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Advances in Production Management Systems

Production Management Systems for Responsible Manufacturing, Service, and Logistics Futures

IFIP WG 5.7 International Conference, APMS 2023
Trondheim, Norway, September 17–21, 2023
Proceedings, Part I

Part I

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Editors

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Preface

The year 2023 has undoubtedly been a year of contrasts. We are experiencing stunning developments in technology, and creating new products, services, and systems that are changing the way we live and work. Simultaneously, we are experiencing multiple conflicts around the world and the brutal effects of climate change. While many experience success and improved standards of living, others face threats to their lives and even loss. A Scientific Conference cannot change this but can be seen as a symbol for aiming for a different future. We create new knowledge and solutions, we share all our achievements, and we meet to create new friendships and meet people from all over the world.

The International Conference on "Advances in Production Management Systems" (APMS) 2023 is the leading annual event of the IFIP Working Group (WG) 5.7 of the same name. At the Conference in Trondheim, Norway, hosted by the Norwegian University of Science and Technology (NTNU), more than 200 papers were presented and discussed. This is a significant step up from the first APMS Conference in 1980, which assembled just a few participants. The IFIP WG5.7 was established in 1978 by the General Assembly of the International Federation for Information Processing (IFIP) in Oslo, Norway. Its first meeting was held in August 1979 with all its seven members present. The WG has since grown to 108 full members and 25 honorary members.

After 43 years, APMS has returned to the city where it started. The venue in 1980 was Lerchendal Gård, and the topic marked the turn of a decade: "Production Planning and Control in the 80s". The papers presented attempted to look into the future – a future which at that time was believed to be fully digitalized. One foresaw that during the coming decade, full automation and optimization of complete manufacturing plants, controlled by a central computer, would be a reality. The batch processing of production plans would be replaced by online planning and control systems.

No other technology can show a more rapid development and impact in industry and society than Information and Communication Technology (ICT). The APMS 2023 program shows that the IFIP WG5.7 still can make and will continue to make a significant contribution to production and production management disciplines.

In 2023, the International Scientific Committee for APMS included 215 recognized experts working in the disciplines of production and production management systems. For each paper, an average of 2.5 single-blind reviews were provided. Over two months, each submitted paper went through two rigorous rounds of reviews to allow authors to revise their work after the first round of reviews to guarantee the highest scientific quality of the papers accepted for publication. Following this process, 213 full papers were selected for inclusion in the conference proceedings from a total of 224 submissions.

APMS 2023 brought together leading international experts from academia, industry, and government in the areas of production and production management systems to discuss how to achieve responsible manufacturing, service, and logistics futures. This included topics such as innovative manufacturing, service, and logistics systems characterized by their agility, circularity, digitalization, flexibility, human-centricity, resiliency, and smartification contributing to more sustainable industrial futures that ensure that products and services are manufactured, servitized, and distributed in a way that creates a positive effect on the triple bottom line.

The APMS 2023 conference proceedings are organized into four volumes, covering a large spectrum of research addressing the overall topic of the conference “Production Management Systems for Responsible Manufacturing, Service, and Logistics Futures”.

We would like to thank all contributing authors for their quality research work and their willingness to share their findings with the APMS and IFIP WG5.7 community. We are equally grateful for the outstanding work of all the International Reviewers, the Program Committee Members, and the Special Sessions Organizers.

September 2023

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Contents – Part I

A Proposal for Production Scheduling Optimization Method with Worker Assignment Considering Operation Time Uncertainty

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Abstract. In a make-to-order factory, the top priority is to meet due date determined in advance through consultation with the customer. However, due to the low degree of repetitiveness of work in each process, work performance tends to fluctuate against the predetermined standard time. This uncertainty in operation time can prevent production from proceeding as planned and affect due dates. In addition, since the work in each process depends on the ability of the worker in charge of it, it is important to consider the worker's ability appropriately. In this study, we propose a scheduling optimization method that includes worker assignment under operation time uncertainty. The method formulates a job shop scheduling problem that takes into account worker skill and operation time uncertainty, and minimizes the expected total tardiness and operation time variance. In experiments, we evaluate the effectiveness of the proposed method by solving problems with various levels of uncertainty and several combinations of workers.

Keywords: Job shop scheduling · Worker assignment · Total tardiness · Uncertainty

1 Introduction

Nowadays, many factories have begun involving advanced information technologies and knowledge discovering methods to facilitate information flow, with the main need to deal with the large volume of data which are generated and collected from manufacturing processes and its related operations [1]. One example is the tracking of products by RFID systems, which facilitates the acquisition and use of various data from processes in factories [1, 2]. On the other hand, the manufacturing industry has been increasing the variety of their products and shortening delivery times in order to meet diverse customer needs [3]. In a production environment that is becoming increasingly complex due to the

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diversification of production types, production planning and scheduling are important in order to satisfy customer requirements [4]. In a make-to-order factory, the top priority is to meet due date determined in advance through consultation with the customer. In the case of individual production in the job shop process, not all tasks are performed automatically by machines, and some tasks require intervention by workers. However, in the case of individual production in the job store process, not all tasks are performed automatically by machines, and some tasks require intervention by workers. In addition, because the specifications vary greatly from product to product [5], the repetitiveness of work in each process is low. Therefore, the work performance tends to fluctuate against the predetermined standard time [6]. This variation in work performance could prevent production from proceeding as planned, and result in tardiness [6]. In addition, the work efficiency depends on the skills of each worker [4, 6]. And the difference in work efficiency can be visualized by the aforementioned recent sensing technology. Therefore, in general job shop scheduling problems, workers are ignored in the modeling, but it is important to consider them. Based on the above, in production scheduling, it is necessary to minimize the risk of tardiness by taking into account in advance the skill level of each worker and the variation in the processing time of each process. In this paper, we propose a production planning method that considers both worker allocation and production scheduling, and aims to minimize tardiness by taking into account the variation in work performance that occurs in manual operations with workers.

2 Target Model

2.1 Factory

In this study, our target factory is a job shop-type process as shown in Fig. 1. The characteristics of job, machine and worker in the factory are as follows:

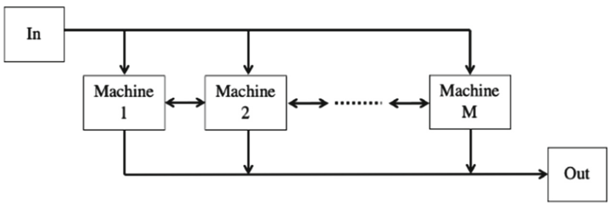

Fig. 1. Job shop model

Job:

- All jobs are known at the beginning of the production.
- Each job is processed by multiple processes.
- The number and order of the processes required to complete a job varies for each job.
- Each process uses both human operators (workers) and automated machines.

Machine:

- All machines can be used from the start of production.
- The machine that processes each process of a job is predetermined.
- No interruption occurs during job processing.
- No machine failure occurs.

Worker:

- All workers can work from the start of production.
- The worker can move between machines and can operate all machines.
- Once a worker starts a manual operation on a machine, he cannot move from the machine until the manual operation is completed.
- Travel time between machines is not considered.
- Workers' skill is classified into 3 levels: advanced, intermediate, and beginner.

2.2 Processing Time and Its Uncertainty in Manual Operations [7]

The processing time for each process defines the following characteristics:

- The processing time for each process of a job is the sum of the manual processing time by the worker and the automatic processing time by the machine.
- In each process, the ratio of standard manual operation time is pre-determined.

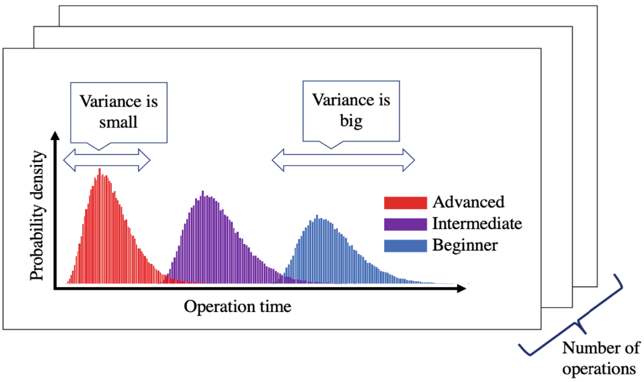

Fig. 2. An example of manual operation time distribution in each skilled type

In individual production process, specifications may differ for each product, and the manual operation performed by workers in each process tends to be fluctuated. Workers' abilities are not uniform, and work efficiency varies from worker to worker. Therefore, in this study, we model the uncertain manual operation time as a random variable. Since the actual work tends to be later than predetermined standard time, this study assumes that the manual operation time for each process follows an Erlang distribution [8]. The probability distribution differs depending on the task and the worker in charge. The higher the skill level of the worker, the smaller both the average and variance of the probability distribution are assumed to be Fig. 2 [9]. The probability distribution for each worker performing each process is assumed to be given.

3 Worker Allocation and Job Shop Scheduling Method Considering Uncertainty of Operation Time

The target problem of this study is to simultaneously determine the allocation of workers in charge of each process in addition to the general job shop scheduling problem [10]. In this study, we propose a production scheduling method that includes worker assignment considering the variation of processing time for each job. Since the manual operation time of each process varies, the proposed method considers the variation as a probability distribution and proposes a schedule that minimizes the sum of expected total tardiness and total processing time variance of each job. The proposed method performs job shop scheduling including worker assignment after pre-processing of scheduling. Section 3.1 defines the symbols used in the formulation of the proposed method. Section 3.2 provides an overview of the proposed method and its specific formulation.

