigms can be a great opportunity for fashion SMEs, however, there are still few practical frameworks to assist the Lean transition. Indeed, SMEs have to face many obstacles such as low budget, inadequate knowledge, and lack of time [16]. In addition, SMEs are strongly attached to traditional approaches due to the difficulties related to changing the company culture and the working methods. Consequently, the main objective of the present work is to provide an approach that could assist a fashion SME enterprise in the transition from a traditional to a Lean plant. Compared to other previous studies, this paper aims to deal with both production and layout planning.

3. Developed Methodology

The flowchart of the developed methodology to implement Lean techniques in a SME is shown in Figure 1.

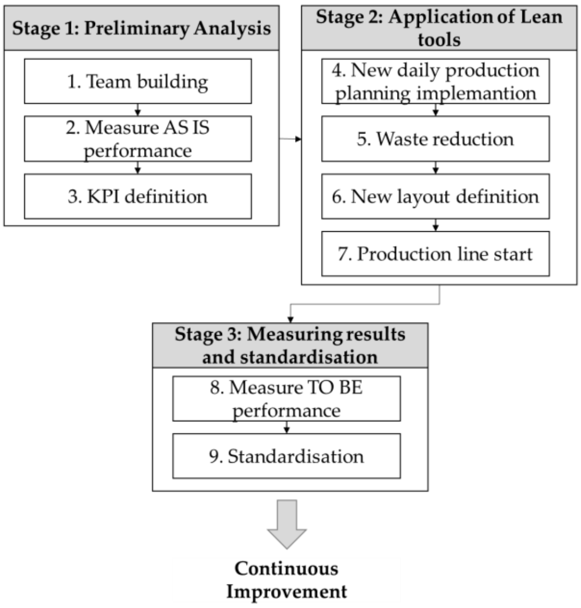

Figure 1: Flowchart and steps of the developed methodology

The proposed framework is characterised by three subsequent stages, which are described in the next sections.

3.1. *Stage 1: Preliminary Analysis*

The first step is team building (step 1). Indeed, it is fundamental to involve the personnel during the change process. The employees should be aware of the need to improve. Furthermore, they should acquire some knowledge of Lean practices. Next, the AS IS condition is studied and its performance is measured (step 2). The last step of the first stage is defining a set of KPIs, along with their target values (step 3). The KPIs should be defined based on the expected improvements. For instance, if the improvements are related to productivity, a KPI could be the lead time.

3.2. *Stage 2: Application of Lean Tools*

The production planning of SME is often chaotic and poorly organised. Accordingly, the fourth step of the approach requires the introduction of a new daily production planning (step 4), which is based on the heijunka box and a Kanban system. Indeed, the heijunka box allows the detection of possible production delays, along with ensuring better communication among the different departments. On the other hand, the Kanban system provides a better overview of the production flow. Next, waste reduction is pursued (step 5) by following the first 3S of Lean, which are Seiri (sort), Seiton (set in order), and Seiso (shine). Seiri aims to eliminate everything that is useless by separating tools and parts, while Seiton's objective is to organize useful tools and parts to facilitate their use. Seiso is demanded to clean the working stations and machines to prevent errors, avoid excessive deterioration and improve safety. Subsequently, a new layout is defined based on the outcomes of the previous phase (step 6), and, finally, the newly identified production line is commissioned (step 7). This final step requires the identification of operation sequence and the tools needed through an iterative process in order to create balanced work packages.

3.3. *Stage 3: Measuring results and standardisation*

After the implementation of the new production process (TO BE), its KPIs are measured (step 8) to assess whether the pre-defined targets are reached. It is worth mentioning that this task should be carried out periodically to ensure that the improvements last over time. After the introduction of the Lean techniques, it is required to standardise the process (step 9) thanks to the adoption of the last 2S of Lean, which are Seiketsu (standardise) and Shitsuke (sustain). Seiketsu is devoted to standardising the methods and techniques introduced through the previous steps, while Shitsuke aims to maintain over time the implementation of the first 4S.
After the final step, it is fundamental to pursue continuous improvement by unceasingly conducting kaizen activities.

4. Results: application of the methodology

To demonstrate the validity of the developed approach, a case study was selected. The case study is a company operating in the luxury fashion industry characterised by more than 50 employees and a gross income graters than 10 M€. Also, the number of employees is less than 250, while the gross income is less than 50 M€. Based on these previous statements, the considered company can be regarded as a medium enterprise. The case study company is characterised by different departments among which one of them was selected for the implementation of Lean practices. Finally, only one item produced in the department was taken into account.

4.1. *Stage 1: AS IS study and KPIs definition*

First, the working team was identified, along with the required training activities. Furthermore, one employee was tasked with the role of team leader to support the team and assist the other employees in case of problems or issues. The aforementioned activities constitute the team building phase (step 1).
Subsequently, the AS IS situation was studied to identify all machines and tools that belong to the considered department. This task was fundamental to obtain a spatial representation of the department and the operators' movements through a spaghetti chart. Finally, the performance of the AS IS scenario was measured, concluding the second phase (step 2). It emerged that almost 40% of the available space was occupied by machines, while only a small portion of the remaining 60% was sufficiently obstacle-free to allow movements. Moreover, the operators were forced to walk for more than 1 km, leading to a strongly inefficient process. A portion of

the spaghetti diagram developed is shown in Figure 2, where WS represents a working station, while SWS is a smaller working station. The areas denoted by M identify machines, while C and SC stand for working carts and small working carts, respectively. As depicted in Figure 2, the work paths are strongly entangled and there is little space left for the workers.

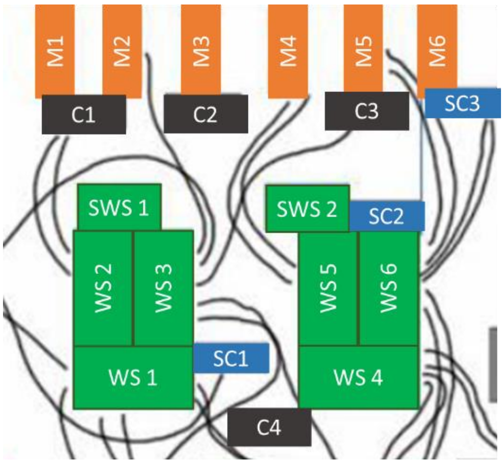

Figure 2 : Spaghetti chart of a portion of the considered department

To conclude this stage, the reference KPIs along with their target values are defined as listed in Table 1 (step 3). Table 1 also reports the value of each KPI measured in the previous step during one month of production. The aforementioned KPIs were identified based on the company's needs, which were higher productivity and better management of the available space.

Table 1: Reference KPIs and target values to pursue

KPI	Unit	AS IS	Target	% Target Improvement
Working Cycle	min/piece	166.4	138	-17
Productivity	paid min/work min	70%	84%	20
Work In Process	Pieces	160	46.4	-71
Lead Time	Days	6.4	1.54	-76
Space	Square meters	142	121	-15
Takt Time	sec/piece	768	637	-17
Production volume	Pieces/days	17	20	20

4.2. *Stage 2: Implementation of Lean practices*

After the preliminary analysis, which consists of an in-depth study of the AS IS condition, the real Lean transformation has begun. Within this context, a new approach to daily production planning was introduced (step 4). Specifically, the heijunka box was adopted to plan daily production, allowing every worker to understand what should be produced and when it should be produced. In fact, the papers reporting the scheduled production were stuck in the heijunka box. Consequently, the department manager could inform every operator of daily objectives. In addition, in case a scheduled production was running late, the associated paper was highlighted through a red sticker.

Wastes were then tackled through the first 3S (step 5). First, the tools that were considered useless were removed and placed in the red label area, while the remaining instruments were left on the work stations (Seiri). Next, to reduce the time wasted due to handling processes, every worker was informed to keep only the relevant tools in the workstation, while the remaining unnecessary ones were placed in the drawers of the work carts (Seiton). Finally, the dirt was mapped to keep track and identify the principal sources (Seiso). For each identified dirt source, a proper action was identified to remove it. Moreover, each removal action was assigned to an operator. For example, appropriate magnets were adopted to collect metal debris.

After the waste reduction phase, a new layout was developed (step 6). To perform this task, first the phases required to produce an item were identified. It is worth mentioning that the identified phases were related to either a work station or a machine. Furthermore, the duration of each phase was determined. Based on this information, the number of workers for the line was set equal to 6, among which two workers were employed for the machines, while the others were tasked with the activities at the working station. Each machine operator was associated with two machines and two workers at the working stations. Moreover, the production batch was reduced to decrease the number of parts that each operator should handle at the same time and, concurrently, increase efficiency. This choice also led to a reduction of the spaces required for activities, resulting in the removal of some working carts. The length of the working station was also reduced since fewer tools and parts were required. All the aforementioned amendments allowed us to reduce the space occupancy along with reducing handling and transportation time. The developed layout is shown in Figure 3, where W identifies a worker at the workstation (WS), while MW refers to a worker at the machine (M).

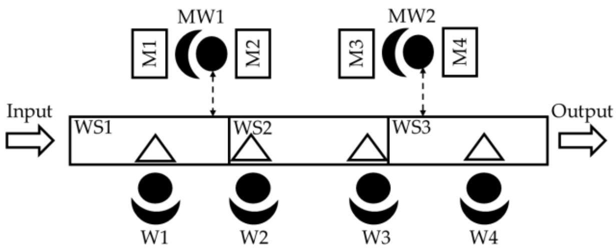

Figure 3: Developed layout to improve productivity and space usage

Then, the new layout was put into work to measure the target KPIs associated with the TO BE condition (step 7), thus determining whether the required improvements were achieved.

4.3. *Stage 3: Verification of the improvements and follow-up*

After the implementation of the new layout, the operator movements were tracked with a spaghetti graph (see Figure 4). By comparing Figure 2 and Figure 4, it can be stated that the operators' movements were drastically reduced; moreover, the flow is more organised. Indeed, operators were required to cover less than 200 m, reducing movements by more than 80%. Furthermore, the new layout has led to a reduction of the required working stations and working carts.

Figure 4: Spaghetti chart of the same layout portion considered in Figure 2

The reference KPIs were measured during one month of operations to evaluate the improvements related to the new layout (step 8). It emerged that all the target values were reached thanks to the new layout, as shown in Table 2. As shown in Table 2, the working cycle was reduced by 35%, which is higher than the target value equal to 17%. The same improvement was obtained for the takt time as well. On the other hand, productivity saw an increase of 53%, much higher compared to the target improvement of 20%. Work in Process and the Lead Time were reduced by 79% and 86%, respectively. The required reduction target for the space (15%) was barely reached, while the production volume increased by 52% compared to the AS IS condition.

Table 2: Reference KPIs and improvements compared to the AS IS

KPI	Unit	TO BE	% Real Improvement
Working Cycle	min/piece	108.16	-35%
Productivity	paid min/work min	107%	53%
Work In Process	Pieces	33.6	-79%
Lead Time	Days	0.896	-86%
Space	Square meter	120.7	-15%
Takt Time	sec/piece	499.2	-35%
Production volume	Pieces/days	26	52%

Since promising results were obtained for a portion of the department, the company decided to implement similar practices for the other areas. Accordingly, a standardisation phase was conducted to extend the adoption of Lean practices (step 9). This step was accomplished through the last 2S, which consists of Seiketsu and Shitsuke. Seiketsu allowed to implement Lean techniques for other sectors thanks to the introduction of standardisation principles, while Shitsuke facilitated the transition towards a leaner production and made it permanent.

5. Discussion

The proposed approach led to the definition of a new layout capable of guaranteeing the desired performance. Indeed, the target value of each KPI was reached thanks to the introduction of Lean practices, following the 5S principles along with the adoption of a new daily production planning method.
To investigate the results even further, the tasks associated with the third worker located at a working station in Figure 4 (i.e., W3) were analysed. Specifically, each task was timed and associated with a category. The categories considered are as follows: I) value-added task, II) handling task, III) inspection task, IV) non-value-added task, and V) extra processing task. The percentage of time that the worker dedicates to each of the aforementioned categories is illustrated in Figure 5.

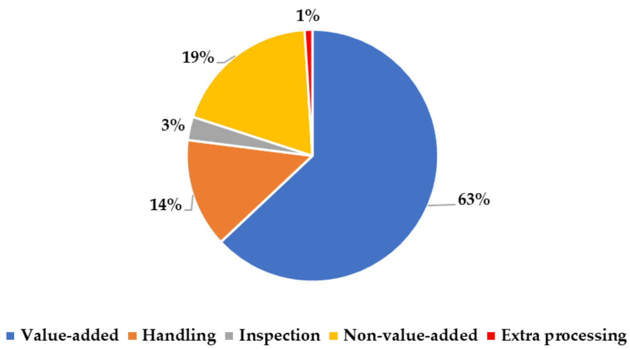

Figure 5: Task categories and their percentage for W3

It emerged that the worker employs most of his time for value-added activities (63%), while only 19% of the time is devoted to nonvalue-added activities. Furthermore, the extra processing tasks are limited to only 1% of the total time, while 14% and 3% of the time are dedicated to handling and inspection tasks, respectively. Accordingly, it is possible to state that the new layout ensures high efficiency thanks to the low impact of non-value-added activities and the handling tasks.
As previously mentioned, it is fundamental to track the relevant parameters over time. In fact, the KPIs are not constant and could vary daily. Therefore, monitoring them is crucial to assessing whether the amendments can guarantee the required improvements and simultaneously verify possible unsatisfactory performance. Based on the aforementioned considerations, the daily production, the time invoiced to the customers, and the productivity were measured for 14 days. The results are shown in Figures 6 and 7. It is worth mentioning that the displayed results are

normalised due to data restrictions. In addition, they are related to three distinct items produced through the line.
Figure 6 reports the production volume of the three items during the considered 14 days. It can be seen that the production volume is almost continuously increasing. The outcome is particularly promising in case a given item is produced for a prolonged period. Indeed, it is evident the great increase in productivity when the third item is realised for seven successive days. Productivity, defined as the ratio between worked minutes and invoiced minutes, is also increasing over time when the same item is produced for enough successive days (see Figure 7). Considering productivity, it is worth mentioning that its decrease between the fourth and fifth day is related to the change of the item, which is accompanied by a setup. The same can be said for the decrease in productivity during the eighth day. Finally, the decrease in productivity between the sixth and seventh day is related to an error in the bill of material associated with the second item.

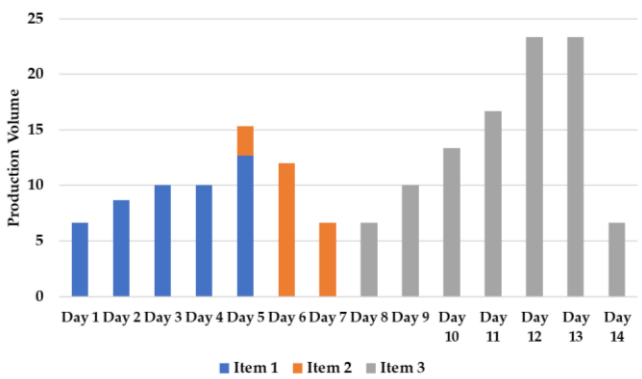

Figure 6: Production volume for each of the three items

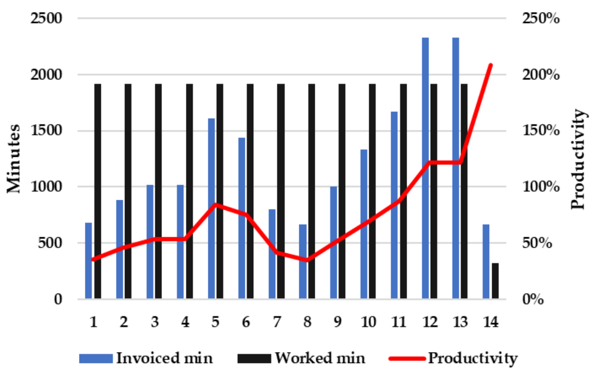

Figure 7: Productivity, worked minutes, and invoiced minutes

6. Conclusion

Most of the SMEs operating within the luxury fields are characterised by high inefficiency and a lot of waste. This paper proposes an approach that can facilitate the transition from a traditional context to a Lean one for a luxury fashion SME, while analysing the outcomes and benefits that arise from the implementation of Lean practices. Furthermore, to validate the framework, a case study has been selected.
The obtained results are promising, thus, it could be possible to state that Lean techniques could bring competitive advantages even for companies that are not operating in the mass production field, where Lean tools are already established. In fact, the adoption of Lean practices led to more efficient operations thanks to the reduction of waste, allowing the company to reach higher productivity (higher than 100%) and production volume, which are also maintained over time. Furthermore, the working stations are deprived of unnecessary tools, facilitating the tasks that workers must perform. Finally, the definition of a new layout generated a better use of the available space thanks to the limited required movements and the removal of obstacles such as working carts. Consequently, the operators' movements resulted smoother.
Even though the exploitation of Lean practices resulted in immediate benefits, it is pivotal to assure that the improvements are kept till the decommissioning of the plant. Accordingly, it is required to adopt continuous improvement techniques within luxury SMEs. Thus, future developments could move in this direction.
Furthermore, the approach was tested on a single company, therefore, considering different case studies could be interesting to evaluate the generalisation of the advantages introduced by Lean tools within luxury SMEs.

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Comparison between Transportation Overall Vehicle Effectiveness (TOVE) and carbon emission impact for last-mile delivery

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Abstract. Among all the key performance indicators (KPIs), Overall Equipment Effectiveness (OEE) is one of the most suitable KPIs to measure the utilization of an industrial asset. In the transportation sector, a variant of the OEE is the Transportation Overall Vehicle Effectiveness (TOVE), which defines the performance of vehicle distribution activities, such as road transportation for last-mile delivery and urban logistics. Although TOVE is appropriate for evaluating vehicle performance in terms of administrative availability, operating availability, performance, and quality, the indicator does not consider the environmental impact related to road transportation activities. Nevertheless, road transportation is the highest emission rate mode with significant environmental impact. For this reason, literature has proposed several formulations to quantify transport carbon emissions, most of which are linear relationships to the distance traveled. However, these models are not appropriate for assessing the performance of road transport activities. Therefore, this paper aims to compare, in two different scenario systems, the performance of last-mile delivery in terms of TOVE and carbon emissions evaluated with a distance traveled formulation. The comparison shows the lack of TOVE adequacy in terms of environmental sustainability, such that maximising road transport performance, in addition to ignoring the environmental dimension, excludes the minimisation of CO_2 emissions. Therefore, the basis of future developments of TOVE for green road transportation can be laid from this divergence.