3.1 Notation

The notations used in proposed method are shown as follows:

Parameters:

- j, p : job number $(j, p = 1, \ldots, J)$
- k, q : process number of each job $\left(k, q = 1, \ldots, K_j\right)$
- $m, m\prime$: machine number $(m, m\prime = 1, \ldots, M)$
- $i, i\prime$: worker number $(i, i\prime = 1, \ldots, I)$
- s : real number called scenario coefficient
- $S^{(UB)}$: upper limit of scenario coefficients
- $S^{(LB)}$: lower limit of scenario coefficients
- PM_{jk} : machine number to process the k th process of job j
- D_j : due date of job j
- PT_{jk} : standard total processing time of the k th process of job j
- APT_{jk} : automatic processing time of the k th process of job j
- $Mode_{jkmi}$: mode of manual operation time for the k th process of job j at machine m by worker i
- V_{jkmi} : variance of manual operation time for the k th process of job j at machine m by worker i
- σ_j : assumed standard deviation of total processing time for job j
- γ_{jk} : standard ratio of manual operation time to total processing time PT_{jk}
- $BigM$: sufficiently large positive number
- W_1 : weight of the first term of the objective function
- W_2 : weight of the second term of the objective function
- Δs : step size of scenarios (constant number)

Variables:

- ST_{jk} : processing start time of the k th process of job j
- CT_{jk} : processing completion time of the k th process of job j
- C_{jkmi} : completion time of the k th process of job j by worker i at machine m

- $T_j^{(+s\sigma)}$: tardiness of job j when scenario coefficient is s
- ET_j : expected value of tardiness of job j
- $X_{jkpq} : \begin{cases} 1 : ifthekthprocessofjobjprecedestheqthprocessofjobp \\ 0 : otherwise \end{cases}$
- $Y_{jkmi} : \begin{cases} 1 : ifworkeriprocessesthekthprocessofjobjatmachinem \\ 0 : otherwise \end{cases}$

In the proposed method, the decision variables are ST_{jk}, X_{jkpq}andY_{jkmi}.

3.2 Algorithm of Proposed Method

The proposed method creates a schedule in the following steps.

STEP1. Initialization of standard deviation of processing time for each job.

STEP2. Worker assignment and job shop scheduling.

First, in **STEP1**, the standard deviation of processing time for each job is initialized in order to solve the scheduling problem in **STEP2.** Next, in **STEP2**, job shop scheduling including worker allocation is performed**.** In **STEP2**, the standard deviation of the processing time of each job calculated in **STEP1** is taken into account, and the worker assignment and schedule that minimize the difference between the expected total tardiness and the processing time variance are obtained. Details of each are described below.

Initialization of standard deviation of processing time for each job (STEP1) This method attempts to minimize the expected total tardiness by considering the probability distribution of the processing time of each job. However, the distribution of the completion time of each job is unknown unless the worker assignment is determined. In addition, if the standard deviation is formulated at the scheduling stage, it becomes a nonlinear problem and is difficult to find a solution. Thus, the scheduling problem is formulated as a linear programming problem by calculating the assumed value of the standard deviation in **STEP1**. In **STEP 1**, the worker processes each operation is unknown. Therefore, the standard deviation of the processing time for each job is calculated assuming that all processes are processed by the intermediate skill workers. The processing time for each process follows an independent Erlang distribution. Since the Erlang distribution is regenerative, the assumed standard deviation of the processing time for each job j (σ_j) is given by the Eq. (1). V_{jkmi} uses the intermediate worker's value.

$$\sigma_j = \sqrt{\sum\nolimits_k V_{jkmi}\{m = PM_{jk}\}} \tag{1}$$

Worker assignment and scheduling optimization phase (STEP2)
The formulation of the job shop scheduling problem, including worker assignment, is described below. This method considers the uncertainty in the processing time of each process and aims to derive a schedule that is optimal with robustness. Therefore, the proposed method minimizes the sum of the expected total tardiness and the standard

deviation of the total processing time. The former is an index focusing on optimality, while the latter is an index focusing on improving robustness. In this study, the weighted sum of these two indices is used as the objective function.5

Objective functions

$$min.\ \ W_1 * F_1 + W_2 * F_2(2) \tag{2}$$

$$where\ \ F_1 = \sum\nolimits_{j=1}^{J} ET_j \tag{3}$$

$$ET_j = \sum\nolimits_{s=S^{(LB)}}^{S^{(UB)}} p_{jt} * T_j^{(+s\sigma)} * \sigma_j * \Delta s\{\forall j\} \tag{4}$$

$$T_j^{(+s\sigma)} = CT_{jK_j} + s * \sigma_j - D_j\{\forall j\} \tag{5}$$

$$F_2 = \sum\nolimits_{j=1}^{J} \left\{ \sum\nolimits_{k=1}^{K_j} \sum\nolimits_{i=1}^{I} \sum\nolimits_{m=1}^{M} V_{jkmi} * Y_{jkmi} \right\} \tag{6}$$

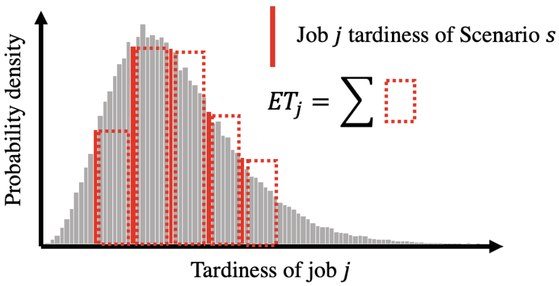

Fig. 3. An example of approximate calculation of expected job tardiness

Equation (2) is the objective function and represents the weighted sum minimization of the two indices. Equation (3) shows the sum of the expected total tardiness, and Eq. (4) is the definition of the expected tardiness for each job. As shown in Fig. 3, these expected values are approximated using several possible scenarios of tardiness of jobs. The tardiness for each scenario used in Eq. (4) is defined by Eq. (5). The constant s (defined as the scenario coefficient) indicates how early or late the completion time of a job is relative to the standard completion time in a scenario. As an example, Fig. 4 shows the scenario with $s = 1$. CT_{jK_j} is the standard completion time. It is the value when all jobs are done in the standard processing time. And, p_{jt} is the probability of tardiness of job j in the scenario coefficient s. The second term of the objective function is then the sum of the variance of the total processing times for each job defined by Eq. (6).

Definition and Constraint:

$$where\ \ APT_{jk} = PT_{jk} * \left(1 - \gamma_{jk}\right)\{\forall j, k\} \tag{7}$$

$$CT_{jk} = C_{jkmi} + APT_{jk}\left\{\forall j, k, m = PM_{jk}, i = PW_{jk}\right\} \tag{8}$$

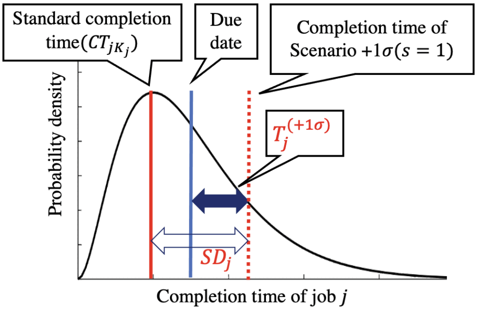

Fig. 4. An example of job completion time and tardiness for scenario $+1\sigma(s = 1)$

$$C_{jkmi} = ST_{jk} + Mode_{jkmi}\{\forall j, k, m = PM_{jk}, i = PW_{jk}\} \tag{9}$$

$$s.t. \quad \sum\nolimits_{j=1}^{J}\sum\nolimits_{k=1}^{K_j}\sum\nolimits_{i=1}^{I} Y_{jkmi} = 1\{m = PM_{jk}\}(10) \tag{10}$$

$$ST_{j(k+1)} \geq CT_{jk}\{\forall j, k\}(11) \tag{11}$$

$$ST_{jk} \geq CT_{pq} - BigM\left(1 - X_{jkpq}\right) - BigM\left(2 - Y_{jkmi} - Y_{pqmi'}\right) \tag{12}$$

$$\{m = PM_{jk} = PM_{pq}, j \neq p, \forall k, q, i, i'\}$$

$$ST_{pq} \geq CT_{jk} - BigM * X_{jkpq} - BigM\,(2 - Y_{jkmi} - Y_{pqmi'}) \tag{13}$$

$$\left\{m = PM_{jk} = PM_{pq}, j \neq p, \forall k, q, i, i'\right\}$$

$$ST_{jk} \geq C_{pqm'i} - BigM\left(1 - X_{jkpq}\right) - BigM\left(2 - Y_{jkmi} - Y_{pqmi'}\right)$$

$$\{m = PM_{jk}, m' = PM_{pq}, j \neq p, \forall k, q, i, i'\} \tag{14}$$

$$ST_{pq} \geq C_{jkmi} - BigM * X_{jkpq} - BigM\left(2 - Y_{jkmi} - Y_{pqmi'}\right)$$

$$\{m = PM_{jk}, m' = PM_{pq}, j \neq p, \forall k, q, i, i'\} \tag{15}$$

Equation (7) defines the machine processing time, the length of which is a constant determined by the standard total processing time PT_{jk} and standard ratio of manual operation time γ_{jk}. Equation (8) defines the completion time of the k th process of job j, and Eq. (9) defines the manual completion time of the k th process of job j. Equations (10) to (15) are constraints. Equation (10) is a constraint that guarantees that each process is always processed by one worker. Equation (11) is a constraint on the precedence relation between processes of the same job. Equations (12) and (13) are precedence constraints for jobs in the same machine, which guarantee that no more than two jobs are processed simultaneously by the same machine. Equations (14) and (15) are precedence constraints for jobs in the same worker, which guarantee that the same operator does not perform two or more operations at the same time.

4 Computational Experiments

In order to evaluate the performance of the proposed method, two types of computational experiments are performed. First, we compare the performance of the proposed method with considering uncertainty of the processing time and the conventional deterministic method without considering uncertainty. Next, we apply the proposed method to combinations of workers with various skill levels and evaluate the characteristics of the proposed method. In each experiment, we solve the optimization problem expressed in the formulation described in Sect. 3 using the branch-and-bound method with IBM ILOG CPLEX 12.10 [11] to produce a schedule. Then, the planned schedules are evaluated by simulating the operation phase of actual factory with variable manual operation time for workers as shown in Sect. 4.1.