Keywords
OEE; Transportation Effectiveness; Carbon Emission; Sustainability; Last Mile

1. Introduction

In today's supply chains, organizations are aiming for transport activities with increasingly fast, accurate, flexible, and cost-effective delivery [1] to satisfy customer needs and requirements. At the same time, transportation is one of the main contributors to carbon emissions. Indeed, the transportation sector is considered the fourth highest source of environmental impact, where road transport accounts for 80% of freight and passenger emissions [2]. For this reason, it is necessary to find a trade-off between economic and environmental sustainability [3]. Regarding economic sustainability, Transportation Overall Vehicle Effectiveness (TOVE) is a well-defined Overall Equipment Effectiveness (OEE) variant to quantify the performance of a distribution process [4] to satisfy customer needs. However, TOVE does not consider the environmental dimension, which impacts are evaluated in literature with different consumption models. In this context, in terms of environmental sustainability, an important indicator of road transportation is the amount of CO_2 emitted along the route of a vehicle based on the distance traveled. These two objectives may not be aligned; in fact, the higher utilization of a vehicle produces a greater environmental impact and vice versa. Therefore, it is necessary to develop a specific indicator for road transportation that evaluates the optimisation of both the aforementioned issues. From this perspective, this article proposes the comparison of TOVE and CO_2 emissions performance in two different system scenarios to highlight the lack of a global indicator. Specifically, it is intended to analyze two road distribution scenarios that apply different routings policy varying the parameters of vehicle speed and maximum customer distance. The first scenario proposes a first-in-first-out (FIFO) last-mile delivery policy whereby the first customer to request an order is the first to be served. In contrast, the second scenario proposes a last-mile delivery policy that minimizes the total route to serve customers. The article is structured as follows. In Section 2, literature research on key performance indicators (KPIs) of the OEE family specific for road transportation and models quantifying their carbon emission on the road is presented. In Section 3, the methodology used is presented, while in Section 4 scenarios are defined. In Section 5, the model results are reported. Finally, in Section 6, conclusions and future developments are summarised.

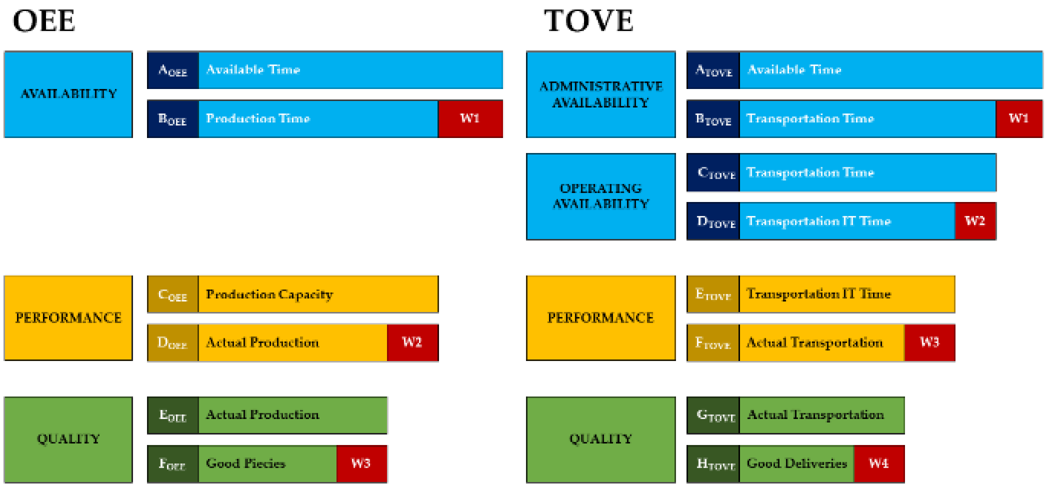
2. Literature Review

2.1. Overall Equipment Effectiveness variants

The OEE is a KPI initially developed to implement Total Productive Maintenance as one of the lean production techniques. OEE quantifies in terms of availability, performance, and quality the assets' productivity for monitoring and continuously improving an industrial system (Figure 1). OEE finds application in various sectors and systems; for instance, some variants of OEE have been developed for measuring the performance of industrial assets (Overall Tool Group Efficiency [5]) or for evaluating specific parameters in industrial processes, such as productivity (Overall Throughput Effectiveness [6]) and layout performance (Overall Space Effectiveness [7]).
In lean theory, transport is classified as one of the seven wastes, being considered a non-added value activity that has to be eliminated. However, service companies operating in the logistics sector consider the delivery process a core activity for customer satisfaction and consequently economic development. For this reason, several variants of OEE have been developed specifically for the transport sector which are all based on the evaluation of the three macro components of availability, performance, and quality. The Overall Vehicle Effectiveness (OVE) indicator measures the performance of the road freight vehicle based on the evaluation of availability percentage, performance rate, and quality mark [8]. However, OVE does not work well in scenarios with multiple destinations per single delivery. To solve this issue, Modified Overall Vehicle Effectiveness (MOVE) breaks down the performance component of OVE into route efficiency and time efficiency. Route efficiency evaluates the efficiency of a route in terms of weight-distance compared to one with optimal efficiency. Instead, time efficiency evaluates the efficiency of the route in terms of time compared to one with minimum time [1]. Another alternative to OVE is Overall Transportation Effectiveness (OTE), which solves the problem of route efficiency by identifying road transport losses in more detail. [9]. The above-mentioned indicators for calculating road transportation performance, such as OEE, begin by assessing the performance net of unscheduled time for shifts and company closures and scheduled time for preventive maintenance activities. However, these times are important to consider to maintain assets as much as possible in the operational phase [10]. For this reason, Transportation Overall Vehicle Effectiveness (TOVE) considers performance on total calendar time instead of the net time of system closure and planned downtime. TOVE, as reported in Figure 1, divides the organization's activities between in-transit and non-transit to quantify the logistic performance. TOVE evaluates the availability of the systems dividing it into administrative and operating availability where the former is referred to both activities, while the latter only for in-transit ones. Moreover, TOVE considers the performance and quality of the systems referring them to in-transit activities [4], [11]. Therefore, TOVE is currently the most established road transport-specific OEE variant.
The above-mentioned indicators do not directly consider the concept of sustainability. Indeed, the literature has proposed sustainable variants of OEE, but these are not conceived for the transportation sector. For example, the Overall Greenness Performance (OGP) allows the environmental performance of value-added activities to be assessed. The assessment is made on the following components: (i) company context for local environmental legislation and organizational culture, (ii) supply chain for supplier conditions and client requirements, (iii) consumption of non-value-added processes, and (iv) consumption of non-necessary non-value-added processes. [12]–[14]. At a more systemic level, the Sustainable Overall Throughput Effectiveness (SOTE) integrates the environmental sustainability of production processes for series, parallel, converging, and diverging flows into the OEE components [15]. Finally, the Business Overall Performance and Sustainability Effectiveness (BOPSE) measures the synergy between Lean practices and Green production. BOPSE is calculated as the arithmetic mean between OEE and the sustainability indicator that considers the dimensions of the Triple Bottom Line [16]. In conclusion, TOVE is a good indicator for assessing the performance of road transport activities in meeting customer needs and achieving economic sustainability goals. However, TOVE does not consider environmental aspects. Hence, literature is lacking on the OEE variant specific for road transportation that integrates the concept of trade-off between economic and environmental domains.

2.2. Carbon emission models

CO_2 emissions are directly proportional to the amount of fuel consumed by a vehicle. In turn, fuel consumption is affected by multiple factors, such as speed, road gradient, congestion on the route, driver behaviour, fleet size and mix, payload, empty kilometers, and the presence of green freight corridors [17].



$$OEE = \frac{B_{OEE}}{A_{OEE}} \times \frac{D_{OEE}}{C_{OEE}} \times \frac{F_{OEE}}{E_{OEE}} \qquad TOVE = \frac{B_{TOVE}}{A_{TOVE}} \times \frac{D_{TOVE}}{C_{TOVE}} \times \frac{F_{TOVE}}{E_{TOVE}} \times \frac{H_{TOVE}}{G_{TOVE}}$$

Figure 1: OEE and TOVE description

Consequently, vehicle consumption models can be classified into three groups: factor models, macroscopic models, and microscopic models [17]. Macroscopic models use average aggregate network parameters to estimate network-wide emission rates. For example, MEET (Methodology for calculating transportation emissions and energy consumption) is a macroscopic model for calculating transport emissions and energy consumption per heavy-duty vehicle. The model evaluates the CO_2 emissions considering two different components, which are first determined through a series of regression functions, then merged into a single macroscopic function. The first component is the CO_2 rate calculated for standard conditions and the distance traveled. The second component considers the correction factors related to the gradient of the road and the load transported. Finally, the product of the two components gives the amount of CO_2 emitted [18]. Another macroscopic model is COPERT (Computer programme to calculate emissions from road transportation) which estimates the vehicle emissions by using specific regression functions for fuel consumption, where each of them depends on the vehicle weight. The function depends on speed and total distance [19]. However, macroscopic models do not estimate the instantaneous vehicle fuel consumption and emission rates at a more detailed level. To this end, microscopic models were developed. Microscopic models calculate emissions more accurately since they are based on instantaneous kinematic variables (speed and acceleration) or aggregated variables (e.g., time spent in traffic mode, cruise, and acceleration). Concerning microscopic models, Bowyer et al. [20] proposed several approaches, such as an instantaneous fuel consumption model (IFCM), a four-mode elemental fuel consumption model (FMEFCM), a running speed fuel consumption model (RSFCM), an average speed fuel consumption model (ASFCM). However, both macroscopic and microscopic models require much information on traffic flows and the vehicle operating mode [17]. This information not always is available. Therefore, several authors have proposed factor models as valid and simpler approaches. Factor models appear to be unaffected by the variables of road transport activities, such as environmental and traffic conditions, driver behaviour, and vehicle operating conditions that are difficult to replicate [21]. Generally, factor models use predefined emission factors to estimate CO_2 emissions, which are calculated per unit distance, per unit weight, per product, and per vehicle [22]. Specifically, in the road transport sector, predefined emission factors measure the CO_2 consumptions of transport activities based on the distance traveled [23]. In contrast to TOVE, although factor models are widely used to quantify the environmental impact of road transport, they neglect customer satisfaction performance. Therefore, it is necessary to develop a specific indicator for road transportation that evaluates the optimization of economic and environmental dimensions. To the best of the authors' knowledge, the current scientific literature lacks a comparison between the performance of a road distribution system in terms of TOVE and factors models based on traveled distance to evaluate CO_2 emissions. Hence, this article aims to fill the gap to highlight opposing optimisations and lay the basis for a global indicator.

3. Methodology

Scenario analysis follows a sequential approach. First, the flow of activities is mapped, collecting quantitative and qualitative process information. Next, the waste associated with each activity is identified and the route is planned.

Finally, performance indicators are calculated. In the following sections, the route definition and KPI calculation phases are discussed in more detail.

3.1. *Route Definition*

Route definition activity corresponds to the identification of the vehicle routing. Consider a set of customers spread over a network within which there is a distribution center operating a vehicle for the delivery of products. The first strategy considered is to serve customers with a FIFO policy whereby the customer who placed the order first is the first to be served. In this case, it is not necessarily the case that the customer sequence is geographically arranged in a logistically efficient manner.
The second strategy is to minimize the delivery route without following the order in which customers arrive. To solve this problem, there are algorithms for vehicle routing problems (VRPs) that define the optimal routing according to an objective function by satisfying a set of constraints.

$$min \sum_{i,j \in V} c_{ij} x_{ij} \qquad (1)$$
$$\sum_{i \in N} x_{ij} = 1 \qquad \forall\, j \in N \qquad (2)$$
$$\sum_{j \in N} x_{ij} = 1 \qquad \forall\, i \in N \qquad (3)$$
$$x_{ij} \in \{0,\ 1\} \qquad \forall\, i,j \in N \qquad (4)$$

Equations (1), (2), (3), and (4) define a general routing optimization problem in a network defined by N nodes. The objective function minimizes the total cost of the selected arcs that individually start from *i* and arrive at *j*, respecting the constraints that each node has one incoming and one outgoing arc and can take the value 1 if selected or 0 if not. Since VRP belongs to the category of np-hard problems, there are numerous heuristic algorithms to define feasible solutions [24]. In this article, a sequential method was applied by identifying the routing based on the next unvisited node with the shortest distance from the previous one.

3.2. *KPI calculation*

Within this paper, the KPIs for scenario evaluation are TOVE and CO_2 emissions from road transport activities. The calculation of TOVE has a similar formulation to the OEE indicator (Figure 1). Each component can assume at most the unit value, indicating the best case. Practical cases define lower values due to the presence of waste. Within logistics activities, many authors have defined waste related to transport [8], [25], [26]. The wastes described in the model proposed by Villareal [4] can be reported comprehensively. Each waste is indicated for the component of the TOVE in which it produces inefficiencies (see Table 1). On the other hand, the calculation of carbon emissions is done as a function of the distance traveled. In fact, due to the lack of information on traffic flows and operational modes [17], a light goods vehicle model with an emission factor of 230 gCO_2 per km traveled was considered [27].

4. Scenario Definition

The comparison of the TOVE indicator and CO_2 emission was carried out in two scenarios, one for policy described above. Each scenario consists of two three-level variables, respectively, speed (40, 60, 80 km/h) and the maximum acceptable distance of customers from the distribution center (30, 40, 50 km).

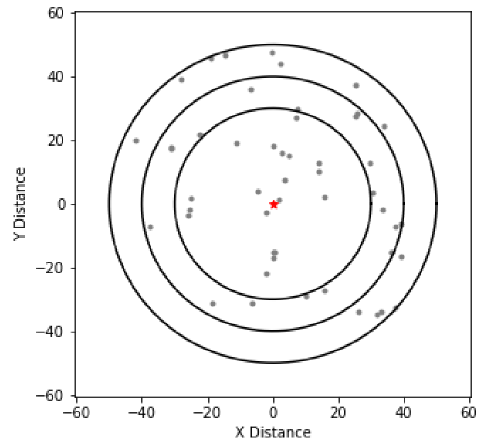


Figure 2: Space of customer

The analysis performed generates a distribution of 50 customers randomly within a circle of radius equal to the maximum acceptable distance (Figure 2). The delivery process is carried out by a single vehicle with a speed loss (P_2) of 10%. The distribution center works in a 12-hour time interval, of which 8 hours are allocated to transport activities. Before delivery, periodic maintenance, provisioning, storage, and truck loading activities are performed. At the end of the in-transit period when part of the customers has not been served, the operators unload and store the undelivered products. Figure 3 represents the sequence of activities performed in the simulation model and their classification between in-transit and non-transit.

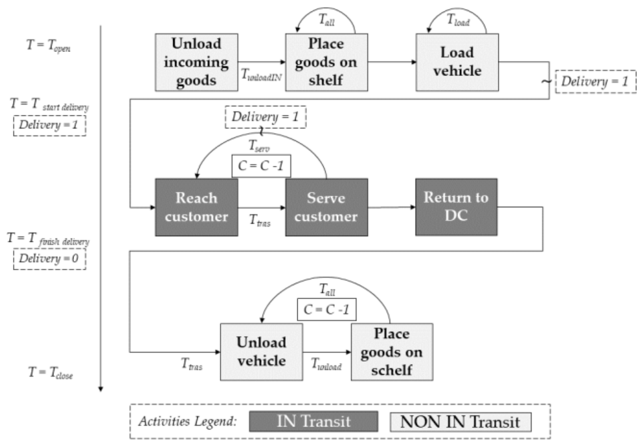


Figure 3: Simulation model

Table 1 : Component and waste of TOVE

Component	ID	Waste	Description
Administrative Availability	AA_1	Non-Scheduled time	Time for which the transport activity is not performed.
	AA_2	Scheduled maintenance	Periodic scheduled maintenance.
	AA_3	NIT external	Activities for which the vehicle is considered non-transit and which do not fall within logistical operations.
Operating Availability	OA_1	NIT internal	Activities for which the vehicle is considered non-transit and that within the logistics operations.
	OA_2	Driver breaks	All stops obliged by some condition can be considered.
	OA_3	Unscheduled maintenance	Failures of vehicle elements that prevent normal or safe operation and require corrective action.
	OA_4	Excess service time	Additional time needed to provide the service requested by the customer
Performance	P_1	Fill loss	Filling losses of the vehicle according to an element, such as volume or quantity.
	P_2	Speed loss	Vehicle speed loss defined as the difference between the maximum permissible speed and the average speed.
	P_3	Excess distance	Additional distance required to provide the service requested by the customer.
Quality	Q_1	Clients not served	Customers for whom the order was not delivered due to administrative and operational inefficiencies.
	Q_2	Demand not met	Application not taken over due to lack of products to be delivered.
	Q_3	Products defects	Non-conforming elements that are damaged in one or more activities performed by the distribution company.

Specifically, the working day begins at the T_{open} time instant in which the initial non-transit activities are carried out. Subsequently, at the time instant T_{start} the distribution activity begins and continues until the customers to be served are finished (C) or until the end of the delivery time ($T_{finish\ delivery}$). At the end of the day, the final activities are carried out to conclude the working day at the T_{close} instant. Table 2 shows the time distributions of each activity.

Table 2 : Parameters for simulation model

ID	Activities	Distribution
$T_{unloadIN}$	Unload incoming goods	Uniform (1200, 1800)
T_{all}	Place goods on shelf	Norm (120, 180)
T_{load}	Load vehicle	Norm (30, 180)
T_{trans}	Reach costumer	-
T_{serv}	Serve costumer	Norm (120, 120)
T_{trans}	Return to DC	-
T_{unload}	Unload vehicle	Norm (30, 180)
T_{all}	Place goods on shelf	Norm (120, 180)

In addition, the following assumptions were considered:

- Scheduled maintenance activities are sufficient to avoid driver breaks (OA_2) and unscheduled maintenance activities (OA_3),
- The vehicle travels at full load according to load and volume regulations, such that waste fill loss (P_1) is negligible,
- Deliveries are made at the minimum distance so that the excess waste distance (P_3) is negligible,
- Demand is always met without backlog/backorder policies, such that waste demand not met (Q_2) is negligible,
- There are no handling errors in the product handling activities such that the waste product defect (Q_3) is zero.

5. Results

Once the activities are specified and the wastes are identified, it was possible to calculate the KPIs of each routing. For each scenario, 10 simulation runs were executed for which the average values of the TOVE indicator (Figure 4) and CO_2 emission (Figure 5) are shown on a color scale from red (worst value) to green (best value).

From a general point of view, TOVE assumes low values for high delivery distances and high transport speeds. It obtains relatively good values for high speeds. By comparing the two scenarios, it appears that route optimization defines benefits for performance results. The second scenario minimizes the route and consequently the vehicle usage time, allowing more customers to be satisfied. The average values of the Quality component for the first scenario fall within a range (36%; 64.60%), while for the second scenario (69.60%; 99.60%). On the other hand, the other TOVE components are independent of vehicle speed and distance to the logistics center. Administrative availability is similar for both scenarios as wastes are identified with the same assumptions and activities assume equal distributions. On the other hand, operating availability assumes lower values for the second scenario (66.86%; 81.01%) than for the first (86.68%; 94.49%) independently of distance to the customer and vehicle speed.

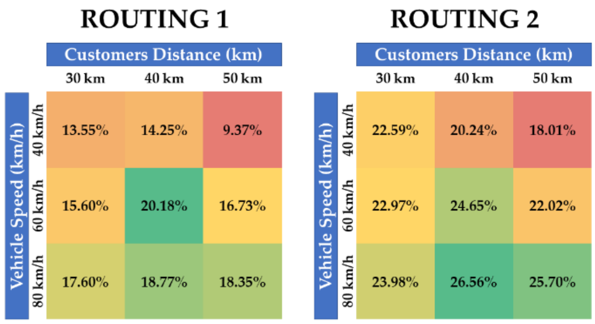


Figure 4: TOVE results for scenarios

Regarding carbon emissions, both scenarios follow the same pattern for each combination of variable levels. Average values assume minimums in the case where orders are processed within 30 km of the distribution center. From the results, it appears that the environmental impact is directly proportional to the speed of the vehicle. For the model used, which is only a function of the distance traveled, the increase in emissions is due to the greater number of customers served and consequently the Quality value of the TOVE indicator. This justifies the maximum value assumed for both scenarios by both high levels of distance and vehicle speed. Finally, at the same levels, the scenario with lower values is the one that applies routing optimization to minimize the distance traveled, in this case, the only dependent variable of transport emissions.