4.1 Operation Phase Simulation

In order to calculate the operational results for the proposed schedule, an operational simulation is performed under the following conditions. The manual operation time for each process is randomly determined based on the Erlang distribution, which is determined by the planned worker assignment and the skill level of the worker. The manual operation time may be extended or shortened relative to the plan, in which case the proposed schedule is modified according to the constraints described below.

- **Machine change constraint**: Even if work on a job is delayed, the job is not assigned to another machine and continues to work on the same machine.
- **Worker change constraint**: Even if work on a job is delayed, the worker who processes the job is not changed and the job continues to be processed.
- **Processing order change constraint**: If a preceding job on the same machine or by the same worker is delayed, the job is interrupted and work continues without interrupting the work of another subsequent job.
- **Start time change constraint**: If the completion time of the preceding job of the same machine or the same worker is earlier, the start time of the subsequent job is brought forward as much as possible.

4.2 Experiment 1: Performance Comparison of Proposed Method and Conventional Deterministic Methods

In Experiment 1, we compare the performance of the proposed method with considering uncertainty of the processing time and the deterministic method without considering uncertainty. The effects of changing the level of uncertainty are also compared.

Experimental Conditions

The experiments are performed with the following conditions. $[a, b]$ means that it is an integer constant between a and b.

- The number of jobs (J) : 6
- The number of processes for each job (K_j): [1, 4]
- The number of machines (M) : 6
- The number of workers (I) : 3 (A, B, C) = (1, 1, 1), (0, 3, 0)

The advanced level is denoted as A, the intermediate level as B, and the beginner level as C.

- Processing time for each process $\left(PT_{jk}\right)$: [5, 30]
- Due date of each job $\left(D_j\right)$: $1.2 * \sum_k PT_{jk}$
- Standard ratio of manual operation time to total processing time (γ_{jk}) : 0.5
- Weight of objective functions (W_1, W_2) :(100,1)
- The range of scenario of uncertainties: $[-2\sigma, +2\sigma]$
- The step size of scenarios : 1σ
- Number of simulations: 1000

In this experiment, the variance of the workers' operation time for each process is varied in order to evaluate the influence of the uncertainty in the proposed method. Experiments are conducted on the 8 cases shown in Table 1 regarding the standard deviation of the processing time when workers of each skill level process the processes. Case 1 has the lowest level of uncertainty, and Case 8 has the highest level of uncertainty.

Table 1. Conditions for standard deviation of processing time for each process at each skill level

	Advanced	Intermediate	Beginner
Case 1	0.00	0.00	0.00
Case 2	0.35	0.43	0.50
Case 3	0.71	0.87	1.00
Case 4	1.41	1.73	2.00
Case 5	2.83	3.46	4.00
Case 6	4.24	5.20	6.00
Case 7	5.66	6.93	8.00
Case 8	7.07	8.66	10.00

Results

Table 2 shows the first term of the objective function, the total tardiness in the planning schedule (F_1) and the total tardiness and the standard deviation in the operational phase simulation ($TT^{(S)}$) against the planned schedule obtained by the proposed method considering uncertainty and the conventional deterministic method without considering uncertainty. Note that the results in Table 2 are for the worker condition (A, B, C) = (1, 1, 1) and Case 8 is used for the mode and variance of operation time for each process. Table 2 also shows the t and p values obtained from the two-tailed t test (degree of freedom 1998) at 5% level of significance for the results of the proposed method and the deterministic method. From Table 2, it has been confirmed that the proposed method reduces the total tardiness more than the comparison method. The results of the p-values obtained from the two-tailed t-test at the 5% level of significance indicate that there is a significant difference. In the proposed method, it is possible to reduce the total tardiness in the operation phase compared to the conventional deterministic method by making a production schedule that minimizes the total tardiness with considering the variation in the total processing time for each job.

Table 2. Comparison of total tardiness between planning schedules and simulation results of the proposed and deterministic methods

		Deterministic	Proposed	t-test	
				$t(1998)$	p-value
F_1		19	45		
$TT^{(S)}$	Avg.	65.23	54.98	11.14	5.2E-28
	S.D.	21.76	19.25		

Next, Table 3 shows a breakdown of the total tardiness obtained from simulations using the two methods. Figure 5 shows Gantt charts of the planning schedule developed using the proposed method and the deterministic method. The difference in Table 3 shows that the tardiness of Job1 was significantly reduced by the proposed method compared to the deterministic method. As shown in Table 3, Job1 has four processes, which is more than the other jobs, and has a large standard deviation in total processing time and a large uncertainty. Therefore, as shown in Fig. 5, the proposed method reduced the tardiness of Job1 compared to the deterministic method by deriving a schedule that advances the submission and completion times of Job1, which has a large uncertainty.

Table 3. Tardiness for each job in the simulation results of the two methods of operation

	Job index	Number of Processes	Deterministic	Proposed	Diff
			Avg	Avg	
Job tardiness	Job1	4	9.67	2.15	7.52
	Job2	1	0.16	0.15	0.01
	Job3	2	4.68	4.52	0.16
	Job4	2	19.05	19.18	-0.13
	Job5	3	28.76	29.39	-0.63
	Job6	1	0.86	0.38	0.48
Total tardiness			65.23	54.98	10.25

Finally, we evaluate the influences of different levels of uncertainty. Figure 6 shows the simulation results of the schedules obtained using the proposed method and the deterministic method for 8 cases with different levels of processing time uncertainty. Note that for simplicity, all workers are assumed to be intermediate ((A, B, C) = (0, 3, 0)). In all 8 cases with different levels of processing time uncertainty, the proposed method reduced the total tardiness compared to the deterministic method, and also the difference

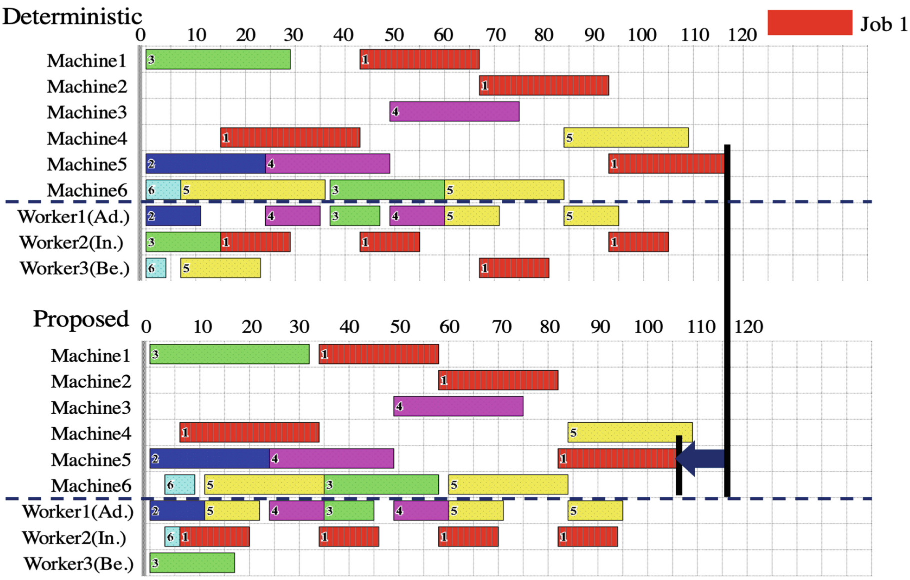

Fig. 5. Gantt charts of planning schedule for proposed and deterministic methods

increased as the uncertainty level increased. Therefore, the proposed method, which considers the uncertainty of job processing time, is more useful than the conventional deterministic method.

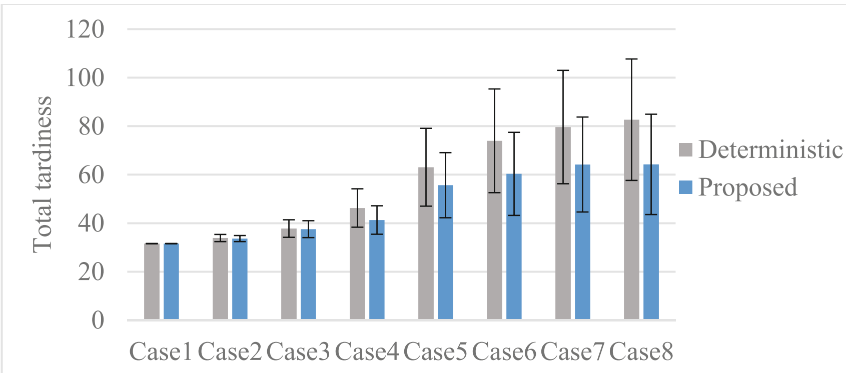

Fig. 6. Comparison of total tardiness between the proposed and deterministic methods under different uncertainty level conditions

4.3 Experiment 2: Analysis of the Impact of Different Combinations of Workers of Various Skill Levels

In Experiment 2, we evaluate the production schedule devised by the proposed method for a combination of workers of various skill levels who are available to work. As explained in Experiment 1, we evaluate the effectiveness of the proposed method and the relationship between the resource utilization ratio and the total tardiness in operation phase simulation. The experimental conditions for jobs in Experiment 2 use the same dataset as in Case 8 of Experiment 1. However, experiments are conducted using combinations of workers with the number of workers and their skill levels changed as shown in Table 4. The number of advanced workers is denoted as A, the number of intermediate workers as B, and the number of novice workers as C.