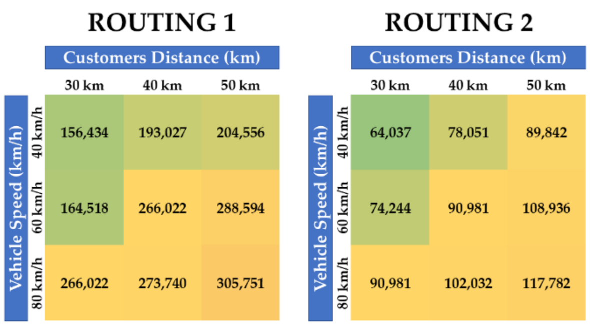


Figure 5: Total CO_2 emissions for scenarios

It is possible to state that the two indicators assume high results for opposite pairs of values. TOVE reaches high values at the higher speed level; however, carbon emissions assume low values at the lower speed and distance levels. The trade-off is found for intermediate values. Indeed, for the second scenario, a good compromise is obtained for the combination of intermediate values of both analyzed variables.

6. Discussion and Conclusion

This article deals with the comparison of TOVE and CO_2 consumption indicators. TOVE, which belongs to the OEE family, quantifies the performance of transport activity on a calendar level according to the components of administrative availability, operating availability, performance, and quality. CO_2 indicator, on the other hand, is representative of the emissions due to road transportation as a function of distance traveled. To the best of the authors' knowledge, the current scientific literature lacks a comparison between the two indicators. To fill this gap, a system of two scenarios was developed, which differed in the use of routing optimization policies. Each scenario was evaluated by combining on three levels the variables of the maximum distance of the customer and the average speed of the vehicle. The result obtained reveals that the two indicators assume better values for opposite pairs of variables, such that the trade-off is the respective intermediate levels. Although TOVE is a well-established indicator for road transport performance, it lacks environmental aspects, so the comparison lays the foundation for its future development. Furthermore, other possible future developments could be the use of more complex models for the detailed calculation of emissions, such as macroscopic or microscopic models. Another development could be related to the vehicle fleet, whereby it may be interesting to consider vehicles in larger numbers and different types. And finally, the comparison could be extended to a higher level whereby the focus is not exclusively on last-mile delivery but all logistical activities of a supply chain according to different and combined modes of transport.

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Conference on Performance Management

Machine Learning Key Performance Indicators (KPIs) for Prognostics and Health management (PHM) of mechanical systems and equipment: a systematic literature review

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Abstract. Machine Learning (ML) is used in many scientific fields nowadays, thanks to the strong artificial intelligence (AI) systems' development, occurred in the last two decades. In ML, there is no universally better model, but developers follow the "try and error" criterion to create algorithms and improve their models. So, the key to obtain a good model is "to experiment" in order to have a result that is as reliable as possible. Therefore, it needs to define methods to estimate the performance of the aforementioned algorithms. Several metrics are used to evaluate ML algorithms, depending on the type of tasks associated with ML. This study aims at conducing a systematic literature review on most commonly used ML's Key Performance Indicators (KPIs) in the field of Prognostics and Health management (PHM) of mechanical systems, dividing them in 2 categories: KPIs for regression tasks, and KPIs for classification tasks. For each metric, a description of the fundamental characteristics was defined.

Keywords
AI; Machine Learning; KPI; Systematic Literature Review; PdM.

1. Introduction

Industry is currently undergoing the so-called "fourth industrial revolution", which has led to the advent of new digital technologies that has prompted many companies to completely renew the concept of maintenance [1]. Among the innovations of industry 4.0, new useful tools have come to the help of industries such as Internet of Things (IoT) sensors, capable of collecting large volumes of data about industrial mechanical systems on which it is possible to conduct analyzes about their state of health through Machine Learning (ML) techniques. Prognostics and Health Management (PHM) represents an essential part of this new era; it is a Predictive Maintenance (PdM) strategy, which is based on systems' Condition Monitoring (CM) through IoT sensors installed on machinery to define their health state in order to avoid unexpected failures, that would translate as costs increasing for companies [2].
A mechanical system is considered to be under a normal healthy state if certain parameters remain above a predetermined threshold [3]. This threshold is often defined based on temperature and vibration, but also on pressure, vibration, sound, pressure, force, tension and still other measurable parameters [4]. These measurements can be used to alert any deviation from normal operating condition, which can help to determine how much longer the system would run before its condition falls below the threshold. Therefore, the main activity in PHM, is the

prediction of the Remaining Useful Life (RUL) of systems. RUL is defined as the time length from the current time to the end of the useful life, i.e., when system condition reaches the failure threshold. RUL prediction is generally based on data-driven techniques, which involves the use of ML algorithms that extracts information from sensors data installed on the monitored equipment [5]. These algorithms range from conventional techniques such as Artificial Neural Network (ANN), Support Vector Machine (SVM), k-Nearest Neighbor (kNN), to more recent techniques such as Deep Learning (DL) or Transfer learning (TL) algorithms [6]. ML is mainly used for solving two types of tasks, namely "Classification" and "Regression". Classification tasks have a finite number of output classes, while, in regression tasks, an infinite number of outputs are represented as real-valued data. The RUL prediction is inherently a regression problem, but there are cases in which the RUL is treated as a classification problem [7]. Regardless of the type of algorithm used or the type of task faced, an important step, in using ML in PHM, is being able to measure the performance of the algorithm. Therefore, it is necessary to define Key Performance Indicators (KPIs) to determine the accuracy of an algorithm and the associated methodology.

The aim of this study is to conduct a Systematic Literature Review (SLR) on the most common KPIs used for ML-driven PHM of mechanical systems and equipment, dividing them in 2 categories: KPIs for regression tasks, and KPIs for classification tasks.

The remainder of this paper is organized as follows: section 2 presents the methodology followed to conduct the research, section 3 shows the analyzed and discussed results and provides a description of the fundamental characteristics of aforementioned KPIs, and section 4 highlights the conclusions.

2. Research methodology

In this study, a SLR was performed to answer the following Research Question *(RQ): what are the main performance metrics for ML algorithms adopted in PHM of mechanical systems and equipment?* The literature search was performed on Scopus database (www.scopus.com) on 15th July 2022. Several combinations of keywords have been used for including all the possible papers related to the concepts of PHM (i.e PdM, data-driven PdM, or prognostic) and ML (i.e., DL). Such keyword was searched in the abstract, title or keywords (TITLE-ABS-KEY) of the document. The first query provided a first set of 570 results. Therefore, to increase the level of details, the words "RUL" and "Failure" were added. In fact, the main activity in PHM is the prediction of the RUL or just the failure moment of systems. The new query provided 422 results. Later, inclusion and exclusion criteria were defined: papers published between 2011 and 2022 (from 1997 to 2010, only 12 papers appeared in the search database, and eight belong to the medical field), papers into final publication stage, and papers in English language were included; 382 papers were found by applying these inclusion criteria. Conference papers were, then, excluded to further limit the 212 studies were found. The final query was the following:

TITLE-ABS-KEY *(("Prognostic PRE/2 Management" OR "PhM" OR "Data-driven PhM" OR "Predictive Maintenance" OR "Data-driven PdM" OR "PdM" OR "prognostic*" OR "condition-based maintenance")* AND *("Machine Learning" OR "ML" OR "Deep Learning" OR "DL")* AND *(fault OR failure OR "Remaining Useful Life" OR "RUL"))* AND *PUBYEAR > 2011 AND PUBYEAR < 2023* AND *(LIMIT-TO(PUBSTAGE,"final"))* AND *(LIMIT-TO (LANGUAGE, "English"))* AND *(LIMIT-TO (DOCTYPE, "ar"))*

From this sample, 165 papers were excluded by simply reading the title and abstract, because they were not related to the scope of mechanical systems and equipment. The final step was the full paper analysis of the 47 residual papers, which allowed excluding 15 documents because they did not focus on prognostics but only on condition monitoring. Hence, 32 papers were recognized as eligible. An overview of the whole search process is provided in Figure 1.

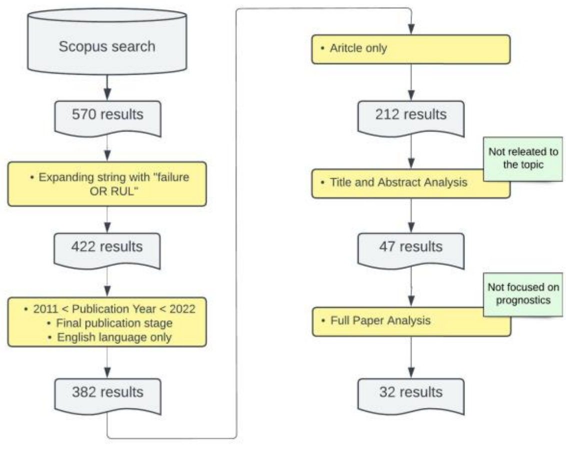


Figure 1: Overview of literature identification process.

3. Results and Discussion

Microsoft Excel® was used to create the several diagrams that follow. The 32 selected papers cover an 8 years period. Figure 3 shows how the papers are distributed over the years.

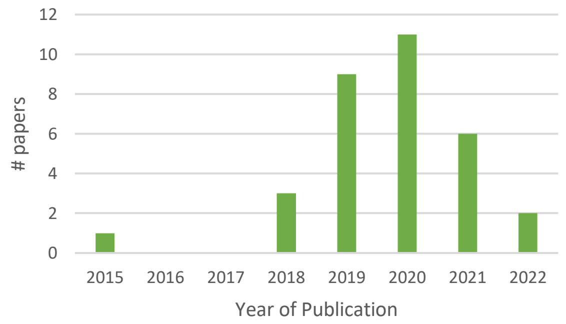


Figure 3: Number of papers between 2015 and 2022 (n = 8).

It was observed that the last 5 years (2018-2022) counts about 97% of the total number of papers on analyzed topic, observing that 1 paper belongs to 2015, while 2016 and 2017 presents no papers. The peak is reached in 2020 (11 papers). Figure 4 shows the journals in which the papers have been published.

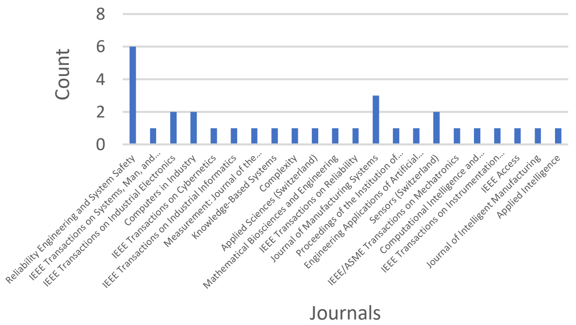
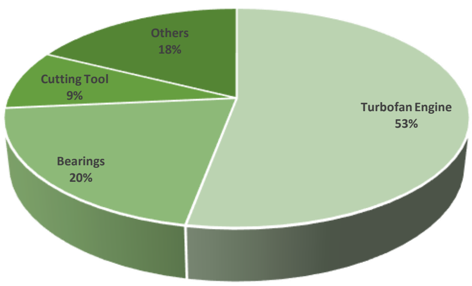
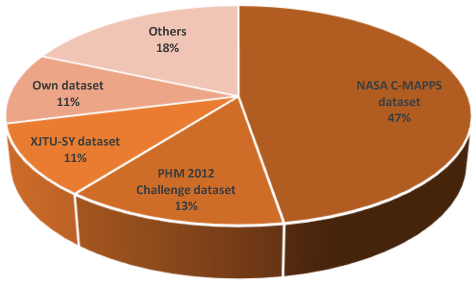


Figure 4: Number of publications per journal.

The 32 papers were published in 22 different journals. "*Reliability Engineering and System Safety*" is the source with the greatest number of publications (6), followed by "*Journal of Manufacturing Systems*" (3), "*IEEE Transactions on Industrial Electronics*" (2), "*Computers in Industry*" (2), and "*Sensors*"(2); the remaining 53% of journals owns 1 paper each. Figure 5 shows the frequency of mechanical systems (a) and datasets (b) on which have been validated the ML algorithms.



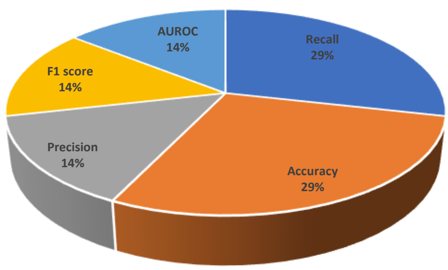
(a)



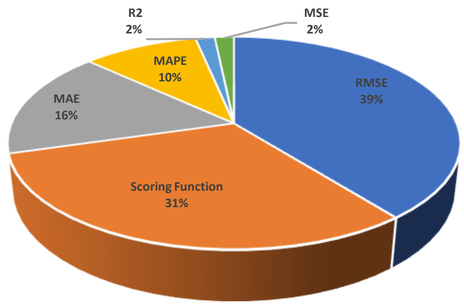
(b)

Figure 5: Frequency of mechanical systems (a) and datasets (b).

From Figure 5, it is possible to note that 47% of works are on NASA datasets. NASA decided in 2008 to share the "Nasa Turbofan Jet Engine dataset", to stimulate research in the field of prognostics. This popular dataset contains simulated data produced by a model-based simulation program, i.e., Commercial Modular Aero-Propulsion System Simulation (C-MAPSS). Since 2010, the "*C-MAPSS dataset*" became very popular in prognostic researches, resulting in a wide use of Turbofan engine as a mechanical system for RUL prediction. Other 2 common datasets about Bearings, even if less popular than C-MAPPS, have been often used over the years: "*PHM 2012 challenge dataset*" (13%) and "*XJTU-SY dataset*" (11%). In fact, the presence of *Bearings* as mechanical systems is 20% of the analyzed papers. 11% of papers present a dataset created specifically for the problem addressed, and 18% regarding other less popular datasets (*SCADA 2017 dataset, PHM 2015 challenge dataset, PHM 2009 challenge dataset, CWRU Bearing dataset, NASA PHM 2008 Challenge dataset, IMS-Foxconn dataset, UC Berkeley* and *NASA Milling dataset*). Lathe's or milling machine's *Cutting tools* are also popular as mechanical systems, representing 9% of the total studies. The remaining 18% of mechanical systems are *Wind Turbine, Helical Gearbox, Spiral Bevel Gear, Aircraft Gas Turbine Engine, Ball Screw* and *Planetary Gearbox*. Figure 6 shows the frequency of the KPIs used in the sample papers dividing them for classification tasks (a) and regression tasks (b).



(a)



(b)

Figure 6: Frequency of KPIs for classification (a) and Regression tasks (b).

Only 4 of 32 analyzed studies present classification tasks, in fact, RUL prediction is inherently a regression problem. 3 of the 4 studies are about failure prediction, so "fault yes/fault no" criterion is followed, while the remaining 1 of 4 studies [38] is about RUL prediction, i.e., the probability that the RUL belongs to determined time windows (time classes) to decide the moment for preparing and performing maintenance activities. *Accuracy* and *Recall* are the most used metric (2 times), followed by *Precision*, *F1 score* and *AUROC*" (1 time).

As expected, the most interesting result is about the KPIs concerning regression tasks, that are distributed in 28 of 32 studies. The *RMSE* is the most used metric (39%, i.e., 24 times), followed by the *Scoring Function* (31% i.e., 19 times), *MAE* (16%, i.e., 10 times), *MAPE* (10% i.e., 6 times), R^2 and *MSE* (2% i.e., 1 time each).

3.1. Machine Learning KPIs for PHM

Evaluation Metrics (EMs) are used to measure the quality of the ML model. There are many different types of EMs available to test a model, but Regression and Classification tasks have different KPIs because the outputs produced by the models are different. Although the RUL prediction is essentially a regression problem, in rare cases it is treated as a classification problem, just like the prediction of a fault. Therefore, in this section, a brief description of the most commonly used ML's KPIs for PHM is carried out, dividing them in KPIs for classification tasks and KPIs for regression tasks.

3.1.1. KPIs for Classification Tasks

When the task output is divided by positive and negative classes[1] (ex. for machine failure prediction, negative can stand for "failure" and positive can stand for "working") in a machine learning model, KPIs for classification tasks are used to validate that model.

Accuracy (A). It is the total number of correctly classified samples divided by the total number of samples within the test set. It is defined as follow [8]:

$$A = \frac{\#\, corr.class.samples}{\#\, all\ samples} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

where:

- *TP* (True Positive) means how many positive class samples the model predicted correctly;
- *TN* (True Negative) means how many negative class samples the model predicted correctly;
- *FP* (False Positive) means how many positive class samples the model predicted incorrectly;
- *FN* (False Negative) means how many negative class samples the model predicted incorrectly.

The Accuracy is bounded to [0, 1], where 1 represents predicting all positive and negative samples correctly, and 0 represents predicting none of the positive or negative samples correctly.

Recall (R). Also called "*Sensitivity*" or "*True Positive Rate (TPR)*", it is the ratio between correctly classified positive samples and all samples assigned to the positive class. It is defined as follow [8]:

$$R = \frac{\#\, true\ positive\ samples}{\#\, samples\ classified\ positive} = \frac{TP}{TP + FN} \quad (2)$$

The Recall is bounded to [0, 1], where 1 represents perfectly predicting the positive class, and 0 represents incorrect prediction of all positive class samples.

Specificity (SP). Also called "*True Negative Rate (TNR)*", it is the negative class version of the Recall, and it is the ratio between correctly classified negative samples and all samples classified as negative. It is defined as follow [9]:

$$SP = \frac{\#\, true\ negative\ samples}{\#\, samples\ classified\ negative} = \frac{TN}{TN + FP} \quad (3)$$

The Specificity is bounded to [0, 1], where 1 represents perfectly predicting the negative class, and 0 represents incorrect prediction of all negative class samples.

Precision (P). It is the ratio between correctly classified samples and all samples assigned to that class. It is defined as follow [8]:

$$P = \frac{\#\, samples\ correctly\ classified}{\#\, samples\ assigned\ to\ class} = \frac{TC}{TC + FC} \quad (4)$$

where:

- "TC" denotes "True Class", i.e., all samples correctly predicted, and the "Class" assumes be either positive (TC=TP) or negative (TC=TN) value;
- "FC" denotes "False Class", i.e., all samples incorrectly

[1] Positive and negative are nothing but just two classes, for example, sick/not sick, on/off, cat/dog, male/female. So, one class is considered as positive and other as negative.

predicted, and the "Class" assumes be either positive (FC=FP) or negative (FC=FN) value.

Therefore, the positive case of the Precision (TC=TP and FC=FP) is also called "Positive Predictive Value (PPV) and it is defined in eq (5), while the negative case of the Precision (TC=TN and FC=FN) is also called "Negative Predictive Value (NPV)" and it is defined in eq (6). Specifically, PPV is the ratio between correctly classified positive samples and all samples classified as positive, while NPV is the ratio between correctly classified negative samples and all samples classified as negative [9].

$$PPV = \frac{\#\, correct\ positive\ prediction}{\#\, samples\ classified\ positive} = \frac{TP}{TP + FP} \quad (5)$$

$$NPV = \frac{\#\, correct\ negative\ prediction}{\#\, samples\ classified\ negative} = \frac{TN}{TN + FN} \quad (6)$$

P, PPV and NPV are bounded to [0, 1], where 1 represents all samples in the class correctly predicted, and 0 represents no correct predictions in the class.

F1 score (F1). The F1 score metric is a combination of the Recall and the Precision. In fact, F1 is the harmonic mean of the two, meaning that it penalizes extreme values of either. It is defined as follow [8]:

$$F1 = \frac{2}{\frac{1}{R} + \frac{1}{P}} \quad (7)$$

The F1 score is bounded to [0, 1], where 1 represents the perfect model (maximum precision and recall values) and 0 represents zero precision and/or recall. Note that a high F1 value symbolizes a high precision as well as high recall, while a low F1 value is not enough to know if the problem of the model resides on low Recall (type-I problem) or low Precision (type-II problem) or both of them (type-III problem). Therefore, F1 is often used together with other metrics, to better understand if the model suffers from the type-I, type-II, or type-III problem.

AUROC (Area under the Receiver Operating Characteristic Curve). Also called *AUPRC (Area under the Precision Recall Curve)* and better known as *AUC-ROC (Area Under the Curve ROC)*, it is a curve plotted between False Positive Rate (FPR) on the x-axis and True Positive Rate (Specificity) on the y-axis, where FPR is defined as follow [8]:

$$FPR = \frac{\#\, false\ positive\ samples}{\#\, samples\ classif.negative} = \frac{FP}{TN + FP} = \\ = 1 - SP \quad (8)$$

FPR, just like TPR, has values in the range [0, 1], and it is the reciprocal of SP, so 1 represents incorrect prediction of all negative class samples, and 0 represents perfectly predicting the negative class. The AUC value can be calculated only after defining the model [9], but in the case of simple binary classification, the AUC looks like as equation (9) [10], while in the case of multiclass AUC measure, the interested reader can take a look at [11] .

$$ROC = \left(TP + FN - \frac{TN(TP + 1)}{2}\right) / TN \cdot TP \quad (9)$$

Greater the value of AUROC, better the performance of the model. Specifically, when AUC is approximately 0, the model is actually reciprocating the classes, i.e., it is predicting a negative class as a positive class and vice versa; when AUC is approximately 0.5, the model has no discrimination capacity to distinguish between positive class and negative class; when ROC is approximately 1, the model has an excellent capacity to separate the classes.

It is not unusual the use of the so-called "*Confusion Matrix*" (also known as "*Error Matrix*") to evaluate a ML classification model, a nxn matrix, where "n" is the number of classes that are to be predicted. In the case of binary classification (n=2), the confusion matrix looks like as follow [12]:

$$\text{Binary Confusion Matrix } = \begin{bmatrix} TP & FN \\ FP & TN \end{bmatrix} \quad (10)$$

It is not exactly a performance metric but it is a sort of basis on which the already mentioned metrics (Accuracy, Recall, Specificity, etc.), definable starting from the matrix, evaluate the results.

3.1.2. KPIs for Regression Tasks

When the task output is continuous (it can assume any values of real numbers) in a machine learning model, KPIs for regression tasks are used to validate that model.

Root Mean Squared Error (RMSE). It is the root of Mean Squared Error (MSE) and represents the standard deviation of the residuals (prediction errors); residuals are a measure of how far from the regression line data points are. The RMSE is more sensitive to outliers than the MSE because the effect of each error on RMSE is proportional to the size of the squared error [13]. The formula of RMSE is shown in equation (11) [14].

$$RMSE = \sqrt{MSE} = \sqrt{\frac{\sum_{i=1}^{N} \left(y_i(t) - \hat{y}_i(t) \right)^2}{N}} \quad (11)$$

where:
- $y_i(t)$ represents the actual value at t-time (ex., the RUL value or the failure/working condition at t-time);
- $\hat{y}_i(t)$ represents the predicted value at t-time (ex., the predicted RUL value or the predicted failure/working

condition at t-time);
- N represents the samples in the dataset.

Mean Absolute Error (MAE). It is the arithmetic average taken between the actual values and predicted values. MAE, just like RMSE, does not provide any "direction" of error i.e., whether the model is overfitting or underfitting the forecast. Moreover, it also measures the average magnitude of error i.e., how far the predictions are from the actual output [13]. The formula of MAE is shown in equation (12) [15].

$$MAE = \frac{1}{N} \cdot \sum_{i=1}^{N} | y_i(t) - \hat{y}_i(t)| \qquad (12)$$

Scoring Function (S). It is the most used ML's metric for RUL regressive prediction. It's been given by PHM2008 competition specifically for RUL prognostics evaluation [16]. The Scoring Function is asymmetric around the true time of failure because it penalizes early predictions (i.e., the estimated RUL value is smaller than the actual RUL value) more than late predictions (i.e., the estimated RUL value is larger than the actual RUL value). This can reduce the risk of dangerous because late predictions may result in more severe consequences [17]. The asymmetric preference is controlled by parameters a_1 and a_2 in the Scoring Function defined below (eq. 13) [18]; the most commonly used values are 10 and 13, respectively for a_1 and a_2. The formula of S is shown in equation (13) [14]. Moreover, a graphic example of a generic Scoring Function is represented in Figure 2.

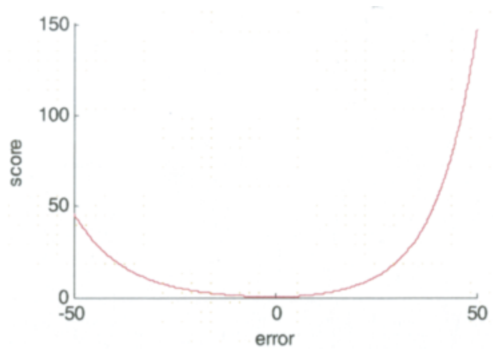


Figure 2: Graphic representation of a generical Penalty Scoring Function.

$$S = \begin{cases} \sum_{i=1}^{N} e^{-\left(\frac{d}{a_1}\right)} - 1 & for\ d < 0 \\ \sum_{i=1}^{N} e^{-\left(\frac{d}{a_2}\right)} - 1 & for\ d \geq 0 \end{cases} \qquad (13)$$

where:
- N represents the samples in the dataset;
- $d = RUL_i(t) - \widehat{RUL}_i(t)$ (i.e., Actual RUL – Predicted RUL);
- $a_1 = 10$;
- $a_2 = 13$.

RMSE, MAE and S are bounded to [0, +∞[. Since these are coefficients that evaluates an error, the lower RMSE, MAE or S value, the greater the accuracy of the forecast.

Mean Absolute Percentage Error (MAPE). It is the arithmetic average taken between the actual values and predicted values, related to the actual values. It measures the forecast accuracy, evaluating the size of the error in percentage terms [13]. The formula of MAPE is shown in equation (14) [15].

$$MAPE = \frac{100\%}{N} \cdot \sum_{i=1}^{N} \left| \frac{y_i(t) - \hat{y}_i(t)}{y_i(t)} \right| \qquad (14)$$

MAPE is bounded to [0, 1]. Since this is a coefficient that evaluates an error, the lower MSE value, the greater the accuracy of the forecast.

Coefficient of determination (R^2). It is the proportionate amount of variation in the dependent variable explained by the independent variables in the linear regression model. It allows to understand how strong is the predictive capacity of a linear regression model [19]. The formula of R^2 is shown in equation (15) [20].

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (y_i(t) - \hat{y}_i(t))^2}{\sum_{i=1}^{N} (y_i(t) - \bar{y}_i)^2} \qquad (15)$$

where $\bar{y}_i$ represents the mean value of the samples in the dataset. R^2 is bounded to [0, 1]. The higher R^2 value, the greater the accuracy of the forecast.

Table 1 summarizes the main characteristics of the selected papers, in terms of: publication year, objective, Mechanical systems, ML technique(s), task types and KPI(s) used.

Table 1 : Characteristics of the selected studies.

Authors/ Publication Year	Objective	Mechanical System(s)	ML Technique(s)	Regression/ Classification	KPI(s)
Z. Wu et al., 2018 [8]	Failure Prediction	Wind Turbine (*SCADA 2017 dataset and PHM 2015 challenge dataset*)	Easy-SMT ensemble algorithm	Classification	Recall, Precision, F1 score, AUROC
C. Wu et al., 2019 [12]	Failure Prediction	Helical Gearbox (*PHM 2009 challenge dataset*) and Planetary Gearbox (*own dataset*)	Convolutional Neural Network (CNN)	Classification	Accuracy, Recall (Confusion matrix)

X. Li et al., 2018 [14]	RUL Prediction	Turbofan engine (*NASA C-MAPPS dataset*)	Deep Convolutional Neural Network (DCCN)	Regression	RMSE, S
X. Li et al., 2019 [15]	RUL Prediction	Bearings (*PHM 2012 Challenge dataset*)	Deep Neural Network (DNN)	Regression	MAE, MAPE, RMSE
J. Deutsch and D. He, 2018 [21]	RUL Prediction	Spiral Bevel Gear (*own dataset*)	Deep Belief Network (DBN)-Feed-forward Neural Network (FNN)	Regression	MAPE, RMSE
E. A. Listou et al., 2019 [22]	RUL Prediction	Turbofan engine (*NASA C-MAPPS dataset*)	Restricted Boltzmann Machine (RBM)-LSTM-FNN	Regression	RMSE, S
C.-G. Huang et al., 2019 [23]	RUL Prediction	Turbofan engine (*NASA C-MAPPS dataset*)	Bidirectional Long Short-Term Memory (BLSTM) neural network	Regression	RMSE, S
K. Javed, R. Gouriveau and N. Zerhouni, 2015 [20]	RUL Prediction	Turbofan engine (*NASA C-MAPPS dataset*)	Summation Wavelet Extreme Learning Machine (SW-ELM), Subtractive-Maximum Entropy Fuzzy Clustering (S-MEFC)	Regression	S, R^2
A. Al-Dulaimi et al., 2019 [24]	RUL Prediction	Turbofan engine (*NASA C-MAPPS dataset*)	LSTM-CNN	Regression	RMSE, S
Z. Chen et al., 2021 [25]	RUL Prediction	Turbofan engine (*NASA C-MAPPS dataset*)	Attention-based LSTM	Regression	RMSE, S
P. da Costa et al., 2020 [26]	RUL Prediction	Turbofan engine (*NASA C-MAPPS dataset*)	LSTM-Domain Adversarial Neural Network (DANN)	Regression	RMSE, S
M. Ma and Z. Mao, 2021 [27]	RUL Prediction	Bearings (*own dataset*)	Convolution-based LSTM (CLSTM)	Regression	RMSE, MAE
Y. Xu et al., 2021 [28]	Failure Prediction	Bearings (*CWRU Bearing dataset and XJTU-SY dataset)*	CNN-gcForest	Classification	Accuracy (Confusion matrix)
X. Li et al., 2020 [29]	RUL Prediction	Bearings (*PHM 2012 Challenge dataset and XJTU-SY dataset*)	Generative Adversarial Network (GAN)	Regression	RMSE, MAE, MAPE
J. Ma et al., 2018 [30]	RUL Prediction	Aircraft gas turbine engine (*NASA PHM 2008 Challenge dataset)*	DNN: Stacked Sparse Autoencoder (SAE)	Regression	MAPE, S
Z. Kong et al., 2019 [31]	RUL Prediction	Turbofan engine (*NASA C-MAPPS dataset*)	CNN-LSTM	Regression	RMSE, MAPE, MAE, S
L. Wen et al., 2019 [32]	RUL Prediction	Turbofan engine (*NASA C-MAPPS dataset*)	Ensemble Residual CNN	Regression	RMSE, S
C.-G. Huang et al., 2020 [33]	RUL Prediction	Cutting Tool of a Milling Machine (*own dataset*)	Bi-directional LSTM (BiLSTM)	Regression	RMSE, MAE
G. Aydemir and B. Acar, 2020 [34]	RUL Prediction	Turbofan engine (*NASA C-MAPPS dataset*)	Linear regressor (LR), Random Forests (RF) and LSTM	Regression	RMSE, S
P. A. Ruiz-Tagle et al., 2020 [35]	RUL Prediction	Turbofan engine (*NASA C-MAPPS dataset*)	Capsule Neural Network (CapsNet)	Regression	RMSE, S
T. Berghout et al., 2020 [36]	RUL Prediction	Turbofan engine (*NASA C-MAPPS dataset*)	Denoising Online Sequential Extreme Learning Machine (DOS-ELM)	Regression	RMSE, S
X. Li et al., 2020 [37]	RUL Prediction	Cutting wheel (*IMS-Foxconn dataset*)	BiLSTM	Regression	MAE
Y. Deng et al., 2020 [38]	RUL Prediction	Ball screw (*own dataset*)	Recorrent Neural Network with Gated Recurrent Unit (GRU-RNN)	Regression	RMSE, MAE
C.-G. Huang et al., 2021 [39]	RUL Prediction	Bearings (*PHM 2012 Challenge dataset and XJTU-SY dataset*)	DCNN–MLP	Regression	RMSE, MAE
G. Hou et al., 2020 [40]	RUL Prediction	Turbofan engine (*NASA C-MAPPS dataset*)	Deep Convolutional Generative Adversarial Networks (DCGAV)-LSTM-FNN	Regression	RMSE, S
Y. Ding et al., 2021 [41]	RUL Prediction	Bearings (*PHM 2012 Challenge dataset and XJTU-SY dataset*)	Deep Subdomain Adaptive Regression Network (DSARN)	Regression	RMSE, MAE, S
C. Zhao et al.,	RUL	Turbofan engine (*NASA*	CNN-BiLSTM	Regression	RMSE, S

2020 [42]	Prediction	*C-MAPPS dataset*)			
T. Kim and S. Sohn, 2021 [43]	RUL Prediction	Turbofan engine (*NASA C-MAPPS dataset*)	CNN	Regression	RMSE, S
T. N. Khanh and M. Kamal, 2019 [44]	RUL Prediction	Turbofan engine (*NASA C-MAPPS dataset*)	Long Short-Term Memory (LMST) neural network	Classification	Probability Confusion matrix
D. Verstraete et al., 2019 [45]	RUL Prediction	Turbofan engine (*NASA C-MAPPS dataset*)	CNN-LSTM	Regression	RMSE, S
J. Luo and X. Zhang, 2021 [46]	RUL Prediction	Bearings (*PHM 2012 Challenge dataset*)	Convolution-based Attention Mechanism BiLSTM (CABiLSTM)	Regression	MAE, MSE, S
J. Zhang et al., 2022 [47]	RUL Prediction	Turbofan engine (*NASA C-MAPPS dataset*) and Cutting tool of a Milling Machine (*UC Berkeley and NASA Milling dataset*)	Bidirectional Gated Recurrent Unit with Temporal Self-Attention Mechanism (BiGRU-TSAM)	Regression	RMSE, S, MAPE

4. Conclusions

This paper has presented a Systematic Literature Review (SLR) on the most common KPIs used for ML-driven PHM of mechanical systems and equipment. After a brief description of the aforementioned Evaluation Metrics, the research methodology has been described, and 32 papers was retrieved from the Scopus database, exporting the relevant pieces of information on Microsoft Excel® to allow the subsequent development of the analyzes on them. Although only 4 of 32 analyzed papers presents the classification task about RUL and failure prediction, the Accuracy and Recall results to be the most used metrics for this type of task, followed by F1-score, AUROC and Precision. About the regression tasks, the use or RMSE and Scoring Function is predominant, followed by MAE and MAPE. The less used were R^2 and MSE. Given the importance that Machine Learning in PHM field has been having in recent years, the outcomes of this research can help the academic world to better choice the most suitable metrics for PHM problems in order to validate ML algorithms.

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Conference on Performance Management

Organizations post Covid-19: New management practices

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Abstract. The strike of the covid-19 pandemic has been translated into an imminent call for change. This health situation is for some people development prospects or for others new challenges with targets, quite new and complex enough to be qualified as stretch.

This study highlights the post-covid organizational context, opens up a field of reflection for performance management, and punctuates the place of management control, in particular with the new world post-covid.

The first step of this study consists in a review of new articles, in order to identify factors potentially associated with the motivation to fix stretch goals and digital development.

The second step of our script aim to analyze organizations in health crisis era, especially the situation after covid disease. Manifestly, a qualitative study based on a semi-structured interview made with almost two companies, focusing on the decisions taken by different actors during and after the period of health crisis.

In result of these turbulences, the digital acceleration induced by the health crisis as well as the use of management control have become at the heart of new organizational strategies.

The expected result aim to confirm that the setting of stretch goals by constraint due to the complexity of the external environment has become one of the main entrepreneurial initiatives, in need.

In parallel, the most use of digitalization allow adaptation to a post-covid universe without having to set stretch goals.

Keywords

Post Covid-19; Stretch goals; Digitalization; Management control; Management Performance.

1. Introduction

The Covid-19 pandemic has had major consequences on the world, in multiple areas, particularly socio-economic development. At the beginning of 2020, when the virus was already present in China, it took very little time for its spread to wreak havoc around the world. The impacts of this crisis have prompted governments to take strict measures such as total and partial confinement of the population as well as distancing, which has pushed organizations to act in a complex and uncertain environment.

Periods of crisis, due to their dark nature, constitute a period when everything is called into question, in particular the quality of management and working methods. We are no longer on a professional routine predefined by repetitive tasks. Indeed, it is a question of going out of the ordinary and trying to place oneself on an unknown and sometimes risky ground, in order to find revolutionary solutions for the organization as a whole. The aim is to allow both adaptation to the said period and continuity. This is how certain elements are forced to build a kind of legitimacy due to their place in the new world.

The various restrictive measures caused a remarkable imbalance between supply and demand, an unprecedented economic crisis, especially since the government was mainly focused on the health sector. During this time, most organizations have faced significant challenges in managing risk and responding.

Instinctively, an organization in a critical situation must ensure its survival by all means. Under certain conditions, it uses very ambitious goals, also known as stretch goals. These objectives are pursued as a last resort in a desperate attempt to save the life of the entity in question and contribute to safeguarding its competitiveness and functionality.

The particularity of a Stretch goal is in the need to use new methods, not tested by the company at the time of its definition, in the hope of generating breakthroughs. Indeed, such a goal implies venturing into completely unknown territory where, at the moment of its adoption, no model of achievement exists [21].

This research highlights the triptych legitimacy of management control: the function, man, and tools. As well as the legitimacy of digitalization accompanying practical changes within a company. And place the role of the two notions in a multi-relational framework in order to designate their impact on the pursuit of a stretch goal.

Admittedly, legitimacy concretely means legality, but according to our research it can be explained either by the habits and behaviours of the majority individuals which have the effect of granting or not granting a level of importance to a rule, which we can translate by the social recognition "obey to be obeyed".

The literature attaches great importance to Management Control, and now to digitalization. These are two functions that have developed over time and have created their place within organizations, but what about today? The first function plays an important role especially at the level of the orientations for the decision-making, and the second function provides a competitive advantage and an automated operational luxury.

The working method used in this research is a mixture of state of the art and case studies focused on the decisions made by the different actors.

The method used in this study consists of a qualitative research based on a semi-structured interview with two employees of two Moroccan companies. The interest of this research consists in describing the performance in general in a particular context, that is to say in the light of an environment characterized by uncertain and complex, where making the right decision becomes crucial.

To answer the research problem, this manuscript aims to broaden our knowledge, distinctively, on the notions: management control, digitalization and stretch goals, in order to make the link between the three themes in a now complex environment. and uncertain. Thereafter we will display our problem, hypotheses, research method, to deduce the results.

2. Management Control

The entrepreneurial era becomes conditioned by making the right decisions, which will lead to what academic authors nowadays call “new normal” [22].

Management plays an important role in decision-making and improve performance.

By definition, performance is "the process by which managers obtain the assurance that resources are obtained and used effectively and efficiently for the achievement of the objectives of the organization" [3].

Any entity measures its degree of success by referring to its performance. In a more proportional framework, such a measure intervenes in a post-evaluation dimension in order to judge its effectiveness and efficiency. For this purpose, management control must be legitimate.