Table 4. Combination of workers

	(A, B, C)
Case1	(0, 2, 0)
Case2	(0, 3, 0)
Case3	(0, 4, 0)
Case4	(0, 5, 0)
Case5	(1, 1, 1)

Results

Table 5. Optimization and simulation results comparison for different number of workers

(A, B, C)	F_1	F_2	Total Tardiness		
			Avg	S.D	C.V
Case1: (0, 2, 0)	74	39	93.04	32.66	0.35
Case2: (0, 3, 0)	64	39	63.27	20.80	0.33
Case3: (0, 4, 0)	60	39	56.30	17.31	0.31
Case4: (0, 5, 0)	60	39	56.95	18.93	0.33
Case5: (1, 1, 1)	45	33	55.77	20.11	0.36

Table 5 shows the bi-objective function values (F_1, F_2) of each planned schedule under different workers conditions, the average, standard deviation, and coefficient of variation of the total tardiness obtained from the operation phase simulation using these obtained schedules. Table 6 shows the utilization rates of each machine and each worker for the planned schedule under different worker conditions. The utilization rate of each machine and worker is calculated by dividing each processing time by its makespan. In

Case5, each skill is Advanced for Worker1, Intermediate for Worker2, and Beginner for Worker3.

First, we discuss the influence of the difference in the number of workers from the results of Cases 1 to 4 in Tables 5 and 6. Table 5 shows that the value of F_1, the expected total tardiness of the planned schedule, tended to decrease as the number of workers increases. The average of the total tardiness in the operation phase simulation was also reduced accordingly. However, when the number of workers was compared between the case with four (Case3) and the case with five (Case4), there was no change in both the objective function value at the time of planning and the simulation results. The coefficient of variation of the total tardiness in the operation phase simulation tended to decrease as the number of workers increases.

Table 6. Utilization ratio of resources in planned schedule under the conditions in Table 5

	Case1	Case2	Case3	Case4	Case5
(A, B, C)	(0, 2, 0)	(0, 3, 0)	(0, 4, 0)	(0, 5, 0)	(1, 1, 1)
Machine1	0.44	0.46	0.46	0.46	0.51
Machine2	0.20	0.21	0.21	0.21	0.22
Machine3	0.24	0.25	0.25	0.25	0.24
Machine4	0.45	0.47	0.47	0.47	0.49
Machine5	0.64	0.67	0.67	0.67	0.67
Machine6	0.71	0.74	0.74	0.74	0.71
Avg	0.45	0.47	0.47	0.47	0.47
Worker1	0.69	0.54	0.25	0.26	0.70
Worker2	0.65	0.37	0.34	0.45	0.49
Worker3		0.46	0.45	0.33	0.16
Worker4			0.34	0.23	
Worker5				0.12	
Avg	0.67	0.46	0.34	0.28	0.46

Table 6 shows that as the number of workers increases, the average utilization rate of workers decrease. This result suggests that the idle time of each worker increases as the number of workers increases. When workers have sufficient idle time, even if the operation time of a given process is longer than planned and delays occur, it is prevented from propagating delays to subsequent processes. As a result of this effect, the coefficient of variation of total delivery delays tended to decrease as the number of workers increases, as shown in Table 5. On the other hand, increasing the number of workers didn't significantly change the utilization rate of each machine. This is because the machines that process each process of a job are predetermined, and increasing the number of workers does not improve the processing efficiency of the machines. Therefore, as shown in Table 5, there was no improvement in the average and variance of total tardiness when the number of workers increases to four or more. In this experiment, all workers in Cases 1 ~ 4 are intermediates. In order to confirm the effect of the difference in the number of workers, it is necessary to conduct the same experiment for the cases where all workers are advanced and the case where all workers are beginners.

Next, we discuss the influence of the difference in the skill of workers from the results of Cases 2 and 5 in Tables 5 and 6. Table 5 shows that the average of the total tardiness in Case 5 was smaller than that in Case 2, but the variation of the total tardiness (coefficient of variation) was larger. Advanced workers can process the work faster on average than other workers, and have less variation (standard deviation) in the operation time. Therefore, in Case 5, the proposed method reduced the value of the dual objective by considering the skill level of the workers and allocating a large number of processes to the advanced workers. About the average machine and worker utilization rates, the both cases were the same, and that the utilization rates of each machine were also the same as shown in Table 6. Regarding the utilization rate of workers by skill, when workers with different skills were included as in Case5, the utilization rate of advanced workers was high and that of beginner workers was low. On the other hand, in Case 2, although there was a difference in the utilization rate for each worker, the difference in the utilization rate of each worker was small. The reason for the large difference in utilization rates in Case 5 is that the proposed method assigns more processing to advanced workers with less variation in processing time in order to reduce the variation in working time. However, as shown in Table 5, the coefficient of variation of total tardiness was smaller in Case 2. This suggests that the load is disproportionately placed on specific workers with high work efficiency, which may affect the variation of total tardiness. These results suggest that in order to reduce the variation in total tardiness, planning that does not propagate process delays is required, taking into consideration about the load and idle time of each resource, in addition to worker allocation that consider the skill level of each worker.

5 Conclusion

In this paper, we proposed a job shop scheduling optimization method with worker assignment for minimizing total tardiness for a production system with uncertain processing times. The proposed method minimized the linearly weighted sum of the expected total tardiness and the variance of the total processing time by considering the difference in the skill level of each worker and the probability distribution of the operation time. The computer experiments suggested that the proposed method can reduce the total latency time better than the deterministic method. The effectiveness of the proposed method became more pronounced as the level of uncertainty increased. The proposed method reduced the load of each worker, and then reduced the coefficient of variation of the total tardiness. In summary, we found that the proposed method can reduce the mean and variability of the total tardiness. We also found that reducing the workload of each worker and providing margin time can reduce delay propagation. Based on this finding, we would like to examine the number of workers and their capabilities required to reduce the risk of tardiness, and how much time should be set aside in the schedule. On the other hand, there are three points where the method needs to be improved. The first is the problem of computation time. The proposed method solves the problem using the branch-and-bound method with a solver, but it can only solve small-scale problems due to the long computation time. Therefore, we plan to investigate methods such as meta-heuristics for large-scale experiments in the future. The second point concerns the accuracy of the solution. Since the probability distribution of the total tardiness is calculated by using intermediate workers in the proposed method, the distribution is different from the true value. Therefore, it is important to calculate a more accurate distribution of total tardiness. And as a third improvement, we will also consider extending the model to take into account of uncertainties other than the variability of operation time.

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The Impact of the Design Decisions of an Order Picking System on Human Factors Aspects of the Order Pickers

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Abstract. Warehouses are crucial for supply chain management and the success of businesses in production and logistics systems. The order picking (OP) system plays a vital role in achieving short lead times and high customer satisfaction and order pickers are essential to achieve flexibility in the OP system due to their cognitive and motor skills.

However, manual order picking is time-consuming and accounts for approximately 50% of overall operating costs in warehousing. It is important to consider the human factors (HF) aspects of the order picker to avoid deviations from expected performance outcomes and reduce the risk of errors that could cause delays and financial losses. Negligence of HF could also lead to musculoskeletal disorders in the order picker.

This study aims to empirically show the impact of such decisions on the HF aspects of order pickers. The study uses case studies and survey-based empirical data to analyze the impact of decisions on the HF aspects of order pickers. The findings suggest that consideration of HF is crucial for the success of the OP system and the wellbeing of order pickers. The study highlights the need for further research on HF aspects in the OP system and provides insights for decision-makers to optimize the performance of the system.

Keywords: Order picking · Human Factors · Design decisions · Empirical study

1 Introduction

Warehouses are considered to key players in supply chain management and are essential for the success for business in production and logistics systems [1]. Order picking (OP) systems are critical in warehousing to achieve short lead times and excellent customer satisfaction. The OP system consists different tasks such as setting up of picking list, travelling inside the warehouse, searching for the desired products, and picking the products from the desired locations in a warehouse to meet customer needs [1].

Fully automating order picking processes brings about various disadvantages, including high investment costs, the need for standardization, and reliance on computer systems, in addition to its lack of flexibility [2]. Despite the high labor costs, manual

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operation persists in up to 80% of order picking warehouses [2]. Thus, order pickers are vital part of OP systems to achieve high amount of flexibility to the OP system due to combination of their cognitive and motor skills. Furthermore, humans can pick complex products from storage locations, something machines and automated systems cannot do reasonably [3]. These explanations demonstrate that the order picking system is a time-consuming operation that requires a significant amount of manual handling of products. As a result, the cost of process in warehousing accounts for approximately 50% of overall operating costs [1].

However, when manual order pickers are in the system, it is important to consider the HF aspects of the order picker. The four HF aspects are the physical, mental, perceptual, and psychosocial aspects. This is because if HF aspects are not considered then it could lead to deviation from the expected performance outcomes of an OP system [3]. This is because there could be high risk of errors in a manual OP system, as order pickers could pick wrong or incorrect number of items. As a result, these pick error could cause delay in delivering the products or financial losses [4]. The negligence of HF not only impacts the performance of the OP system, but also impacts the wellbeing of the order picker. This is because of handling heavy products in awkward body postures, which thereby increasing the chances of developing musculoskeletal disorders (MSDs), with low back disorders being the most common injury. Thus, the human factors in the OP system are one of an important player in the performance of the system [2].

Even tough, it is important to consider the HF aspects in an OP system, there has been negligence of HF in the decision making of setting up of the OP system or for the introduction of technologies into the system [5]. If these aspects are not considered, then as said before negative consequence could lead to the performance outcomes of an OP system [5]. According to [6], most OP research has concentrated on establishing a mathematical model and simulation model but has rarely included case studies and survey-based empirical data.

Therefore, the aim of this study is to conduct an empirical study to show the impact of decision regarding the system settings and technologies in an order picking system on HF aspects of the order pickers.

The remainder of the paper is organized as follows. Section 2 explains the literature review. Section 3 explains the methodology adopted in this paper. Section 4 presents the findings and analysis from the study. Section 5 summarizes the paper by highlighting key points, limitation of the study and the future research opportunities.