Legitimacy is an expression of the principle of legality. According to Weber's three types of legitimate domination [6], sociologists, political scientists and philosophers have grouped legitimacy into three categories: “traditional, charismatic and rational legitimacy”. However, if we want to update these notions in the contemporary world, we have found that traditional legitimacy and charismatic legitimacy are today difficult to apply. The current examples still cited by some authors are so varied that they add to the confusion more than they enlighten. [11].

Adejuwon [16] finds that corporate social responsibility also confers legitimacy. Gardberg and Fombrun [10] distinguish two motives for social activities: altruistic – doing good for self and instrumental – doing good for financial benefits. Whatever the case, social activities are key elements through which an organization integrates with the community in which it operates, earns favourable reputation and, as a result, creates legitimacy.

Similarly, Suchman [15] argues that firms known to regularly care for their customers through economic exchanges can be considered socially desirable. For example, reductions in prices and bonuses are the means by which these exchanges can be facilitated. Therefore, companies known for these types of economic exchanges may be rewarded with greater public acceptance [16].

3. Sustainable performance

Particular interest is now given to the notion of global performance. “The measurement of sustainability performance involves the simultaneous use of economic, environmental and social indicators. Recently, the ecosystem scope of sustainability indicators has expanded to include impact on biodiversity as well as many other socio-economic and governance issues, including the cumulative impacts of multiple human activities [4].

Distinctively from classic performance, the evaluation of such performance requires specific environmental, economic and social data which should be subject to regular monitoring and classification in the form of performance measurement indicators.

Basically, a sustainability indicator targets measures such as sustainability. To this end, the United Nations Commission on Sustainable Development launched a program in 1995 to establish such indicators. Then, as an initiative, a test was carried out in around twenty countries in order to test a set of 134 dedicated indicators. Subsequently, the European Union adopted sustainable development as a development strategy added to its political agenda [17].

Sustainable development is characterized by three essential pillars [4].

- Economic Growth
- The environmental Protection
- Social equity

Indicated by the same authors, the so-called standard

indicators according to the GRI Global Reporting Initiative in economic terms are: economic performance; Market presence; indirect economic impacts; purchasing practices. These diversified indicators support the multidimensional nature of sustainable performance, and include expectations from many interlocutors, instinctively integrating environmental protection, resource management and economic results.
Management control intervenes in this area as an element of measurement. If classic management control is oriented towards a logic of competitive, profitable and productive performance. Hence the need to adapt the function, as well as its indicators, to the ideals of the sustainability of the new performance [19].

4. Digital transformation

Several testimonies in favour of digitalization as the digital world spreads, then even more with the advent of the current crisis.
Indeed, if we take the case of telemedicine, an area at the heart of the health situation, the latter has been able to remedy several obstacles, in particular distance and insanity, thus meeting the need for distancing and care in the immediate. According to the study by Dr. Md. Mubasheer Ali and Dr. Ayesha Nazneen [2], the use of communication information technology in a Digitalized ambiguity has made it possible to adapt to the complexity of the external environment, allowing an adequate exchange of information, in particular with the case of the telemedicine platform which can be used for post Covid-19 management.
Other authors have also shared their testimony on the role of technology and digital operations thus providing opportunities in the context of the digitalization of work and employees in a creative way [22].
However, the ardent recourse to digitalization is not without consequences, particularly in the sense that stakeholders will see their working habits suddenly change, in particular with the integration of AI technology -artificial intelligence- in their daily lives.
Although new technologies provide comfort at work. However, most employees are threatened and risk being replaced by an automated complement framework. It is certainly beneficial to move more and more towards digitalization given that the post-covid-19 world favours it. However, it is also necessary to establish a balance between the human-robot universe since it is the most rational choice [22].

5. Stretch Goals

In the circumstances of covid19, the decisions taken by governments to counter the spread of the virus have pushed companies to resort to miracle solutions to save their grip on the market, increased digitalization among others, and to set very ambitious objectives in in order to ensure their survival or, at least, to adapt to the conditions of the current environment. These initiatives that go beyond usual practices do what we call Stretch goals.
According to the study by Sim B. et al. [21], an objective can only be qualified as extended – stretch – when it meets the following two criteria:
Criterion 1: Extremely difficult. This condition involves drastic expectations with goals that are very difficult, if not impossible, to achieve without considerable effort and in-depth study. The objective in question goes beyond the usual methods and surpasses current capabilities.
Criterion 2: Extremely new. This condition requires the use of new methods while radically breaking the routine, with a need for learning and training for employees. In principle, there is no model for the completion of the stretch goal at the time of its fixing.
Thus, meeting the criteria of the extended objectives, digitalization and digital acceleration are at the heart of the main changes made by companies in order to adapt to the external environment. Insofar as a stretch goal is perceived as impossible, the latter can hinder or even slow down their pursuit.[8].
Setting a stretch goal is primarily set to promote performance within a team. The latter is pursued beyond the normal objectives to stimulate innovation, productivity, involvement and enthusiasm within an organization.
However, it has been found that the advent of periods of crisis, thereby placing companies on survival alert, pushes managers to establish very difficult objectives, this is what we call by setting an objective by constraint.

6. Methodological and epistemological positioning

Among the causes of the difficulties that most organizations had to face during the advent of the pandemic and continuing to suffer its consequences, Tahir Sufi [22] points his fingers at the place and role of leadership, namely incompetence and poor decision-making, consequently losing the support of different stakeholders.
Tahir Sufi [22] also emphasizes the role of digitization in driving change, making it possible to restore AB2C trust (administration-to-consumer and business-to-consumer, which means restore trust in public and private sector that are both concerned), which prompts us to build the problem below.
Faced with an uncertain environment, what is the role of digitalization and management control in managing performance?
However, to go further in the announced research question, we formulated the three hypotheses below.
H 1: The demands of the external environment push organizations to use stretch goals.
H 2: Increased digitalization makes it possible to adapt quickly to a post-Covid world.
H3: Performance management in times of crisis is

conditioned by the management control methods and tools used

To answer these questions, we relied on two theories:

• Theory of constraint;

• Contingency theory.

Through the theory of constraint, we will explain the element that limits the yield. In the production domain, it calls the bottleneck. In our case, the bottleneck studied will be related to the external environment which can be considered as a disruptive factor in performance management.

The contingency theory implies personalized results according to the criteria of a company. The interest lies in the analysis upstream of the implementation of a tool or making a change. This makes it possible to list the factors specific to each character and adapt the choice and the desired change to the standards of the corresponding company [20].

The objective of our study is to improve our understanding of the legitimacy of the management control function, as well as the role that digitalization can play in a post-covid world. It aims to contribute, to a certain extent, to increasing knowledge relating to the concept of management control and tools and, above all, to contribute to the understanding of the interactions that there could be between both control of management / digitization and Stretch goals. From the review of the literature made in the first part, it emerged that the increased use of digitalization is becoming in a way a normality that the world now imposes.

We have chosen the case of two Moroccan companies. Both of them having lived through the Covid period and came out of it with completely different results. Data collection was carried out using a semi-structured interview with two responsible. We will treat anonymously data for confidentiality measures, to deal first with the Management Control function. The impact of the covid 19 crisis. The role of digitalization during the crisis. And finally, the management of the recovery using digitalization.

We called the first company **X** and the second **Y.**

Company X

Company X is a large one specializing in consulting. The interlocutor having worked within the organization since 2011.

It places management at the heart of its business, management control in this context plays an important role. Knowing that the decision-making process is first made following an in-depth study of the market and the environment, both internal and external, while taking into account the various advice from the management control entity.

The decision is also based on special risk maps relating to each country, each region, updated instantly. Indeed, as quoted by the interlocutor "Today the world is changing rapidly, and after the covid, decisions have become difficult because there is less visibility". Thus, performance is based on good advice, the relevance of the recommendations, the respect of deadlines, the quality of the rendering, and henceforth, the most use of digitalization.

Company Y

Company Y is a small business specializing in finance.

Decision-making within company Y is done by decision of the general manager, without experts, following the movements. The practice of management control is based on a purely financial analysis.

In order to analyze the content of the interview, we opted for thematic analysis using a verbatim table. To this end, first we proceeded to write a monograph for each case studied, before proceeding to the analysis and interpretation of the results. Then we analysed the results of the survey by identifying the verbatim that are common to the interviews and draw conclusions. This analysis allowed us to identify the main aspects to be taken into account and, above all, the interdependencies of the three keywords in order to answer the central question of this research, namely: Performance; management control; Digitalization; Stretch goals; Covid. Secondly, we correlated the results with the important points that emerge from the first part of the manuscript.

we have defined the words that most closely match our search: Performance; management control; Digitization; stretch; Covid. Each keyword constitutes an imperative research element within the framework of this analysis. Which allow us to generate the following verbatim table (Table 1: Semantic analysis).

Table 1 : Semantic analysis

Verbatim (**enterprise X**)	Verbatim (**enterprise Y**)	Themes
Good advice, the relevance of the recommendations, the respect of deadlines, the rigor and the quality of the rendering	Necessity of experience	Performance
Improvement and optimization of expenses	Financial analysis, summary statement, forecasts. Allows less waste. Gives a clear image of the company. Summary state. Financial analysis.	Management control
Dehumanizes, an irreversible process, a	Lack of means, orientation towards a	Digitalization

technology that is increasingly being put in place, it creates jobs and destroys them at the same time, it provides savings	mainly administrative culture. Simplification of work	
A practice that is being adopted more and more	State of alert and culture of crisis	Stretch goals
Containment and teleworking, reduced social contact, human relations; social instability, changing habits	Increased risk	Covid

The interest of using this method in this context will allow focus on the body of qualitative research, in order to explore the values, attitudes, opinions, feelings and behaviors of individuals and to understand how our theme affect them. Each part of the verbatim has been classified into a category according to the idea it exploits.
This method of analysis allowed us to relate all the key themes in order to analyze the effective framework of each on all the constituent elements of our research.

7. Results

As a result of this exploratory analysis, the various case studies demonstrate the key role played by digital transformation in supporting change. The choice and recourse to the adopted stretch goals result from the requirements of the external environment which leave little room for hesitation or intuition.
We find that there is a direct link between the notion of performance and the term covid. Indeed, according to the interviewees, the management control service provides a link between the top of the hierarchy upstream and decision-making downstream.
However, in times of health crisis, rigorous performance monitoring has become crucial. In post covid, several changes have taken place, mainly in terms of working methods. Now it is necessary to perform performance monitoring very often. While learning from the experience accumulated at the time of the advent of the health crisis.
Also, according to the interlocutor of company X, covid 19 has favored the use of digitalization. Especially since the post-covid world based on the experience learned, will be focused on the use of digitalization at all levels to deal with any unforeseen events.
The use of stretch goals could be inevitable in the event of poor performance management.
Company Y, not having this digital culture, saw its condition worsen. And for lack of adaptation to the aggregates of the health crisis, it was forced to set an extended objective which led it to go bankrupt, given the difficulty of said objective but also for lack of managerial practices.
However, company X was able to adapt quickly and effectively thanks to the degree of digitalization that the organization was showing.
The interview guide included questions relating to the two situations with a zoom on the role of digitization and then the digitization of management control, in particular in managing performance in a context of health crisis. Then the criteria that lead to the use of Stretch goals. To finally come to a link between the degree of use of stretch goals and digitalization.
Indeed, periods of crisis, and particularly that of Covid-19, place companies in delicate situations where making the right decision becomes a decisive element for the survival of the entity. Among these decision-making initiatives, the definition of stretch goals.
However, a well-equipped organization, better prepared for the various environmental changes, will be able to cope well without having to set difficult objectives in order to survive. Defining a stretch goal is a major element of change within an organization, for managers, employees and, practically, the management controller. The latter is obliged to adapt these working methods to follow the developments and changes due to the health environment.
However, the entity in charge of management control could take advantage of the various turbulences caused by the pandemic to improve and innovate. To this end and while being aware of the place occupied by information in an unstable external environment, access to reliable, precise, detailed and relevant data is undeniably essential. In this sense, the establishment of an information system and the digitization of management control will facilitate the collection, processing, distribution and archiving of data, and thus contribute to the construction of a solid basis on which the management controller can rest during his reports, by highlighting the discrepancies more comfortably, explaining the causes and indirectly contributing to decision-making through evaluation, control and correction.

8. Conclusion

A period of crisis is synonymous with economic recession, bankruptcies, over-indebtedness, revaluation of the currency at the international level, and consequently, a drop in tax revenues. The social repercussions of the crisis are explained by the revenue and expenditure of public administrations as well as cyclical fluctuations [18]. Among the difficulties that accompany this change, the modification of the habits of the employees thus leading to stress and complaints.
Today's world is not limited to circumstances due to the coronavirus health crisis. Henceforth, the environment characterized by the socio-economic world is described as multidimensional.
Companies have to apply themselves under pressure and

in an uncertain world, where any decision taken is not without risk.

The obligation to face the pandemic by all means will encourage entrepreneurs to focus on the weak points of the firm, including training and improving the level of skills of employees. Such an initiative will allow innovation and development in the future. Moreover, prioritizing human capital in these health circumstances will encourage employees to voluntarily participate in achieving the objectives set, including stretch goals.

Even more, the obligation for certain companies to pursue extended objectives will push entrepreneurs to forge strategic alliances and to prioritize innovation, immediately allowing the organization to surpass itself and improve its qualities (procedures and products) to stand out and cope with environmental uncertainties [5].

These different case studies demonstrate the key role played by digital transformation in supporting change. The choice and recourse to the adopted stretch goals result from the requirements of the external environment which leave little room for hesitation or intuition.

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However, the entity in charge of management control could take advantage of the various turbulences caused by the pandemic to improve and innovate. To this end and while being aware of the place occupied by information in an unstable external environment, access to reliable, precise, detailed and relevant data is undeniably essential. In this sense, the establishment of an information system and the digitization of management control will facilitate the collection, processing, distribution and archiving of data, and thus contribute to the construction of a a solid basis on which the management controller can rest during his reports, by highlighting the discrepancies more comfortably, explaining the causes and indirectly contributing to decision-making through evaluation, control and correction.

To this end, this need for digital change must be taken positively insofar as the integration of new adapted management software would be able to generate the relevant indicators for managing performance under the best conditions, and therefore contribute to the achievement of objectives, including stretch goals. But still, a good information system will automate and facilitate the administrative process, while saving time.

As for management control systems, they should interactively encourage the various actors to work cooperatively to promote innovation and decision analysis in order to counter strategic uncertainties. In this context, the management controller will have to play a role of clarifying and accompanying change to facilitate the adaptation of the company to the increased complexity of its external environment.

On the other hand, it is necessary to pay great attention to the human capital of a company, namely the level of skills, training and knowledge management. According to a study carried out in Nigeria, training and development activities have a positive effect on the performance of Nigerien organizations [1].

It is also necessary to pay increased attention to employees to engrave a positive trace in their minds, which will allow them to voluntarily participate in the achievement of the company's objectives, even within the framework of a stretch goal.

In the case of societies where power is concentrated mainly at the top in which only the entrepreneur can induce change and make adjustments at the organizational level, it will be better to take China as an example. Indeed, according to the case study of Abodohoui [1], in China employees value learning by doing or trial and error, moreover, public enterprises in this Asian country use modern evaluation measures as effective tools to improve efficiency and productivity.

This work is limited only to the framework of covid 19 knowing that there are many other more serious crises, in particular the Ukrainian-Russian war, the climate and the ecological incidents which worry, so it would be instructive to widen this field of research towards broad horizons and to have a broader vision of performance management, with a large research sample in order to fully understand the impact of an uncertain and complex environment. the ideal would be to carry out an observational study of a few samples of companies in order to better study their development in this new world.

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Conference on Performance Management

Management accounting innovations & business intelligence: Decision support and outcome benefits

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Abstract. Contemporary organizations have become increasingly sensitive to management accounting innovations (MAI). The importance of these innovations lies in providing managers with essential tools leading to the survival and sustainability of their organizations, particularly for those operating in an environment characterized by fierce competition.

Traditionally, management accounting is the primary support for decision-making and control in an organization. As such, it has clear links to and can benefit from applying Business intelligence (BI) technologies. The result indicates an exciting research area for accounting researchers. However, a review of the literature in top accounting and information systems journals indicates that little research has focused on this link. Although various benefits are expected to arise from BI functions, research and models that determine the effect of BI functions on the decisional and organizational benefits are rare. Thus, case studies illustrating the use and effectiveness of BI and visualization techniques in management accounting would be particularly welcome.

This paper aims to study BI adoption as a MAI and its impact on organizational performance in the context of the decision environment.

This research conducts a qualitative survey-based study within a Moroccan bank to represent the impact of BI adoption on decision-making and organizational benefits. The study explains how BI systems are adopted within management accounting entities and highlights their corporate outcome benefits. Findings aim to confirm a meaningful relationship between BI adoption and organizational performance.

Keywords

Management accounting innovations; Business intelligence; Decision making; Organizational performance.

1. INTRODUCTION

Nowadays, several companies are facing unexpected situations that affect negatively their improvement and performance. In fact, Business intelligence tools can be seen as an answer to face these confusing experiences that can hit companies unexpectedly, regardless of their size, [1,2]. Business intelligence systems are defined as techniques and processes that transform information into data, which is then switched into business knowledge [3]. In order to provide interesting information for business managers, data integration and technological solutions are set through BI systems. The primer subject of this research is that BI, as a main term, is defined as a group of technologies such as data warehouses, data mining, online analytical processing (OLAP), decision support (DS) systems, balanced scorecard, etc. to upgrade work-progress and decision-making processes [4,5]. Mainly, BI systems are used to conduct decision making through handing the needed tactical and strategic data. This helps managers into understanding, managing, and planning the activities and cycles for the company [6]. All in all, the main goal is to provide users with the needed help required to accomplish their decision-making process. Different advantages of organizational DS arised through research and litterature [7,8]. On this behalf, BI can be considered as one of the most important spheres of data innovation and has been laid out top priority for some executives [9].

The only few research that sharpens BI effects on management accounting [10,11] is based on the conclusion that querying, dashboards, and visualization capabilities integrated into BI systems, enhance organizational learning [11]–[13] activate the ability to measure performance [11,13] and facilitate alignment with strategy and performance gain [11,14,15].

There is a lack of knowledge and empirical evidence regarding the extent of the use of BI techniques in management control and their relative effectiveness [10].

BI systems are solutions generally designed to support decision-making in an organization [3,16]. However, the measurement of decision-making support of an individual is mainly absent in research around BI systems [16]. Thus, case studies illustrating the use and effectiveness of advanced BI functions in management control would be particularly welcome [10].

Consequently, in the following paper, we examine the impact of BI on decision support. The study seeks to address the following research questions:

Q: How does business intelligence (BI) impact organizational performance through decision support (DS)?

This study aims to ascertain if and how business intelligence systems assist the progress of timely organizational decision-making and end users' better knowledge processing within the firm.

The rest of this paper is structured as follows: Section 1 concerns related studies. The importance of the decision support concept and BI in the business environment is discussed as a theoretical background within section 2. The research model and hypotheses formulation is detailed in section 3. The methodology is described in section 4, then in section 5 we report the results followed by an analysis of risen elements in section 6. Finally, section 7 contains the conclusion of the research, outlining a brief overview of the paper, followed by the research limitations and recommendations for future researchers.

2. LITERATURE REVIEW

Because BI appears sometimes indisctinct, it usually tends to be perceived in different theories and approaches. On the one hand, [17] sustain two important approaches, one is managerial and the second is technical. The first approach underlines the greatness of organizational decision-making, and the second one considers BI as an instrument to support the managerial process. Inversly, [18] appraises past examinations by introducing another methodology called system-enabler, in which the primer spotlight is on the value added features of the company's systems (with a wide range of functions) to afford the needed information in decision making.

All along our study, we consider BI as a tool designed to support essential decision-making by setting up a proper DS climate. By evaluating the DS idea, we separate result benefits into two unique layers incorporating DS benefits and organizational advantages. Here, we adjudje DS benefits as the primary advantages determined across the decision-making process. Furthermore, organizational advantages mean all positive things that stems from the results of decisions. All in all, DS benefits are those that start from the process of decision-making. However, organizational advantages are considered as long-term results mediated by decision support [19]. In the following, a detailed description of relevant research on BI tools and decision support.

2.1. Business intelligence tools

In order to work on the organization's strategy, directors need to use a few explicit instruments to support their decisions across the decision-making process. From the various advantageous points, BI can be valuable by giving exceptional results to improve the decision-making capacities of decision makers [20] These tools cover many strategies and advancements used to accumulate, give admittance, and examin data from different sources and to help decision-makers afford more viable organizational decisions [21,22]. Several techniques and advances with DS jobs have been proclaimed lately. [23] expressed that integrating multiple criteria decision-making instruments with DS systems can be more favorable and impressive for supervisors to work with decision-making processes.

Moreover, various mobile , web and email channels were considered supportive tools in organizational decision-making [24]. Additionally, [25] presented databases (data warehouses and data marts) as one of the primary elements of BI. Significantly, the strategic use of BI in the company is positioned in three significant fields as follows: performance measurement, monitoring business exercises, and reporting [26].

On the other hand, [17] assembled BI capacities into three main categories, including analysis (data mining and OLAP), monitoring (dashboards, scorecards, ready systems), and reporting.

Moreover, [22] approved another scientific classification for business examination, including descriptive, predictive, and prescriptive groups. Separately, the descriptive group tries to clear-cut business issues and opportunities, the result of the predictive group is to characterize accurate projection, while the prescriptive group aims to give the ideal business decisions and exchanges.

In a more defined review, BI is seen as a systems-empowering agent approach that has extensive capacities by [18,27,28]. In their classification, 34 criteria were investigated as BI functions, then gathered into six primary groups, including:

1- Analytical and intelligent decision support (AIDS)
2- Furnishing related trials and mixing with natural data
3- Optimization and recommended model (ORM),
4- Reasoning
5- Enhanced decision-making tools (EDMT)
6- Stakeholders' satisfaction (for more information, see [18]).

Considering the above arguments, it is good to notice in

our study that we see BI as a set of tools belonging to [17] categorization (Analysis, Monitoring, and Reporting), especially when dealing with interviews and interviewees. However, to formulate our hypothesis in section 3, we lay on some functions belonging to [18] categorization to suppose a relationship between BI and studied variables of DS.
Thus, in our approach, we conclude that BI functions of enterprise systems may impact decision support. These functions are monitoring (dashboards, scorecards, alert systems) and reporting.

2.2. *Decision support*

In order to reinforce companies competitiveness, managers are supposed to take the right decisions no matter the complexity of the cases and situations. For this sake, companies require a particular kind of organizational support system to assist them in processing decisions. Previously, different advantages have been recorded that persuaded firms to adopt BI. Although, containing all the potential benefits from BI was not possible. Therefore, a theoretical construct was established by exploring the literature and informal meetings with a few BI experts with important information in IT fields. Subsequently, we recognize the DS benefits into three fundamental developments [29,30] better knowledge processing, reduced decision time, and decreased decision cost, which BI functions might influence.
We suggest focusing on better knowledge processing and reducing decision time in our study.

2.2.1. *Better knowledge processing*

The main threat for today's firms is that the executives ask for data to transform it into valorised and supportive information for business decisions [31]. Information is now seen as a strategic resource and is used while decision-making. Though, the capacity of collecting new information and knowledge is important for managers to handle the companies in the best possible way [32,33].
Thus, firms need to adopt a better knowledge of their business processes. Eventually, the Decision-making process involves processing or applying data/information, which allows a better understanding of business issues and further more information [34]. This tends to be perceived as a standard alliance between decision-making and knowledge-creation processes [35]. [29] presents knowledge processing as a DS benefit and reviews it through upgrading decision makers' capacity to handle information. Likewise, data/information processing capacity was pointed to as the main wanted benefit of hierarchical support systems. On the other hand, [36] proclaim that DS should play a significant role in upgrading the decision makers' decision-making capacities.
Besides, they are able to act as an impetus to develop the decision-making process further as they give the capacity to sort out and share information and provide a new understanding to directors [37]. "Better knowledge processing" is viewed as improved capacity (quality and worth) to process and make information for decision making.

2.2.2. *Reduced decision time*

The development of managerial decisions has been allying with complexity and uncertainty in processing data, and closing up the process of decision-making in the briefest possible time has been proposed as a clear prerequisite on behalf of the directors [38]. As per [32], planning data in an ideal way is expected to support decision-making fruitfully. In reality, it can prompt speed up the time of data processing and thus decision making [39]. Moreover, [40]'s research presumed that time saving is the main need regarding substantial advantages of DS systems. As [31] expressed, to reduce time's desicison process, business managers should have the option to figure out a rising volume of information and data rapidly. Likewise, accelerating the decision-making process is considered the primary improvement to advancing business investigation programming. In momentum research, "diminished decision time" is regarded as a variable that shortens the period and time of the decision-making process by any specialized or practical system. This issue has likewise been examined by [29,30,34] as the primary advantage of the DS environment inside the venture.

3. RESEARCH METHOD AND HYPOTHESES

Our research model and its hypotheses are featured in Figure 1. In this study, we consider the exploration model given an extensive review of the literature on BI and the decision support concept. The proposed model considers that [17] BI is made by analysis (data mining and OLAP), monitoring (dashboards, scorecards, alert systems), and reporting tools. Better knowledge processing and decreased decision time, are connected with decision-making, they are viewed as DS benefits.
As referenced previously, analysis capability incorporating data mining, data warehouse, and OLAP is known as one of the significant capabilities concerning BI [17]. This capability helps to break down business data in order to support and develop decision-making in business exercises [25]. [18] made a self-comprised system in which examination tools were introduces specific AIDS capability. All in all, the reason for this capability is to support decision makers through visual reports and inform them using alarms and warnings via specialists and channels. [41] debated on how the analysis tools prepare supervisors for decision-making by giving more itemized and detailed data. As [8] states, an analysis tool helps take advantage of the accessible data to restore data and valuable information in supporting complex decision-

making process. Essentially, [42] discovered that smart DS advances decision-makers capacities in better acknowledgement of information. For instance, data mining as a rule of AIDS capability focuses on finding the key information that upgrades the managers abilities to make further accurate decisions [43].

Decision-makers need to consider different parts of a decision that other criteria might influence. Regarding this fact, the ability to break down unclear values and multi-standards decision-making are considered BI functions [44,45]. [18] have discussed that these capabilities are called EDMT. Through the decision-making process, managers can deal with many challenges in different degrees of vulnerability [46] which shows the importance of a fluid thinking capacity to manage a decision circumstance. Though, the capacity to sort data is essential in an organizational support system [47]. Simultaneously, data as a nucleus key in the decision-making process is related to intricacy and vulnerability, which implies that decision markers require a good DS with the unperceived capacity to bear the cost of the uncertainty of issues. Lastly, processing information in a wanted manner [33]. Meanwhile, concerning the way MCDM appliances have been created to tackle down decision issues with different criteria, it tends to be beneficial to rather develop organizational decision making by giving information processing capacity in an effective way [48].

In every organizational decision-making, a statement of reasons is significant for giving judiciousness to decision makers. Thus, in the reasoning (REAS) function of BI, the knowledge reasoning all along with financial analysis tools are seen as BI capabilities. Reasoning capability is organized to show why the suspicions ought to be acknowledged or deserve thought. In the most straightforward definition, it only means that the main function of this category is to accept or deny the claims [49]. [50] declared that the analysing procedures could deliver insight or proposals similar to an expert by processing knowledge. Also, it is more interesting to sort data into useful information. Yet, reasoning capability can be used to analyze issues and to control information in various decision circumstances [51]. Also, [24,52,53] mentioned that thinking capability in DS systems can be considered as a key knowledge processing to upgrade to decision makers ability. These examinations showed that there is a positive one-way connection between the adoption of the reasoning function of BI and DS benefits for a better knowledge processing.

According to what is mentioned above, in our model, better knowledge processing, which is a DS benefit, is driven and affected by the BI functions. Thus, the following hypothesis predicted that:

H1. BI functions positively affect DS in better knowledge processing.

Concerning decision time, [54] affirmed that this capability has likewise prompted quicker decision-making in knowledge processing. [38] also established that the analysis tools are created to give managers the needed data and help them make the right decisions while taking into consideration the importance of time. Besides, [26] states that BI analytical systems can be effective while preparing fundamental data for management accountants and decision makers. The point of these instruments is to work on the timeliness and quality of inputs to the decision process.

Furthermore, as per the complex nature of critical thinking with numerous angles, the decision-making process demands more time investment to explain issues and connections and distinguish quantitative and qualitative variables. Subsequently, MCDM tools and unclear logic can be indispensable in DS climate to reduce decision time [48,55,56].

Moreover, intelligent optimization using dynamic and developmental prototyping is thought of, and proposals to decision makers would be offered based on them. [57] discovered that this capability could diminish the time required for tasks and decision-making through dashboards by understanding a significant amount of information in a minimum amount of time.

Moreover, optimization tools and simulation models can diminish the options of decisions and subsequently decline decision time by addressing the possible result of the situation [37,58]. In dashboards, [41] contended that firms could give status data on key performance indicators to introduce essential and timely data to act promptly. In addition, it can provide primary data using timely and crucial information, which can be helpful in decision time reduction [5]. Although the connection between "ORM" capability and reduced decision time has not been explored previously, these past examinations appear to show that the ORM capability can influence decreasing decision-making time. Accordingly, we expect that this BI function positively influences the reduced decision time as DS benefits.

As indicated by the significance of securing environmental data and general information for adjusting to current settings [32], DS must enable clients by giving pertinent data [59]. Hence, to comprehend the whole business climate, managers require a solid capability to provide a wide range of essential data [46]. Therefore, [18] presented giving EEI capability as one of the five central elements of BI. Here, Decision makers get support and help by bringing in express information and recorded tests from business conditions and furnishing them with groupware to choose from by collective intelligence. Collective intelligence rises out of the coordination, collaborative experiments, and competition of numerous individuals and shows up in agreement decision making. Regarding the relation between EEI and decreased decision time, [51] note that giving environmental data through bringing in

information and trading reports can help decision makers reduce decision time. This capability can likewise affect decision-making time through problem clustering [60]. Similarly, managers with appropriate admittance to environmental awareness and involving group decision-making can make decisions more rapidly [56,61,62]. Somewhat, it is logic to expect that the giving EEI capability of BI drives reduced decision time.
Hence, in our model, it is reasonable to expect that BI drives the DS benefits derived from reduced decision time. Thus, the following hypothesis is given:

H2. BI functions positively affect DS in reduced decision time.

Numerous analysts have created a different scale for estimating the viability of a decision. For example, [42] contended that meaningful choices could be assessed through survey items, such as reduced decision time and costs.
Besides, the viability of a decision-making movement extensively relies upon the use of relevant knowledge and its processing [35]. [36] investigated that effective decisions are driven by upgrading decision-makers capacities. Meanwhile, effective decision-making expects users to create suitable mental portrayals, where the psychological processes that decision makers make give the connection between narrative and task [57]. Consequently, because some data or information is fundamentally more important than others, [63] communicated that effective business decisions depend on the procurement, processing, and use of important information. Here, it can be concluded that better knowledge processing, and reduced decision time, will lead to effective decisions as an organizational benefit. Thus, the following hypothesis is presented:

H3. Better knowledge processing and reduced decision time positively affect organizational performance in practical decisions.

This examination considers the DS as a mediating layer to correspond BI functions to organizational performance. Thus, we ignore the H3 hypothesis and focus on H1 and H2.

4. METHOD

This study is based on a qualitative descriptive approach. Semi-structured interviews were directed on a Moroccan firm's hierarchy to gather information on issues regarding BI. Arising topics from these interviews are then discussed. The exploration target was a Moroccan bank that carried out and used an updated BI framework for more than a year.
The survey began by enrolling 15 exploration members who were classified into managers and subordinates. The members were drawn from 5 different business entities within the firm that already use BI tools. Also, an employee of the entity that carries management of BI solutions was interviewed– a member of this entity was selected as the critical informant because it is an employee who knows about central BI tools deployed within the firm-. From each entity, one director and two subordinates were chosen. Consequently, the review ended up with five managers and ten associates. A semi-structured interview comprised of inquiries regarding different parts of BI was given to every member (cf. Appendices). A. All members finished the review. The outcomes from the meeting were then analyzed, and the arising topics were examined as depicted in the following sections.

5. RESEARCH RESULTS

This research illustrates the results of interviews concerning the impact of business enterprises on organizational performance. Mainly we analyze the effect of BI on Decision support as a mediating concept. We studied the effect of BI on two principal elements: Better knowledge processing and reduced decision time. Tables 1, 2, and Figures 2 and 3 (cf. Appendices) show a summary of employees' responses on several aspects of BI systems and how those systems are perceived within the firm.

6. ANALYSIS

6.1. Recognition of BI Usage

One of the themes that emerged from the results is recognition of BI deployment and usage in the firm. From the results obtained by interviewing the managers and their subordinates, it is clear that most confirm they use BI tools within the entity. For the remainder, all entities selected for the study are using BI tools. Our interviewee of the BI management entity confirmed this information. The study shows that only one manager and three subordinates don't recognize they use BI tools. The tool is based on BI data retrieved from the central data warehouse but is a transparent layer for the employee.
For those employees, we let them know about the purpose of BI and inform them that data (reporting and dashboards) come from a BI system. Also, we noticed that two subordinate employees don't know about BI systems. This meet with the concept of diffusion of BI as an innovation - theory that seeks to explain how, why, and at what rate new ideas and technology spread- [64]. Then we confirm that almost all employees know about this innovation.

6.2. Availability of Skilled BI Maintenance Personnel of BI Usage

The outcomes show that many organizations lack the expected workforce to deal with these innovations. As indicated by the results, just two managers concurred that their organizations have skills representatives who can

deal with BI systems and their outputs.
The meeting results directed at managers are steady with those done with subordinates. The panel led on the subordinate shows that just 2 of them know how to manage BI outputs.
The complexity of BI systems is that they include mathematical functions that are vital in predicting a particular phenomenon in a firm to bring a given solution. IT skills are also essential when dealing with BI systems [65]. As portrayed in the interviews, most employees lack knowledge of BI, which could be affected by the deficit in IT skills.

6.3. *Impact of BI on Decision support*

The third subject that arose in this review was the effect of BI on DS. As per the meeting, 4/5 managers and 8/10 subordinates attest that BI affect decision support positively in their entities.

6.3.1. *Impact of BI on DS over better knowledge processing*

[66] indicate that BI systems prompt the value of information. The data produced is of top quality as it is liberated from errors and profoundly analyzed: the main work left for the business chiefs is interpreting the results. The business analysis capability of a BI system is likewise significant because it permits an organization to recognize changing patterns and dangers to make suitable decisions. Almost all participants confirm that BI positively affects DS in better knowledge processing (cf. figure 2 & figure 3). One interviewee attested, "In our company, we rely on business intelligence. It allows us to aggregate information and understands things we can't notice when dealing with standard tools like sheets". This testimonial shows that BI tools improve better knowledge of data. Results of interviews indicate that BI tools decrease the total effort in examining output data and a better knowledge processing of information. This is in line with [56] results, where we conclude that "This decreases the total effort to examine the data manually. Consequently, recognition and visualization of patterns within produced data play an important role in the insight-gaining progression and improve decision-making". According to [53], visualizations in real-time business intelligence reduce cognitive load, and end-users can achieve markedly improved decision-making performance when time is crucial, and data is fast-paced.

6.3.2. *Impact of BI on DS over reduced decision time*

According to interviews, it is clear that BI tools lead to reduce decision time (cf. figure 2 & figure 3). One of the business managers said, "Our organization has deployed business intelligence frameworks which give constant information. This data is fundamental since it permits us to make rapid choices". This admission reaction shows that BI tools give significant mechanical instruments that empower firms to pursue choices in light of reliable information and quick time. The market patterns remain profoundly questionable and severe, and as such, arrangements of essential data on time are of the substance. BI is adequate for businesses since it gives fundamental data used in decision-making processes and reduces decision time. Study shows that those tools are situated to make colossal additions in diminishing working expenses and better uptime. Hence, it is clear that BI is significant in aiding business managers in diminishing decision time. BI subsequently assists cutting-edge representatives and company chiefs with making informed decisions. They consolidate both verifiable information and ongoing information that are accessible to the business chiefs at whatever point required. This way, they enable the business chiefs to pursue choices rapidly and with a high degree of certainty because the data is solid. This is in line with [56], who conclude that BI reduced error performance increases the performance ratio with minimum time delay in the presence of a system. BI, in this way, gives a business complete data that is crucial for decision-making in reduced time [56].

7. CONCLUSION, LIMITATION, AND FUTURE RESEARCH

This review aims to study how business intelligence impacts organizational performance through the decision support concept. Mainly, we focused on two variables representing the benefits of decision support: Better knowledge processing and reduced decision time.
The study confirms that BI positively affects organizations, particularly decision support. First, BI facilitates decision-making for managers by giving quality, opportune and precise information. The information produced informs about the past, present, and future occasions and permits end-user to go with informed choices. As discussed above, BI tools improve knowledge of data and the capability of knowledge processing. Also, BI tools lead to reduced decision time as they enable the business chiefs to pursue choices rapidly and with a high degree of certainty because the data given is profoundly solid. These findings are similar to those of [19,53,56,67].
Like every study, this one has some limitations. First, we focused on a predetermined number of advantages of decision support. Although these are known as the most popular advantages, different advantages, such as more excellent reliability, and better communication and coordination, could likewise be thought of [19]. Second, although our research model and hypotheses were established through logical reasoning on BI tools associated with DS benefits, our exploration doesn't have a solid theoretical background in presenting the connections between BI tools and DS benefits. Third, there are possible ways to detail BI Tools instead of taking it as

a set. This may affect results if we want to focus on the impact of each item within BI Tools. Further testing of the proposed model might be done in a different context.

Given referenced limitations and in considering the outcomes acquired in the review, further future research is welcomed. First, it is recommended to establish the validity of findings in another context. Quantitative analysis based on a questionnaire may be conducted. Second, using a detailed approach to the BI concept rather than taking it as a set might present more valuable knowledge in studying the impact of each BI tool on organizations. Finally, testing and adding other variables to the proposed model is possible.