2 Literature Review

The OP system could be classified into two method, picker to parts and parts to picker. In a picker to parts system, the order picker moves towards the desired parts which are the products remain stationary. On the other side, the order picker remains stationary, and the products moves towards the order picker. It is understood that for two different method of OP system, different system settings are required. According to [6], the system setting of an OP system could be classified into mechanization level, information availability and warehouse dimensionality. Few years ago, [7] have explained the system settings of an OP system could be categorized into layout and storage assignments. These factors are considered because they are related with the design of an OP system. The layout design is associated with the number, length, and width of aisles in the blocks and also, the shelf layout and configuration. The storage assignment defines the allocations of the products to the storage locations in the warehouse based on the product characteristics. Thus, it is important to understand the impact of human factors on the system settings. In the case of focusing human factors of order pickers with the design of the warehouse layout, [8] studied on an optimal layout problem as mixed-integer programming with the aim of minimizing the total ergonomics strain on the order pickers.

When it comes to the focus on human factors aspects of order pickers in combination with system settings. [22] have represented a new ergonomic storage location assignment algorithm which reduces the mechanical load of the lumbar spine on the order pickers. [23] introduced a model for storage assignment problem using the integer linear optimization with consideration of the OP time, energy expenditure rate and health risk associated with the order pickers. [26] have studied on order pickers picking from different pallet rack layout considering the economic and ergonomics objectives. [8] with the help of mixed integer programming have achieved to minimize the ergonomic strain during the order picking. [9] have developed a mathematical model to address the storage assignment with respect to the fatigue level of the order pickers. [10] introduced a bi-objective approach considering the total order picking time and human energy expenditure into a storage assignment problem. [11] has talked on storage assignment decisions based on the learning and forgetting of order pickers. [12] introduced an algorithm to help in selecting the highly efficient storage locations thereby reducing the probability of mis-picks and improving the ergonomics for the order pickers.

When it comes to the technologies in OP systems, [13] have described the transition of automated order picking systems and its impact on the order picker's learning and work organization. [14] have proposed a model that considers the capacity, ergonomics, and cost of training an automated system. [15] have presented a simulation model to evaluate the fatigue on order pickers, who work in close collaboration with the picking robots. [16] has evaluated the workload and ergonomics design of workstations in picker to parts order picking system. [17] has compared the horizontal carousels with shelving systems with the consideration of space, time, and ergonomics. [18] studied the influence of paperless picking and the usage of forklifts for transportation on order picker's well-being and productivity. [19] presents an empirical analysis of learning curves in pick by voice and semi-automated OP systems.

3 Methodology

This section describes the research design, which contains a description of the study strategy, data gathering procedure, and analytic methodologies. The section begins with a thorough discussion of the research approach, followed by a description of the data gathering procedure, and continues with an overview of both descriptive and content analysis techniques (Table 1).

Table 1. Research design

Method	Technique	Purpose
Case Study	Questionnaire	To understand the well-being of the order pickers (from order pickers perspective)
	Interview	To understand the design characteristics of the warehouse (from managers perspective)
		To understand the well-being of the order pickers (from managers perspective)

3.1 Research Method

The research method adopted for this study is case study. The case study is conducted with the help of a Norwegian grocery distribution centre. The case study managed to provide a detailed investigation, with the empirical data collected to deliver an analysis and the process involved in the context [20]. The main objective of the case study is to do intensive research on a specific case to highlight the essential process and relationships [21]. In this study, the focus is to find the essential system design of the three different warehouses of the case company and to evaluate their relationship with the HF aspects of the order pickers.

3.2 Data Collection Technique

Two types of data collection technique are used to support the case study research method: questionnaires and interviews. These data collecting techniques are described in further detail below.

Questionnaire
This study used the NASA TLX questionnaire, a multidimensional rating method that provides an overall workload score based on the weighted average of ratings on six subscales [24]. They are mental demands, physical demands, temporal demands, own performance, and frustration. Mental Demand assesses cognitive requirements and complexity. Physical Demand measures physical effort. Temporal Demand evaluates time pressure. Performance gauges perceived task success. Effort considers overall mental and physical exertion. Frustration captures emotional strain and dissatisfaction. These dimensions provide a comprehensive understanding of workload, enabling identification of high workload areas and informing task design and resource allocation improvements. The questionnaire is provided to the order picker to collect the information regarding the well-being of the order pickers. The duration of order picker to fill the questionnaire is approximately 30min. The questionnaire is distributed to all the order pickers in the warehouse.

Interview
A semi structured interview is conducted with the managers and order pickers [20]. The questions for the manager's interview would address the data regarding the design of the

order picking system. For e.g., layout, storage assignment, technology etc. As a result, an understanding of the warehouse's system setting is provided. One manager, who is responsible for the order picking system, was selected for the interview. Secondly the questions for the order picker's interview would evaluate HF aspects of the order picker. One experienced order picker from each warehouse who is comfortable to communicate in English were selected for the interview. The duration of the interview with the manager and order pickers were approximately 1 h each.

3.3 Data Analysis

Triangulation is employed in the case study to enhance the validity of the acquired data by conducting two distinct types of data analysis, namely descriptive analysis and content analysis. This approach ensures a more robust and comprehensive examination of the findings. By combining these two approaches, the study benefits from a more holistic understanding of the phenomenon under investigation, strengthening the validity and reliability of the research outcomes.

Descriptive Analysis
In the initial phase of the study, a descriptive analysis is conducted using quantitative data collected through a questionnaire [24]. This analysis involves presenting the raw data without manipulation to understand the trends in the HF aspects when altering the system settings for the order picker. By analysing the unprocessed data, authors can observe patterns and changes in the level of workload on the order pickers. The descriptive findings derived from this analysis provide a comprehensive overview of the observed trends, serving as a foundation for further exploration of the relationship between system settings and HF aspects. This analysis aims to gain insights into the impact on the order picker's working conditions and performance.

Content Analysis
After completing the descriptive analysis, content analysis is utilized to gain a more profound comprehension of the observed trends [25]. The coding process in content analysis involves identifying significant themes, concepts, or words within the qualitative data obtained from semi-structured interviews conducted with order pickers [25]. The constructs used in this analysis may focus on the order pickers' perceptions, experiences, and attitudes towards the system settings and their impact on HF aspects. Evaluating the performance in content analysis involves examining the order pickers' narratives and identifying any references to changes in their performance or productivity resulting from the system settings. The objective of this analysis is to assess the presence, meanings, and connections of specific words, themes, or concepts, shedding light on the reasons behind the alterations in the human factors aspects when the order picker's system settings were modified.

4 Findings and Analysis

4.1 Case Company

The case study focuses on three key warehouses within a major Norwegian grocery distribution centre. These warehouses, namely Warehouse A, Warehouse B, and Warehouse C, have been selected for in-depth analysis.

Warehouse A is the most automated among the three, employing the parts to picker OP method with the assistance of an AS/RS (Automated Storage and Retrieval System). This means that the system retrieves the necessary parts and brings them directly to the order picker, streamlining the picking process. Warehouse B is a semi-automated warehouse that utilizes the picker to parts OP method. It incorporates pick by voice technology, where order pickers are guided by a microphone to perform various picking tasks. This technology assists them in setting up the picking list and locating and picking the required parts from designated locations. In contrast, Warehouse C is a fully manual warehouse, relying on the manual picker to parts OP method. Order pickers perform all the picking tasks manually, without the aid of automated systems or voice technology.

It is worth noting that Warehouse A is the largest in size, while Warehouse C is the smallest among the three. The varying degrees of automation and manual involvement in these warehouses provide an opportunity to study and compare the effects of different system settings and technologies on the HF aspects of the order pickers.

4.2 Descriptive Findings

The findings from the NASA TLX obtained from the three distinct warehouses are described in this section.

Figure 1 in the study provides a visual representation of the data collected from the three warehouses (A, B, and C) and how it is classified and categorized into four primary order picking tasks: setup, travel, search, and pick. These tasks represent different stages or activities involved in the order picking process.

To assess the workload associated with each task, the study utilizes the NASA Task Load Index (TLX), which consists of six dimensions: Mental, physical, temporal, performance, effort, and frustration. These dimensions capture different aspects of the workload experienced by order pickers during their tasks.

By evaluating each dimension within the context of the three warehouses, a comprehensive analysis of the workload is conducted. This analysis allows for a deeper understanding of how workload factors vary across different aspects of order picking and between the warehouses (Figs. 2, 3 and 4).