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9. Appendices:

Figure 1: *Proposed conceptual model and research hypotheses*

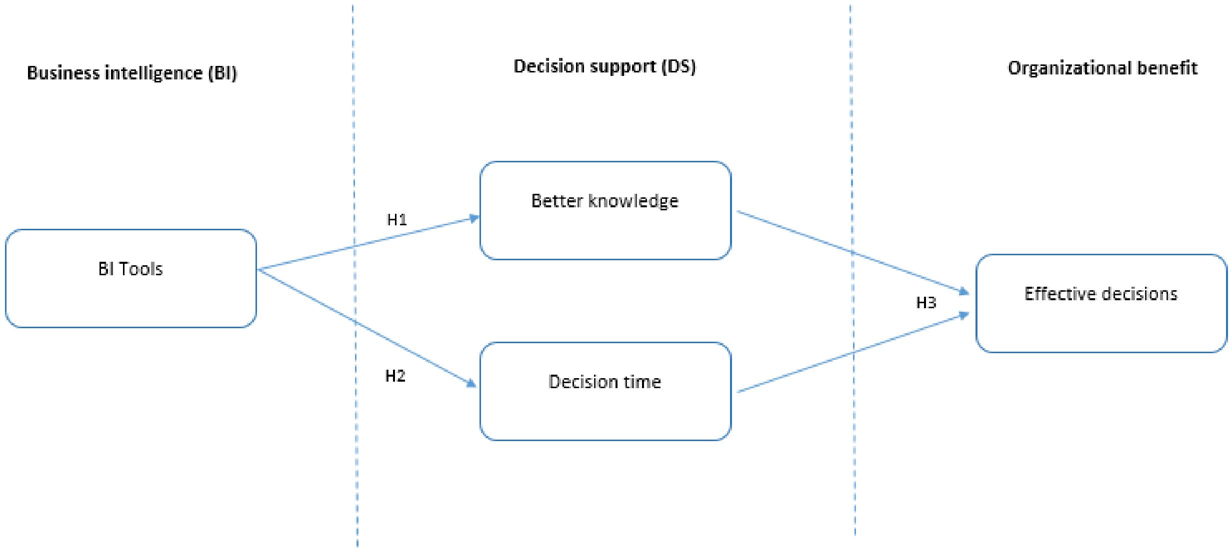


Table 1: *Table showing a summary of managers' responses on various aspects of BI.*

BI Systems Aspects Tested Through Managers Interviews (5 managers)	YES	NO
Recognition of BI usage within the company	4	1
Availability of skilled employees to manage BI outputs	2	3
BI positively affects DS in better knowledge processing (H1)	4	1
BI functions positively affect DS in reduced decision time (H2)	4	1
Perception of the continuation of the use of BI systems	5	0

Table 2: *Table showing a summary of subordinate employees responses to various aspects of business intelligence systems.*

BI systems Aspects Tested Through subordinates (10 employees)	YES	NO
Usage of BI within the company	7	3
Knowledge of managing BI outputs	2	8
BI positively affects DS in better knowledge processing (H1)	8	2
BI functions positively affect DS in reduced decision time (H2)	9	1
Perception of the continuation of the use of BI systems	9	1

Figure 2: Number of responses of Managers on various aspects of BI systems

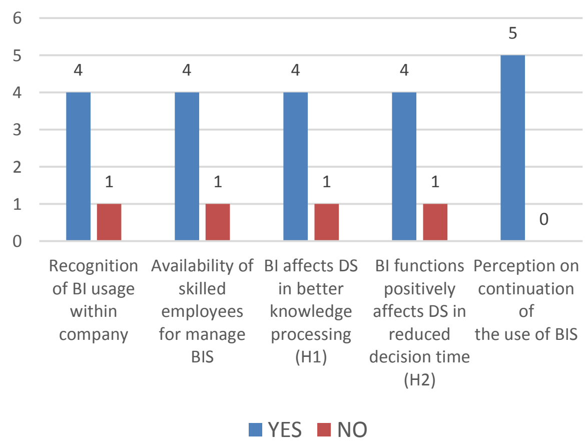
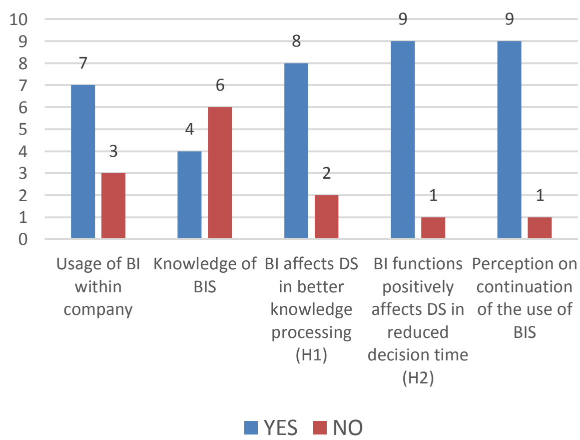


Figure 3: *Number of responses of subordonate on various aspects of BI systems*



The interview questions:

1. Does your company use business intelligent tools?
2. Does your department use business intelligent tools?
3. Do you have skilled employees to manage these systems? (Question for managers only)
4. Are you conversant with the uses of business intelligent tools? Yes/No
5. Does the information that is generated by the business intelligence tools help concerned department in making timely decision making? If yes, how?
6. Does the business intelligence tools help in better knowledge processing? If yes, how?
7. Do you think that the business intelligent tools help to improve overall organizational performance? If yes, how?
8. Should the company continue using business intelligent tools? if yes, why?

Conference on Performance Management

Assessment of the Social Life Cycle in the Textile Industry: proposition of indicators for sustainable performance

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Abstract

Some factors, such as competition and demand for low prices by some consumers, end up encouraging the textile and garment production industries to migrate to underdeveloped countries, where environmental, social, and labor legislation are not so strict. These places end up allowing working patterns in inhumane conditions, such as: low wages, gender and racial discrimination, excessive working hours, working in places with exposure to health and safety risks, slave, and child labour, among others. The textile industry is one of the most polluting in the world causing a strong environmental and social impact. However, on the other hand, the sector also offers social benefits such as wealth and employment when undertaken in a way that balances environmental, social, and economic aspects. In this context, innovation plays an important role and can help to create a new perspective for the future. Currently, a change in the consumer profile is already perceived, which is resulting in the emergence of awareness movements on the part of some non-governmental organizations (NGOs), which aim to reduce the negative consequences arising from the textile sector and others. The objective of this study was to evaluate the use of the methodology "Social Life Cycle Assessment (SLCA)" and social indicators in the textile industry. For this, a literature review was carried out in the Scopus database, where three documents related to the proposed theme were found, which suggests that there is a field for research in this area, sixty nine (69) indicators were identified (distributed in 6 categories of stakeholders) related to SLCA for textile and clothing industries, considering the impacts generated in the social and environmental scope.

Keywords

Social indicator, Textile, Social life cycle assessment.

1. Introduction

Since the elaboration of the Brudtland Report in 1987, sustainable development (SD) and sustainability have been progressively incorporated into government policy and corporate strategies, aiming to "the needs of the present generation without compromising those of future generations". This document relates excessive consumerism in first world countries, in contrast to extreme poverty in third world countries, highlighting one of the causes of serious environmental crises. A subject that became a basis for the structure of Agenda 21 [4].

One of the industries that has a high impact in terms of sustainability is textiles. The operation of these industries consume a high amount of water, mainly, in dyeing and finishing. Its effluent causes a high impact, both due to the high volume produced and its chemical composition. Competitiveness in the fashion sector makes companies end up migrating to countries where legislation is more flexible. This fact impacts the entire value chain [5].

In order to assess the real impact generated by a particular product and to list in which points it can be improved [3], the Life Cycle Assessment (LCA) emerged, which today covers not only the product itself but its entire life cycle (cradle to the grave), involving environmental, economic and social aspects. Thus, this study aims to evaluate the use of the methodology "Social Life Cycle Assessment (SLCA)" and social indicators in the textile industry.

2. Review of the literature

With the purpose to better understand the themes and relationships between them, a conceptual review of the Textile Industry, SLCA and Social Indicator follows.

2.1. Textile Industry

The textile and clothing industry is considered one of the largest and most polluting in the world, having a direct impact on four aspects, being: 1) Energy consumption in yarn production, finishing and use (washing and ironing). 2) The consumption of water in cotton production and dyeing, which has the use of chemical substances as an aggravating factor. 3) Solid waste from the textile and clothing industry as well as product disposal after use. 4) High levels of CO2 emission [5, 7].

Recent studies have also highlighted the social, environmental and economic impacts caused, mainly, in developing countries where labor and environmental laws are not so strict [8]. Amoung these impacts, we can highlight low wages, child labor, work in sub-human conditions, gender discrimination, lack of safety in the workplace, exposure to the community to risks due to the disposal of products from the production process, in addition to the use of natural resources, amoung others [6, 8].

For this reason, it is important that the textile industry undergoes a profound reorganization, taking into account the impact caused by these factors, both internally and externally (stakeholders). This initiative, which we can call a "sustainable initiative", can be monitored through quantitative and/or qualitative indicators, thus allowing the implementation of improvements throughout the textile chain [4].

2.2. Social Life Cycle Assessment (SLCA)

Developed from the Product Life Cycle Analysis (LCA), the Social Life Cycle Analysis (SLCA) is a methodology that aims to collect, assess and report environmental, economic and social impacts [2], arising from a particular product or process along the supply chain [1, 3, 6, 8]. Its guidelines were formatted from a cooperative effort between the Environment Program of the United Nation (UNEP) and the Society for Toxicology and Environmental Chemistry (SETAC) [8].

The SLCA has been widely used, although it is in the development phase and has some challenges due to the complexity of social systems and the difficulty in transforming qualitative data into quantitative [6].

However, according to Benoît Norris, Norris and Aulisio (2014) the results from this method are positive, since they can help in business decision making and be applied in several areas, such as in the survey of business reports aimed at improving processes and products , elaboration of new public policies and environmental or resource allocation.

3. Material and Methods

For this study, a literature review was performed to answer the following questions:

Q1 - Is SLCA used in the textile industry? How and what results were found?

Q2 - What indicators are presented in the literature for use in the textile industry?

To answer these questions, the following steps of bibliometric research were carried out:

Step 1 – A search was carried out in the Scopus database with the following search terms: "social indicator", "textile" and "social life cycle".

Step 2 – Data were collected using: search white "All fields" and "AND" connector. Neither the search period nor the type of document was defined.

Step 3 – The documents found were organized in a specific folder, and analyzed in order to answer questions Q1 and Q2. The analysis was organized in a classification table, which can be found in the discussion of the results (next section).

4. Discussion

From the execution of the methodological steps, three documents were found, which reveals the lack of published studies on this topic. Table 1 classifies the information from the documents found in the research and is composed of title, author(s), year of publication and journal in which it was published.

Table 1 – Title, author(s), year of pubication and journal

	Títle	Author(s)	Journal
1	Hotspot identification in the clothing industry using social life cycle assessment—opportunities and challenges of input-output modeling	[8]	The International Journal of Life Cycle Assessment

2	Socio-Economic Effects in the Knitwear Sector—A Life Cycle-Based Approach Towards the Definition of Social Indicators	[5]	Social Life Cycle Assessment
3	Using Social Life Cycle Assessment to analyze the contribution of products to the Sustainable Development Goals: a case study in the textile sector	[6]	The International Journal of Life Cycle Assessment

Based on a case study based on the LCA-S methodology, Zamani et al. (2018), carried out the analysis from the consumption of Swedish clothes through a model of inputs and outputs from the cradle to the gate. The research purpose was to identify risk social points, using the Social Hotspots Database (SHDB) evaluation methodology. The social hotspots, for each set of indicators, were defined through a survey carried out with 1175 consumers aged between 16 and 30 years. As a result, some critical points were found in the value chain such as child labor, fatal injuries and wages below 2 USD, in addition, the commerce and services sectors in Bangladesh, surprised by their criticality. For this study, 10 indicators were selected, as shown in Table 2.
Through the analysis of LCA, at all stages of the production process, of a sweater produced in Italy, Ferrante, Arzoumanidis and Petti (2019), aimed in their study, to highlight the positive impacts caused by the use of natural dyeing. The authors submitted questionnaires, by category, to four groups of stakeholders, namely: workers, actors in the value chain, consumers and society.
As a result of the study, the authors report three significant positive impacts, being these:

1) Consumer health and safety protection due to reduced chemical substances, plus assurance that sweaters are naturally dyed through the use of a labeling system.
2) Increased community awareness and responsibility in relation to sustainability-related issues.
3) Use of new technologies aimed at reducing the impacts caused by technological resources on the environment.

Herrera Almanza and Corona (2020), sought to identify, through a case study, the link between the indicators of the Assessment of Social Life Cycle (SLCA) and the Sustainable Development Goals (SDGs), creating a new category of indicators . For this, the PSILCA database was used. From this study, social risks related to the following SDGs were identified: Health and well-being (03), Clean and affordable energy (07), Decent work and economic growth (08) and Responsible consumption and production (12).

Table 2 - Indicator, Author(s), Database and SDG

SDG	Indicator	Author(s)	Database
	1. Decent salary compared to the cost of living. 2. Workers get decent pay compared to top executives.	[5, 6, 8]	SHDB PSILCA
	3. Voluntary commitment to human rights by the company in order to strengthen the health of the community. 4. Workers receive social benefits such as paid sick leave and pensions. 5. Management policies related to private security personnel. 6. To work in safe and healthy conditions. 7. Number of incidents attributed to the organization due to unsafe working conditions. 8. Risk of fatal injuries by sector. 9. Global risk of years of life lost from exposure to carcinogens. 10. General risk of loss of life years from inhalation of airborne particles. 11. Preventive measures and emergency protocols for exposure to pesticides and chemicals.	[5, 6, 8]	SHDB PSILCA

4 EDUCAÇÃO DE QUALIDADE	12. Presence of community education initiatives by the company.	[6]	PSILCA
5 IGUALDADE DE GÊNERO	13. Proportion of male and female employees in management positions. 14. Equality of pay between men and women by employee category.	[6, 8]	SHDB PSILCA
6 ÁGUA POTÁVEL E SANEAMENTO	15. Proper management of waste stream and wastewater discharge.. 16. Access to drinking water. 17. Certification in environmental management systems.	[6]	PSILCA
7 ENERGIA LIMPA E ACESSÍVEL	18. Consumption of fossil fuels. 19. Biomass consumption.	[6]	PSILCA
8 TRABALHO DECENTE E CRESCIMENTO ECONÔMICO	20. Eradication of Child Labour. 21. Promotion of local work. 22. Workers can join unions. 23. Regular and documented payment of workers. 24. Strength of Policies on Local Hiring Preferences. 25. Presence of forced labor in the organization. 26. Retention of the worker's birth certificate, passport or other original documents. 27. Freedom of workers to terminate the employment contract within the prevailing limits. 28. Existence of fire-fighting equipment and emergency exits. 29. Provision of medical assistance and first aid. 30. Notification of accidents, incidents and occupational diseases. 31. Provision of protective equipment. 32. Presence of diversity in the workforce. 33. Number of hours worked per week. 34. Overtime Pay Rate. 35. Presence of unions within the organization. 36. Participation of workers' representatives in decisions that affect working conditions. 37. Involvement and/or investment in technology transfer or research and development. 38. Use of secure employment contracts.	[5, 6, 8]	SHDB PSILCA
9 INDÚSTRIA, INOVAÇÃO E INFRAESTRUTURA	39. Technology development.	[5]	
10 REDUÇÃO DAS DESIGUALDADES	40. Strength of policies in place to protect the rights of indigenous communities. 41. Annual meetings held with members of the indigenous community. 42. Respect for indigenous rights. 43. Number of resettled individuals that can be assigned to the organization. 44. Strength of organizational procedures to integrate migrant workers into the community. 45. Equal Opportunity/Discrimination.	[5, 6]	PSILCA

	46. Strength of policies in place to protect cultural heritage. 47. Is information from the relevant organization available to community members in their spoken language(s)? 48. Contribution to the development economy. 49. Community engagement.	[5, 6]	PSILCA
	50. Presence of publicly available documents such as promises or agreements on sustainability. 51. Organizational engagement to present an annual progress report. 52. Management of Hazardous Materials. 53. No use of deceptive marketing. 54. Access to material resources. 55. Access to intangible resources.	[5, 6]	PSILCA
	56. Organizational support (volunteer-hours or financial) for community initiatives. 57. Number and quality of meetings with community stakeholders. 58. The organization cooperates with internal/external entities to prevent corruption. 59. The organization carries out an anti-corruption program. 60. Statements or documented procedures to avoid involvement or complicity in anti-competitive behavior. 61. Employee awareness of the importance of compliance with competition law. 62. Timely payments to suppliers. 63. Presence of an explicit code of conduct protecting the human rights of workers among suppliers. 64. Participation of suppliers audited in social responsibility in the last year. 65. Support to suppliers in raising awareness and advising on social responsibility. 66. Adherence to an initiative that promotes social responsibility along the supply chain. 67. Prevention and mitigation of armed conflict. 68. Freedom of expression in the company. 69. Respect for intellectual property rights.	[5, 8]	SHDB

5. Conclusion

In order to evaluate the use of the methodology "Social Life Cycle Assessment (SLCA)" and social indicators in the textile industry, two questions were sought, being them: Q1 - Is SLCA used in the textile industry? How and what results were found? and Q2 - What indicators are presented in the literature for use in the textile industry?
In this way, based on the documents evaluated, we identified that the SLCA has been used in the textile industry at a slow pace, we can see this through the low number of articles found in the Scopus database from the search terms listed.
Even though the number of documents found was low (three), sixty nine (69) indicators were identified, distributed in twelve of the seventeen Sustainable Development Goals.
It was also identified that there is a lack of research in the area covered by this article, which opens a vast field for future research.

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Conference on Performance Management

Review of prior art in patents authored by Brazilian inventors on life cycle assessment

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Abstract. The evaluation of organizational performance is an important mechanism for conducting an adequate management of companies in their businesses and processes. In this scenario, environmental aspects become of paramount importance for the success of organizational sustainability, where life cycle analysis, whose standards were introduced by ISO in the 14000 series, is an important tool to be used. The research of this article, which is exploratory, aims to investigate the scenario of patents on life cycle analysis, by identifying the existence of 190 patent processes with Brazilian inventors in the Espacenet database. Analyzing each of the results individually, it was possible to identify that most patent processes have their publication originated in the United States and the most used international patent classification is "Medicinal preparations containing organic active ingredients" (A61 K31/00). It was also found that the oldest process dates from 1990, and the holder with the highest number of processes is the company Human Genome Sciences. The mention of life cycle analysis is found in different approaches in the identified processes, being detailed throughout the work analysis. The review of patent processes made it possible to map the technological advances linked to life cycle analysis, identifying that the system is still little explored and can present competitive advantages for the organizational management that uses it.

Keywords
Organizational performance; Life cycle analysis; patents; Espacenet.

1. Introduction

Organizational performance nowadays looks beyond the aspect of the profitability of the business, passing through several variables, including the environmental aspect, but not limited to this area. In this sense, sustainability must support economic growth, social development and environmental protection, thus creating business advantages [1].

In the search for sustainable development, environmental issues become fundamental, a process that, in addition to accelerating industrialization, also tends to mitigate possible harmful effects on sustainability. Since then, processes focused on an eco-efficient perspective have been initiated in environmental management systems, such as ISO 14001, in addition to the elaboration of environmental performance analyses, life cycle assessment, among others [2,3].

Life Cycle Assessment can be a leading tool to guide sustainable development strategies [4]. For this reason, looking at such a tool from the perspective of patents becomes relevant for a promising and effective management of organizational performance under the concept of innovation.

1.1. *Life Cycle Analysis and patents*

To support decision making, methods have been developed to assess environmental impacts in the life cycle of products, processes or activities, where the Life Cycle Assessment method has been applied as a management tool, pointing out the loads environmental issues and the potential impacts involved in the process [5].

According to ISO, the objective of an environmental management system is to control or influence the way in which the organization's products and services are designed, manufactured, distributed, consumed and discarded, using a life cycle perspective that can prevent the involuntary displacement of environmental impacts within the life cycle, still achieving financial and operational benefits that can result from the implementation of environmental alternatives that reinforce the organization's position on the market, among others [6].