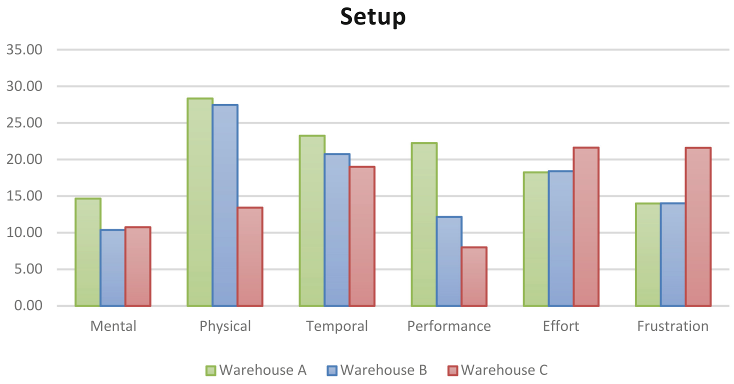

Fig. 1. Descriptive findings of the setup task

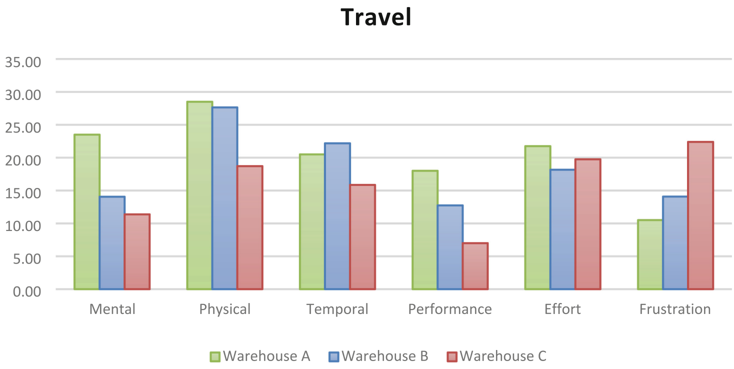

Fig. 2. Descriptive findings of the travel task

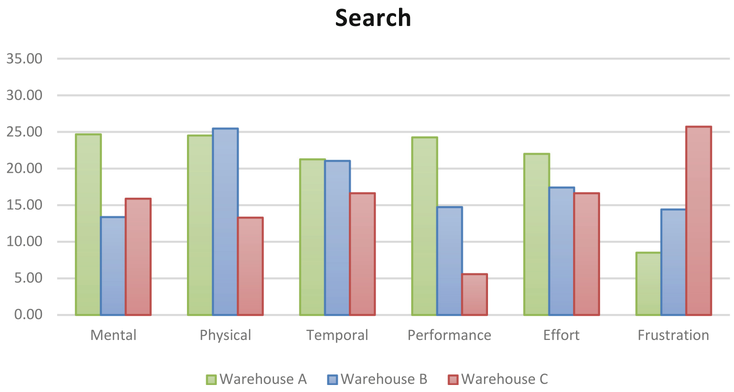

Fig. 3. Descriptive findings of the search task

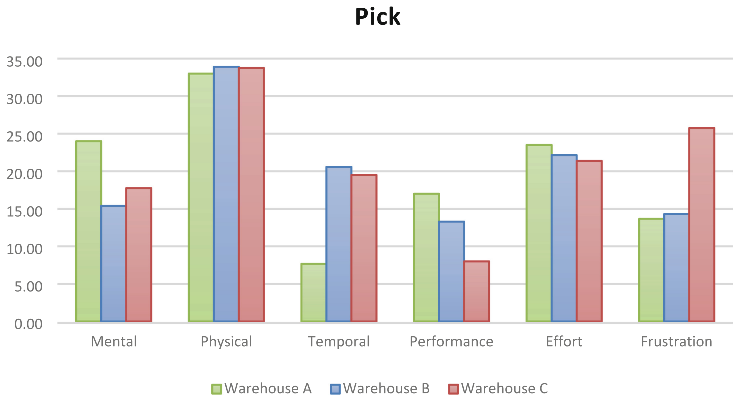

Fig. 4. Descriptive findings of the pick task

4.3 Content Analysis

Moreover, the content analysis provides a detailed exploration of the trends identified in the previous section, offering further explanations and insights specific to each order picking task. This analysis delves deeper into the findings, providing a more comprehensive understanding of the factors and patterns influencing performance within each task of the order picking process.

Setup

Of all the dimensions, the physical demand is reported more from all the warehouses and the least for mental demand. The mental demand is least in the setup task for the warehouse B because the search list for the picking is prepared by the pick by voice technology. This could reduce the mental demand for the operators to make decisions on picking the orders and warehouse A has the most mental fatigue because the order pickers have reported that the system crashes in between and this would annoy the order pickers in picking the orders and order pickers have also reported that they have to reboot the system to retrieve the picking list from the system. It is also more physically demanding for the warehouse A and least for warehouse C because order pickers from warehouse A notified that the standing in the same position for preparing the collection could case back pain to the operators and in warehouse C the order pickers feel less fatigue because order pickers have less parts to pick compared to other warehouses. The temporal demand for creating the setup list is equally same for all the three warehouses but bit high for the warehouse A and less for warehouse C because warehouse A being the biggest with huge movement of goods than warehouse C, the pressure on order pickers from warehouse A is more when compared with the warehouse C.

When it comes to performance, the warehouse A is performing better than the remaining warehouses and the least performance was reported by warehouse C because the order pickers of warehouse A stated that if the system work without crashing then they could prepare more picking list faster than the conventional paper picking list of warehouse C. Also, in case of effort and frustration both the warehouse A and B has shown equal level and warehouse C has the highest because the warehouse C has conventional picking list, that causes order pickers more frustration and effort on cross checking the orders that they need to pick.

Travel

When it comes to the travel tasks, the mental demand is reported in warehouse A and the least for the warehouse C because the order pickers of warehouse C are used to follow the same route all the time which led them with least mental demand. On the other hand, the order pickers of warehouse A travel less often only when there is need of intervention with the AS/RS. Secondly, the physical workload is rated the most among all the dimensions. The physical demand is stated more for warehouse A and least for warehouse C because during the time of intervention for warehouse A, the order pickers has to climb to check the problem, which causes more fatigue to the them. Thereafter, the temporal demand is more for warehouse B and the least for warehouse C because warehouse B is bigger than warehouse C and the order pickers from warehouse B has to cover a greater distance to meet their picking target.

However, when it comes to the performance, the warehouse A has better output and the least for warehouse C because if there is no intervention for AS/RS, there doesn't exist a need for the order pickers to travel. Secondly, the effort is most for warehouse A and the least for the warehouse B only when there is an intervention in warehouse A and the order picker has to take actions to rectify it. Finally, the order pickers faced more frustration for warehouse C and the least for warehouse A because the order pickers of warehouse C states that they have to keep on travelling over the warehouse repeatedly causing them frustration.

Search

In the search task, the mental workload in stated most in warehouse A and least for warehouse B because if there is an intervention the order picker of warehouse A takes time to find the location of the item. But, in warehouse C since the order pickers are used to pick the parts, they remember the storage locations effecting in lower mental demand. Secondly, in case of physical demand and temporal demand is equally high for warehouse A and B and the least for warehouse C because both the order pickers of warehouse A and B has to pick more items in comparison with C.

The performance is best reported for the warehouse A and least for warehouse C because order pickers from warehouse A has less travel to pick the items, but only have to travel during the need of intervention for robot. The effort is rated most for warehouse A and the least for warehouse C because during the intervention for robot in warehouse A, the order pickers has a greater effort to rectify and bring to work when compared with conventional warehouse C. As in the most cases the frustration is most of warehouse C and the least for the warehouse A because the order pickers of warehouse C has no assistive technology to help find the location of the item, which is not the case for warehouse A that provides the assistance to the order pickers to find the right item with its location.

Pick

Finally, in the case of pick task, the mental demand is rated most for the warehouse A and the least for the warehouse B because order pickers of warehouse A feels that standing at a single place and picking the items from one point is boring. The physical demand was reported equally high in all the three warehouses, but a slightly higher for warehouse B because the order pickers of warehouse B has to pick more items from the shelf when compared to other warehouses. The temporal demand is high for both the warehouse B and C and the least for warehouse A because both the warehouse B and C are parts to picker OP method and the order pickers from both warehouses has reported that they have to pick the parts from the warehouses from different locations within the provided time span to meet the picking rate.

The pick performance is high for warehouse A and the least for the warehouse C because the rate of picking is decided by the system and the order pickers has to perform the pick task based on the feedback from the system while in the case of warehouse C the rate of picking is entirely depended on the speed of the order picker. The effort for picking is rated equally in all the three warehouses because the picking task is same in all the three warehouses. Finally, the frustration is rated most for the warehouse C and the least for the warehouse A because the order pickers from warehouse C informed that the frustration for picking is due to the temporal demand of the work to keep up the picking rate.

5 Conclusion

The study has evaluated the impact of the design decisions of an order picking system on human factors aspects of the order pickers. It was fascinating to see that parts to picker OP method has better performance but could lead to more effort to order pickers if there is a need for interventions for the AS/RS. Overall, order pickers in a manual warehouse reported more frustration doing OP tasks than order pickers in a warehouse that made use of assistive technology for the picker to part OP method.

This study's managerial implications emphasize that effective decision-making by managers plays a vital role in attaining the intended performance outcomes in order picking systems. Managers can optimize system performance and align it with planned goals by taking into account human factors and making well-informed design decisions. Additionally, fostering open communication channels and prioritizing the well-being of order pickers contribute significantly to achieving the desired performance outcomes.

One significant drawback of this study is its limited scope, as it solely examines a grocery distribution centre located in Norway. By confining the research to this specific context, the findings may lack broader applicability and generalizability to other settings, limiting the validity of the findings to internal factors. However, by examining various sectors and conducting comparative analyses, researchers can enhance external validity and gain a deeper understanding of how different design choices influence order pickers' performance and well-being. Another limitation of this study is its narrow focus on a limited set of technologies within the order picking system, specifically paperless picking technologies and AS/RS. While these technologies were thoroughly examined, other emerging or alternative technologies that could impact order pickers may not have been included. To address this limitation, future steps of this research could involve exploring and evaluating the effects of a broader spectrum of technologies. By considering a wider range of technologies, a more comprehensive understanding of their impact on order pickers could be achieved. This expanded analysis would provide managers and decision-makers with a more holistic view when making informed choices about integrating different technologies into order picking systems. Additionally, it would ensure that the study's conclusions remain relevant and applicable in a rapidly evolving technological landscape.

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SME 5.0: Exploring Pathways to the Next Level of Intelligent, Sustainable, and Human-Centred SMEs

From Surviving to Thriving: Industry 5.0 at SMEs Enhancing Production Flexibility

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Abstract. This study explores how human-centered digitalization can contribute to the flexibility and adaptability of small and medium-sized enterprise (SME) production processes, resulting in more resilient systems. This study explains the relationship between digital technologies and production system features through progressively more human-centric stages of a digitalized manufacturing system. The authors present a case study of an SME that implemented a human-centric strategy, placing people's needs and interests at the center of its processes, leading to more flexible and inclusive production processes and consistent with the goals of Industry 5.0. The results suggest that a digitalized working method that considers human capabilities and needs can enable a more diverse workforce and the rapid setup of new and additional production processes, thus helping SMEs respond to supply chain disruptions. The findings have implications for managers and practitioners interested in driving or supporting the transition of SMEs to human-centric, resilient, and sustainable businesses.

Keywords: Adaptability · Flexibility · Human-centric production

1 Introduction

Industry 5.0 (I5.0) is a concept that acknowledges the potential of industries to contribute to society beyond just creating jobs and generating economic growth. It aims to create a sustainable and prosperous future by ensuring that production processes align with our planet's limits and prioritizing workers' welfare within the industry [1]. At the same time, the I5.0 paradigm promotes systems' agility and resiliency with the utilization of flexible and adaptable technologies. I5.0 is still a relatively new concept, and there are ongoing discussions about the extent and speed to which manufacturers will adopt it. However, many experts see the concept as a potential solution to challenges that Industry 4.0 (I4.0) does not address. It has become evident that the I4.0 concept is highly technology driven and doesn't include sustainability and human orientation to the extent necessary when digitalizing the industry. Hence, there is a risk that I4.0 emphasizes digitalization as a goal rather than a mean.

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During the COVID19 pandemic, organizations and companies in almost all industries realized digital technologies' potential to address disruptions. Some went on board with digital transformations, while others prioritized digital initiatives to cope with supply chain disruptions [2]. The Ukrainian war and the energy crisis are critical drivers of digital and business model transformations [3]. The resilience of industrial organizations is one of the central themes of I5.0 to alleviate the challenges of uncertainties [4]. Emerging technologies play a key role in I5.0; with technologies such as AI, digital twins, and the big data analytics, the industry is already improving product design and manufacturing processes. In contrast to I4.0, under I5.0, the purpose of technology implementation is expanded to support sustainability and resilience. Technology is applied to societal problems triggered by high-impact shocks, and problems can be monitored and analyzed in real-time to prepare and apply early measures and to avoid shocks turning into crises [5].

Focusing on I5.0 could also contribute to resilience in small- and medium-sized enterprises (SMEs). SMEs are the backbone of the European economy, representing 99% of all businesses in the EU [6], and are seen as fundamental to the EU's transition to a sustainable and digital economy. Research has shown that digitally transformed SMEs can capitalize on opportunities during a crisis and reorganize resources to cope with a crisis [3]. A critical factor in building the resilience of SMEs is the flexibility that fewer but key individuals add to the organizations. However, even though introducing new technologies and practices is always uncertain in SMEs, research on Industry 4.0 at SMEs has shown a limited but thus positive impact of new technologies on SMEs' operational performance [7, 8].

Since I5.0 is a rather new topic recently studied by researchers and practitioners [1, 4, 9, 10], there are yet scarce reflections of I5.0 practices in general and even less at SMEs. SMEs' business strategy is often based on adaptability, a reactive approach, and customer proximity. In this sense, SMEs need to be flexible by nature, and one can argue that the more flexibility an SME can demonstrate, the higher the chances of surviving the market and staying competitive. Thus, the promise of enabling greater flexibility and resilience at the industrial level through I5.0 motivates exploring the topic in the context of SMEs.

This study focuses on a unique case of an SME utilizing the digitalization of work processes to increase the flexibility and transferability of the production work across individuals regardless of their cognitive and physical capabilities or skills. The case company has collaborated with academia previously around ecological and social sustainability [11–13], though the studies were not directed to resilience and flexibility. The digitalized work method was initially developed to integrate marginalized people into Sweden's workforce and manufacturing. However, as the SME was hit by the shortages and lockdowns triggered by the COVID19 pandemic, this work process was adapted to the context during 2020–2022 by using voluntary workers without previous training. The method was deployed to quickly industrialize a production process for protective equipment for hospitals and care providers in Sweden. The case represents a unique application of agile digitalization for human-centric production that helped a Swedish SME survive and thrive.

Consequently, the study presented in this paper explores a central research question: *How can the human-centric digitalization of production work processes enhance SMEs' flexibility?* We consider this unique case and its digital implementations to demonstrate what I5.0-related practices in SMEs could look like. Here, we focus on process flexibility, i.e., the ability of a company to change or adapt its manufacturing setups according to demand and supply changes and place.

The first section of the paper presents the aim of the research and its considerations. Section 2 presents the theoretical background regarding resilience and flexibility at SMEs and I5.0 as an approach from now on. In Sect. 3, the method followed is presented. Section 4 includes the case findings and analysis based on our conceptual framework for flexibility in a human-centric manufacturing system. Section 5 covers discussions about flexibility in human-centric digitalization of production processes at SMEs and further reflections on our proposed conceptual framework. Lastly, as we advance, conclusions and recommendations are provided in Sect. 6.

2 Theoretical Background

2.1 Resilience and Flexibility in SMEs

SMEs are essential to Europe's competitiveness and prosperity, industrial ecosystems, economic and technological autonomy, and resilience to external shocks. Large enterprises may have relatively more resources, such as capital and manpower, to absorb the shock of unexpected events. SMEs may face limitations such as resource scarcity, cash flow, and dependence on external systems [14]. Still, they may have more agility and flexibility due to the shorter chain of command, allowing them to pivot and adapt to changing circumstances more quickly [15–17], making the context arguably suitable for I5.0 practices. To manage supply disruptions, SMEs often rely on mobilizing resources within their supply network [18–20].

Flexibility refers to the ability of a system to change (adapt) in dynamic environments. It is often used interchangeably with adaptability [2]. Flexibility is about how the whole manufacturing system can change what it does and how individual parts can change [21]. It concerns both technical and human responsiveness to disturbances [22]. Moreover, an efficiently flexible organization is one that is adapted to what the environment needs [23]. Process flexibility examines the ability of a company to change manufacturing setups at flexible lines according to demand or supply changes [24]. It also refers to the company's ability to provide goods or services using different facilities or resources, for instance, multiple facilities or lines [24, 25].

Flexibility has been extensively studied in manufacturing, services, and supply chain at different levels, i.e., strategic, tactical, and operative perspectives [21, 23, 25, 26]. In their study, [26] considered emerging issues in flexibility, such as risk and uncertainty management, environmental sustainability, optimal strategies under competition, and optimal operations with strategic consumer behaviors.

Flexibility mechanisms comprise the tools, management practices, and systems that can be used to achieve a particular type of flexibility, i.e., product variety (modification flexibility), location of production (volume flexibility), and rapid introduction of new products (changeover flexibility), for instance, ERP system, design-for-manufacture principles, multi-skilled workers and holding inventory [27]. In manual assembly, reducing complexity is a key factor for increased flexibility, whereas digital systems may increase or decrease complexity [22].

Risk mitigation is a crucial challenge for SMEs, especially in the manufacturing sector, as supply cost usually represents the most considerable budgetary portion [28]. Studies on risk mitigations classify solutions into either redundancy or flexibility approaches [29, 30]. Redundancy is a less common strategy in SMEs. It is an expensive strategy since many of the built redundancies will wait for use in an emergency case without creating any value in business-as-usual times [31]. Studies [30] have found that more efficient strategies for risk mitigation focus on flexibility rather than redundancy for supply chain failures. Ellegaard [32] also reported that SMEs do not implement buffer-related, supplier development, or formal process-oriented measures due to their limited internal resources, weak position power in the supply chain, and informal management structure. Thus, the mindset and orientation of SMEs play an essential role, as many prefer to network with suppliers for risk mitigation [33].

2.2 Early Insights on Industry 5.0

According to the European Commission, I5.0 demands technologies to address new industrial, societal, and environmental requirements. It means using technologies to increase production flexibility during disruption and making value chains more robust. It also means implementing technology that adapts to the worker rather than the other way around. It means using technology for circularity and sustainability [33], ultimately becoming a competitive industry that respects planetary boundaries and minimizes its negative environmental impact [34].

The EU Commission states that I5.0 has three characteristics: human-centricity, sustainability, and resiliency, which frame the vision for industry evolution [10]. This approach contributes to three of the commission's priorities: i. an economy that works for people", ii. "European Green Deal" and iii. "Europe fit for the digital age". According to the EU Commission [34], policy brief report, the I5.0 characteristics are defined as:

Human-centricity refers to the industry putting core human needs and interests at the heart of the production process. The vision is to use technology to adapt the production process to the worker's needs, rather than the industry worker to adapt their skills to the rapidly evolving technology needs. It also includes securing industrial workers' privacy, autonomy, and human dignity.

Resilience refers to the need to develop higher robustness in industrial production, be prepared against disruptions, and ensure it can provide and support critical infrastructure in times of crisis. It includes developing suitable resilient strategic value chains, adaptable production capacity, and flexible business processes, primarily where value chains serve basic human needs, e.g., healthcare or security.

Sustainability refers to industry respecting the planetary boundaries and includes developing circular processes that reuse, re-purpose and recycle natural resources, reduce waste, and have an environmental impact. It also means reducing energy consumption and greenhouse emissions to ensure the needs of today's generations without risking the needs of future generations. Technologies play a prominent role in optimizing resource efficiency and minimizing waste.

A challenge concerning adopting I5.0 in SMEs is the scalability in ensuring a broad-scale implementation of technologies across value chains and ecosystems, including the small players. According to the European Commission 2020 report from technology leaders [35], the technologies under the umbrella of the I5.0 concept comprise:

i. Human-centric solutions and human-machine-interaction technologies that interconnect and combine the strengths of humans and machines.
ii. Bio-inspired technologies and smart materials that allow materials with embedded sensors and enhanced features while being recyclable.
iii. Real-time-based digital twins and simulation to model entire systems.
iv. Cyber-safe data transmission, storage, and analysis technologies that can handle data and system interoperability.
v. Artificial Intelligence, e.g., to detect causalities in complex, dynamic systems, leading to actionable intelligence.
vi. Technologies for energy efficiency and trustworthy autonomy, as the technologies mentioned earlier, will require large amounts of energy.

Literature on how digital technologies supported industry to cope during the COVID19 pandemic [36] demonstrate that investing in long-term resilience and business sustainability over short-term optimization and improvements must be a priority for manufacturers and managers to be prepared for similar circumstances in the future. In addition, industries may face a higher demand for personalized products while having the requirement to ensure that the human needs of industrial workers and environmental impact are not compromised by the economic drive to satisfy product demand.