Studies have shown that there is an increase in the production of clean technology inventions, thus expanding the rapid growth of patents, indicating that this area is one of those that has contributed a lot to the next technological advances. This can be seen as a result of favorable institutional environments to promote the development of clean technologies and innovation [7].

The use of information contained in patents is suitable for innovation studies, as such data can be classified into detailed technological fields and have been successfully applied in empirical research using data from the United States and the European Union. Patent information and data can be used to address determinants of the rate and direction of technological progress [8].

Patents are titles granted by the State, with temporary validity to the holders of patent processes, who, after the granting of the patent application, begin to exercise territorial exclusivity over the technology object of the process. In Brazil, patents are divided between invention patents and utility model patents, which are valid for 20 years and 15 years, respectively, from the filing date. After the concession by the State, which occurs through a declarative act, once the legal requirements are present, the patent holder can exploit it commercially in an exclusive way throughout the national territory [9].

This study aimed to identify the patent processes of Brazilian inventors related to life cycle analysis. As a reminder, the rest of the article is structured as follows: Section 2 describes the methodology used in data collection, while Section 3 presents the results and analysis of the 190 identified patent cases. Finally, in Section 4 we indicate the conclusions of the work.

2. Methodology

Based on the understanding that patents can signal the development of innovations, a prior art search was carried out in a patent database with the objective of identifying the state of the art. Through an exploratory research, the database of the European Patent Office (EPO) was determined, whose Espacenet base provides data on patent processes from more than 80 countries, including Brazil. The base used can be considered one of the most complete in the world, as it contains information on over 130 million patent documents. Access can be made free of charge through the link *worldwide.espacenet.com*. The search used the terms "life AND cycle AND assessment" in all search fields and was filtered by "Inventors" and country "Brazil". The data were obtained in a search carried out on March 27, 2022. The results were treated in this work as processes as they include both patent applications, granted patents and even public domain patents.

3. Results

The search to identify technologies that are related to life cycle analysis, developed by Brazilian inventors, resulted in 190 patent processes. As it is possible to identify in Figure 1, most of the processes are about methods, composition, use and systems.

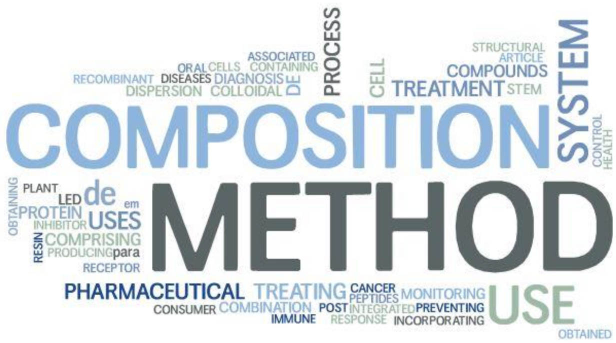

Figure 1 : Word cloud from title

The oldest application that met the search criteria was deposited in the Instituto Nacional da Propriedade Industrial (INPI) on April 17, 1990, authored and applicanted by Celso Savalli Gomes, having as title "Filtros removedores de sulfeto de hidrogênio e/ou desnitrificadores-desfosfatizadores", under process number BR9001841.

The applicants with the highest number of cases are the american company Human Genome Sciences ("HUMAN GENOME SCIENCES INC [US]") with 10 processes, followed by Fundação Oswaldo Cruz ("FUNDACAO OSWALDO CRUZ [BR]" or "FUND OSWALDO CRUZ FIOCRUZ SUPERINTENDENCIA DE PLANEJAMENTO [BR]"), with 8 processes.

Most of the cases are published in the United States (101 cases), followed by several other countries or offices: European Property Office (37), Canada (24) and Brazil (10), even considering the cases whose entry occurs via World Intellectual Property Office (109). It is necessary to note that the same technology may be present in more than one country, if protection has been requested by its applicant in more than one territory.

Looking at the International Patent Classification (IPC) is an important tool in patent processes, because it organizes and facilitates access to technological information contained in documents. Through the identification of the most used classifications we can detect the appointment of Key Performance Indicators (KPIs) to evaluate the development of technologies in different sectors. The most used classifications in the 190 cases, considering the IPC are those indicated in table 1. It is also possible to verify in the referred table the "total uses", which indicates how many times each of the classifications was used in the 190 identified patent processes.

Table 1: IPC description

Classification symbol	Description	Total Uses
A61K31/00	Medicinal preparations containing organic active ingredients	53
A61K38/00	Medicinal preparations containing peptides	38
C07K14/00	Peptides having more than 20 amino acids; Gastrins; Somatostatins; Melan otropins; Derivatives thereof	33
C12N15/00	Mutation or genetic engineering; DNA or RNA concerning genetic engineering, vectors, e.g. plasmids, or their isolation, preparation or purification;	31
A61K39/00	Medicinal preparations containing antigens or antibodies	30
G01N33/00	Investigating or analysing materials by specific methods	30

As can be seen, the most used classifications are those belonging to category A61, which describes technologies associated with “MEDICAL OR VETERINARY SCIENCE; HYGIENE”. It is important to note that each patent process can receive one or more classifications, according to the scope of its content.

The Brazilian inventor with the highest number of processes is identified as Reiner Gentz (“GENTZ REINER L [BR]”), consisting of 11 processes. Next we have Irina Kerkis (“KERKIS IRINA [BR]”) with 6 processes, followed by Paulo Anchieta da Silva (“DA SILVA PAULO ANCHIETA [BR]”), Fernando Dotta (“DOTTA FERNANDO [BR]”), Augusto Maria Durvanei (“MARIA DURVANEI AUGUSTO [BR]”), all with 4 processes each.

In table 2 we can check all 11 patent processes that count Reiner Gentz as at least one of the inventors.

Table 2: Processos de patentes de Reiner Gentz

Patent number	Title, inventors and applicants	Earliest priority
US2008274109A1 US7851596B2	**Myeloid Progenitor Inhibitory Factor-1 (MPIF-1), Monocyte Colony Inhibitory Factor (M-CIF), and Macrophage Inhibitory Factor-4 (MIP-4)** Inventors: GENTZ REINER L [BR]; and others / Applicants: HUMAN GENOME SCIENCES INC [US]	1993-12-22
US2004224387A1 US7232667B2	**Keratinocyte growth factor-2** Inventors: GENTZ REINER L [BR] and others / Applicants: HUMAN GENOME SCIENCES INC [US]	1995-02-14
US6693077B1	**Keratinocyte growth factor-2** Inventors: GENTZ REINER L [BR] and others / Applicants: HUMAN GENOME SCIENCES INC [US]	1995-02-14
US2009226456A1 US7709218B2	**Tumor Necrosis Factor Receptors 6 Alpha & 6 Beta** Inventors: GENTZ REINER L [BR]; and others / Applicants: HUMAN GENOME SCIENCES INC [US]	1997-01-14
US2003208044A1 US7041803B2	**Galectin 11** Inventors: GENTZ REINER L [BR]; and others / Applicants: HUMAN GENOME SCIENCES INC [US]; JOLLA INST ALLERGY IMMUNOLOG [US]	1997-01-21
US2004013664A1	**Tumor necrosis factor receptors 6 alpha & 6 beta** Inventors: GENTZ REINER L [BR]; and others / Applicants: GENTZ REINER L.; YU GUO-LIANG; NI JIAN; EBNER REINHARD; FENG PING; RUBEN STEVEN M.	1997-01-14
US2004136950A1 US2005112090A9 US7452538B2	**Death domain containing receptor 4** Inventors: GENTZ REINER L [BR]; and others / Applicants: HUMAN GENOME SCIENCES INC [US]; UNIV MICHIGAN [US]	1997-01-28
US2008241155A1 US8329179B2	**Death domain containing receptor 4** Inventors: GENTZ REINER L [BR]; and others / Applicants: UNIV MICHIGAN [US]; NI JIAN [US]; ROSEN CRAIG A [CA]; PAN JAMES G [BR]; GENTZ REINER L [US]; DIXIT VISHVA M [US]; HUMAN GENOME SCIENCES INC [US]	1997-01-28
US2005244857A1 US7476384B2	**Death domain containing receptor 4** Inventors: GENTZ REINER L [BR]; and others / Applicants: HUMAN GENOME SCIENCES INC [US]; UNIV MICHIGAN [US]	1997-01-28
US2007203070A1 US7781176B2	**28 HUMAN SECRETED PROTEINS** Inventors: GENTZ REINER L [BR]; and others / Applicants: HUMAN GENOME SCIENCES INC [US]	1997-03-14

US2005037966A1	**Keratinocyte growth factor-2** Inventors: GENTZ REINER L [BR]; and others / Applicants: HUMAN GENOME SCIENCES INC [US]	2001-01-08

When we look at the most used classifications from the processes of Brazilian inventors with more results, we have for Reiner L Gentz the classifications C07K14 and A61K38, both among the most used classifications in the total of processes of the search performed. Also highlighted is the classification C07K16, corresponding to Immunoglobulins, e.g. monoclonal or polyclonal antibodies, as show in Figure 2.

Figure 2: main IPC from inventor Rener Gentz's processes

In table 3 we can see the details of the patent processes that are included in the inventor Irina Kerkis.

Table 3: Processos de patentes de Irina Kerkis

Patent number	Title, inventors and applicants	Earliest priority
WO2014141210A2 WO2014141210A3	**MULTIFUNCTIONAL IMMATURE DENTAL PULP STEM CELLS AND THERAPEUTIC APPLICATIONS** Inventors: KERKIS IRINA [BR] and others / Applicants: AVITA INT LTD [GB]; KERKIS IRINA [BR]; GLOZMAN SABINA [IL]	2013-03-15
US11278574B2 US2019000887A1	**USE OF STEM CELLS EXPRESSING MESENCHYMAL AND NEURONAL MARKERS AND COMPOSITIONS THEREOF TO TREAT NEUROLOGICAL DISEASE** Inventors: KERKIS IRINA [BR] and others / Applicants: AVITA INT LTD [VG]; FUND BUTANTAN [BR]	2013-03-15
US2019010462A1	**STEM CELLS EXPRESSING MESENCHYMAL AND NEURONAL MARKERS, COMPOSITIONS THEREOF, AND METHODS OF PREPARATION THEREOF** Inventors: KERKIS IRINA [BR] and others / Applicants: AVITA INT LTD [VG]; FUND BUTANTAN [BR]	2013-03-15
US11207352B2 US2016184366A1	**COMPOSITIONS COMPRISING STEM CELLS EXPRESSING MESENCHYMAL AND NEURONAL MARKERS AND USES THEREOF TO TREAT NEUROLOGICAL DISEASE** Inventors: KERKIS IRINA [BR] and others / Applicants: AVITA INTERNAT LTD [VG]; FUND BUTANTAN [BR]	2013-03-15
EP3936609A1	**STEM CELL COMPOSITIONS AND METHODS OF PRODUCING STEM CELLS FOR THERAPEUTIC APPLICATIONS** Inventors: KERKIS IRINA [BR] and others / Applicants: AVITA INT LTD [VG]; FUND BUTANTAN [BR]	2014-08-14
RU2018134710A RU2018134710A3 RU2741839C2	**STEM CELLS EXPRESSING MESENCHYMAL AND NEURONAL MARKERS, COMPOSITIONS THEREOF AND METHODS OF PRODUCING SAID MESENCHYMAL AND NEURONAL MARKERS** Inventors: KERKIS IRINA [BR] and others / Applicants: AVITA INTERNESHNL LTD [VG]	2016-03-09

Irina Kerkis has in her patent processes the classifications C12N5 (Undifferentiated human, animal or plant cells, e.g. cell lines; Tissues; Cultivation or maintenance thereof; Culture media therefor) and A61K35 (Medicinal preparations containing materials or reaction products thereof with undetermined constitution) , with greater intensity, as seen in Figure 3.

Figure 3: main IPC from inventor Irina Kerkis's processes

In table 4 are located the processes of Paulo Anchieta da Silva and Fernando Dotta, as they appear as inventors in the same processes.

Table 4: Processos de patentes de Paulo Anchieta da Silva e Fernando Dotta

Patent number	Title, inventors and applicants	Earliest priority
WO2015192194A1	**STRUCTURAL HEALTH MONITORING SENSORY ARRANGEMENT INTEGRATED WITHIN A SELF-HEALING SYSTEM** Inventors: DA SILVA PAULO ANCHIETA [BR] DOTTA FERNANDO [BR] and others / Applicants: EMBRAER SA [BR]	2014-06-19
WO2016065446A1	**METHOD AND SYSTEM FOR STRUCTURAL HEALTH MONITORING WITH FREQUENCY SYNCHRONIZATION** Inventors: DA SILVA PAULO ANCHIETA [BR]; DOTTA FERNANDO [BR] and others / Applicants: EMBRAER SA [BR]; FACULDADES CATÓLICAS [BR]	2014-10-28
EP3096123A1 EP3096123B1	**INTEGRATED SYSTEM AND METHODS FOR MANAGEMENT AND MONITORING OF VEHICLES** Inventors: DA SILVA PAULO ANCHIETA [BR]; DOTTA FERNANDO [BR] and others / Applicants: EMBRAER SA [BR]	2015-05-19
US10149631B2 US2017021918A1	**STRUCTURAL HEALTH MONITORING SENSORY SYSTEM INTEGRATED TO A SELF-ADAPTING MORPHING SYSTEM** Inventors: DA SILVA PAULO ANCHIETA [BR]; DOTTA FERNANDO [BR] and others / Applicants: EMBRAER SA [BR]	2015-07-24

These, in turn, highlight more intensely the classifications G01N29 (Investigating or analyzing materials by the use of ultrasonic, sonic or infrasonic waves; Visualization of the interior of objects by transmitting ultrasonic or sonic waves through the object) and and G01M5 (Investigating the elasticity of structures, e.g. deflection of bridges or aircarft wings). according to figure 4.

Figure 4: main IPC from inventosr Paulo A. Silva's and Fernando Dotta's processes

Finally, we observe the detailing of Maria Durvanei Augusto's patent processes, in table 5.

Table 5: Processos de patentes de Maria Durvanei Augusto

Patent number	Title, inventors and applicants	Earliest priority
EP2054365A2 EP2054365A4 EP2054365B1	**METHODS TO PREPARE PENTA-1,4-DIEN-3-ONES AND SUBSTITUTED CYCLOHEXANONES AND DERIVATIVES WITH ANTITUMORAL AND ANTIPARASITIC PROPERTIES, THE COMPOUNDS AND THEIR USES** Inventors: MARIA DURVANEI AUGUSTO [BR] and others / Applicants: UNIBAN UNIVERSIDADE BANDEIRANTE DE SÃO PAULO [BR]; FUNDAÇÃO DE AMPARO PESQUISA DE SÂO PAULO FAPESP [BR]	2006-07-06
CN101142232A CN101142232B	**KUNITZ-type recombinant inhibitor** Inventors: MARIA DURVANEI AUGUSTO [BR] and others / Applicants: UNIÃO QUIMICA FARMACEUTICA NAC [BR]; FAPESP FUNDAÇÃO DE AMPARO A; CHUDZINSKI TAVASSI ANA MARISA	2004-09-15

EP2441452A1 EP2441452A4 EP2441452B1	**PHARMACEUTICAL COMPOSITION AND USE OF THE PHARMACEUTICAL COMPOSITION FOR THE TREATMENT, PROPHYLAXIS OR PREVENTION OF NEOPLASTIC DISEASES IN HUMANS AND ANIMALS** Inventors: MARIA DURVANEI AUGUSTO [BR] and others / Applicants: UNIV BANDEIRANTE DE SAO PAULO ACADEMIA PAULISTA ANCHIETA S C LTDA [BR]; JOSE AGUSTIN QUINCOCES SUAREZ [BR]; DURVANEI AUGUSTO MARIA [BR]; PAULO CELSO PARDI [BR]; FERNANDA FAIAO FLORES [BR]; REGINALDO PEREIRA SANTOS [BR]; DANIELA GONCALES RANDO [BR]; UNIV ANHANGUERA DE SAO PAULO UNIAN SP [BR]; FUND DE AMPARO A PESQUISA DO ESTADO DE SAO PAULO FAPESP [BR]	2009-06-09
WO2020041851A2 WO2020041851A3	**PHARMACEUTICAL COMPOSITION, PROCESS FOR OBTAINING AND USING SECONDARY METABOLITES PRODUCED BY THE FUNGUS EXSEROHILUM ROSTRATUM IN CELL REGENERATION** Inventors: MARIA DURVANEI AUGUSTO [BR] and others / Applicants: INST BUTANTAN [BR]	2018-08-31

Among Maria Durvanei Augusto's processes, the most used classification is A61K31, which is among the most used classifications in the total number of processes of the search performed. Subsequently, the classifications with greater intensity are C07C45 and C07C49, which indicate Preparation of compounds having C=O groups bound only to carbon or hydrogen atoms; Preparation of chelates of such compounds; and Ketones; Ketenes; Dimeric ketenes; Ketonic chelates; respectively, as can be seen in Figure 5.

Figure 5: main IPC from inventosr Maria Durvanei Augusto's processes

When we observe the classifications with greater intensity only among the inventors highlighted with the largest number of processes, we will find the classifications highlighted in Figure 6.

Figure 6: rankings among inventors with the highest number of processes

The International Patent Classification separates technologies into eight technology groups, which are identified by the letters A through H [10]. We observed in this research that the group with the highest classification intensity in the patent processes is the letter C, which includes technologies from the Chemistry and Metallurgy sectors. Next, we have the A classification, where the technologies identified by Human Needs are classified.

Finally, it was observed that among the 190 results, only one process was specifically directed to the environmental issue through the use of the term "environmental" in the title, being entitled "Unit for producing pozzolanic cement of low environmental impact, obtained from mixed construction and demolition waste (cdw), process and resulting products for civil engineering", publication number WO2015081402A1. This process has as applicant the company Intercement Brasil and the Universidade Federal de São Carlos, having as inventors the brazilians Valdecir Angelo Quarcioni, Sergio Cirelli Ângulo e Mario Sérgio Guilgue.

4. Conclusion

Looking at patent processes is fundamental for organizational performance management, because the use of such information allows mapping technologies, evaluate investments and indicate technological trends.

Throughout the work, we observed that the analysis of the life cycle between the patent processes of Brazilian inventors is related to the chemical areas, including pharmaceuticals and the area of human needs, with a greater tendency in the development of specific technologies. Knowing that there is an academic tendency to relate life cycle studies to environmental issues, this hypothesis is not confirmed when evaluating the patent processes of Brazilian inventors.

Of the 190 processes found in the search carried out on the Espacenet database, we had five inventors who stood out with the highest number of processes, which originate in different countries: Reiner Gentz, Irina Kerkis, Paulo Anchieta da Silva, Fernando Dotta and Augusto Maria

Durvanei.

The most used international patent classification in all 190 cases is "*Medicinal preparations containing organic active ingredientes*" (A61 K31/00), while if we consider only the processes of the five greatest inventors it is "*Peptides having more than 20 amino acids; Gastrins; Somatostatins; Melanotropins; Derivatives thereof*" (C07K14). It was also observed that the oldest process dates from 1990, and the applicant with the largest number of processes is the company Human Genome Sciences.

Future studies can assess the status of the processes, that is, an in-depth assessment of whether they have been granted, are in force or are already in the public domain. Furthermore, expanding the study to other countries besides Brazil shows an interesting perspective. as it will allow to describe the global situation of sustainable development.

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