In their study, Lu et al. [37] present a framework for a human-centric manufacturing system in an unstructured and distributed manufacturing environment to enable "ultra-flexible" (as described by the authors) manufacturing automation of personalized products. The framework contextualizes the human-centric manufacturing system towards mass personalization. Here, flexibility must include human wellness and working freedom to be optimized while ensuring good system productivity, which is different from traditional production scheduling and control. According to the authors, the highly dynamic team collaboration and contingencies resulting from maximum freedom given to industrial workers will directly cause traditional centralized production scheduling algorithms to fail. Learnings from Lu et al. [37] helps us understand the system characteristics concerning human and technologies of the I5.0 approach. Our study tries to understand how digitalization enables flexibility at the plant level at SMEs.

3 Methodology

The research presented adopts a qualitative research design based on data collection through mainly semi-structured interviews and observations [38]. The study focused on a Swedish SME called the PS case, which has faced significant disruptions in its production system due to COVID19's impact on its market and supply networks. The case strongly supports answering the research question, as it allowed us to investigate how, despite those disruptions, the SME implemented human-centric digitalization in their production work processes and how it enhanced the SMEs' flexibility.

3.1 Data Collection and Analysis

The study relies on two main types of primary data, i.e., phenomena in reality and people's perceptions and experiences of reality [39]. Therefore, data was gathered from workshops, presentations, semi-structured interviews, and on-site observations at the SME firm. Data was collected from March 2021 to Dec 2022 (see Table 1). Our study focuses on the operations management and strategic aspects of enabling flexibility and resilience in SMEs' production processes, with emphasis on inclusive workspace design; therefore, interviews were conducted with the CEO of the case company (also acting as COO), and production workers' interviews were not included at this stage in this study (in a previous inclusive work study, operators have been interviewed [11, 12, 40]). Workshops included the PS case and two other SMEs in similar situations, focusing on resilience and flexibility while responding to disruptions. At one of the workshops, the CEO of the PS case gave a 60-min presentation on their transformation efforts/projects and their background, and an on-site visit of the transformation operations was carried out. The data collection targeted two main areas: first, to investigate the experienced unexpected events (with emphasis on COVID19), the production disturbances at the SME, and understanding the effects on the SME; and second, to capture the strategic actions, practices, and flexibility of the SME in response to the shocks. The CEO of the PS case described the internal operations and working methods in the initial interview. All interviews and workshops were recorded and transcribed. The transcripts and notes were then reviewed to 1) develop the overall story of the case and 2) extract the information according to the concepts and themes identified in the literature review.

Triangulation improves the accuracy and completeness of a case study, strengthening the credibility of the research findings [38, 41, 42]. At least two researchers were part of all semi-structured interviews and presentations to ensure triangulation. One researcher complemented the process with input from previous studies [11, 12, 40]. Two leading researchers analyzed interview transcripts and notes from the workshops separately and discussed them afterward. Later, those were complemented by documentation of

Table 1. Data collected throughout the research process at PS case

Form of data collection	Description
Presentations	3 × 30–60 min presentations on the transformation by the CEO and project lead (March 2021, March 2022, Sept 2022)
Semi-structured interviews	4 interviews (60–90 min each) CEO and head of operations (May 2021, Sept 2022, Oct 2022)
On-site observations	1 × 120 min site visit (May 2022)
Workshops	4 × 240 min joint workshops focused on the transformation for resilience, challenges, and opportunities in connection to other industries (Dec 2021, March 2022, May 2022, Sept 2022)

firms and on-site observation notes. The data analysis combined different techniques to get the most out of each data set. A summative content analysis of all transcripts and presentations was conducted to build a timeline of events that identified both occurrences of high-impact events and patterns in connection to our conceptualization.

4 Findings

4.1 Introduction and Development of the Digital Working Method

The SME in this study was a Swedish firm that has divided its operations into two sub-firms, one focusing on packaging solutions (PS) and one on assembly systems for innovative construction solutions (CS). PS supplies packaging, preassembly, and kitting solutions to the manufacturing industry. They deliver manufacturing packaging solutions to the automotive, electronics, pharma, and food industries. CS is a manufacturing startup developing wooden housing modules composed of standardized components. The modules are built on standardized demountable, recyclable single-story units.

The firm makes every effort to keep short lead times in high-quality products, accomplished by two key characteristics. First, it is an independent firm choosing which materials and subcontractors to work with. Second, sales associates' function as project managers, meaning that the customers' point of contact will be the same person from the idea definition to the delivery of the finished solution.

Over the past six years since the initialization of the company, CS has developed a digital working method supporting the development of manufacturing stations for people with limited cognitive and physical capabilities, allowing flexibility in educational and language backgrounds [11, 12, 40]. Based on their developed concept of manufacturing their products, people without industrial experience can quickly learn and start productive work in assembly operations. The concept includes training individuals with no previous industrial experience in performing industrial work. It involves designing inclusive workstations with digitalized and animated visualizations of standardized work instructions, less language limitations, and assembly templates with a fault-proofing process. In addition, developing a learning culture and inclusive attitudes between colleagues is emphasized. The company provides individual coaching and feedback to encourage positive energy and learning, which has been seen as an essential enabler for training [13]. The digitalized method has enabled jobs to be suitable for a broader spectrum of individuals regardless of having special cognitive and physical capabilities, for instance, hearing impairment, low proficiency in the Swedish language, and lack of previous industrial experience. Hence, the SME has utilized digitalization as a means to develop a new and more inclusive training method.

In March 2020, the pandemic hit the world, with most countries having compulsory measures to slow the spread of the virus, including limited access to or closure of borders and physical workplaces. Many industries (including the SME in our study) continued to deal with material shortages following this time. The case company was not an exception and was heavily impacted by the shortages in supply (e.g., glue) and lockdowns. Here, PS tapped into the experience gained from the digitalized working method; before COVID19, it was mainly used to build housing modules. The method was successfully deployed during COVID19 for building personal protective equipment

(PPE). The production was set up at different manufacturing facilities and public spaces that have shut down due to the national restrictions to battle the pandemic. The workers used for PPE production were all volunteers or part-time workers e.g. students. The digitalized production method helped fulfill demand from the healthcare sector equivalent to thousands of PPE -protective coats and visors.

4.2 Exemplary Leverage of Human-Centricity for Flexibility in Production

Table 2 summarizes the types of flexibility and the human-centric characteristics displayed in the case. For instance, the digitalized working process method enabled the increase of product variety (modification flexibility), expanded the possibilities of production location (volume flexibility), and allowed for products to be rapidly introduced (change over flexibility) as no specific training per new product is required.

Table 2. Flexibility mechanisms and human-centric characteristics in PS case

Case		**Type of displayed flexibility**		
		Modification	**Volume**	**Changeover**
Mechanisms implemented	**Tools, methods**	The digitalized working process method allowed the introduction of new products and processes	The digitalized working process method was deployed at multiple locations to produce PPE	Products are rapidly introduced, and no specific training per new product is required
	Management practices	N/A	The practice of employing a workforce with different cognitive and physical capabilities expands the production capacity by being able to employ a more diverse workforce	The workforce can do productive work right from the start, and the learning curve is shortened
	Systems	The digitalized working process deployment to multiple locations and products is seen as a way of working and developing the production system		
Human-centric	**Level 1**	The digitalized working process integrates ergonomics consideration in the development of fixtures and workforce capabilities		
	Level 2	Removing physical and cognitive capabilities limitations is embedded in the design of the method; the digitalized working process accommodates lowering complexity and supports workforce diversity		
	Level 3	PS case already working with a broad range of personalized products in combination with reaching workforce wellbeing and skills development		

By designing a digitalized work process system that could employ a workforce with diverse cognitive and physical capabilities, the firm managed to increase production capacity during disruptions by employing, e.g., volunteers. At the same time, the method allows for the rapid setup of new and additional production processes if needed. Under this method, the workforce can do productive work right from the start. Hence the learning curve is shortened. In this way, PS managed to secure supply and fast response to their customers; for instance, when a shortage of a particular material happened, they would propose alternative products as a substitute. For the supply of PPE, the fast production enabled by the digitalized working process method alleviated the healthcare shortage in the region, helping battle the crisis with COVID19.

It is indicated that PS displays the human-centric characteristics envisioned for level 3 (see Fig. 1), where technologies allow for optimizing human well-being. The digital method considers human capabilities, needs, and skills development while responding to customer requirements. In alignment with the I5.0 human-centric vision, the PS case company puts human needs and interests at the heart of the production processes. By design, the digitalized working process method removes physical and cognitive restrictions to the workforce, enabling diversity and inclusiveness of the personnel at PS.

5 Discussions: Flexibility and Adaptability in Human-Centric Digitalization at SME Manufacturer

The findings illustrate how human-centric digitalization may play a critical role in enabling SMEs to achieve process resilience and flexibility during high-impact events. In their study, Chou et al. [24] show that partial flexibility structures, properly designed, can already accrue most of the benefits of the full flexibility system. The case study company illustrates how adopting digital technologies that leverage human-centric characteristics, such as their digitalized working process method, can enhance the production process's ability to adapt to the environment, increase agility and responsiveness, i.e., process flexibility, and enable SMEs to overcome crises more effectively.

In Fig. 1, the link between flexibility mechanisms enabled by digital technologies, i.e., digital tools, systems, and management practices, and the production system characteristics is demonstrated through progressive levels of a human-centric manufacturing system. Under this framework, firms can leverage human-centric characteristics to increase process flexibility.

On the initial level 1, the workforce preferences, capabilities, and ergonomic aspects are considered for task assignment. On level 2, a human's physical, cognitive, and psychological capacities are considered, and the capability information determines the feasibility of assigning a manufacturing task to a human [37]. At the highest level 3, technologies allow for optimizing human well-being by considering human capabilities, needs, and skills development while also responding to customer requirements.

The different mechanisms under a digital strategy can support the development of different types of flexibility by integrating human-centric characteristics. For instance, for the rapid introduction of new products, a company may need to rapidly train the workforce in new skills and mobilize the production location. Often these activities

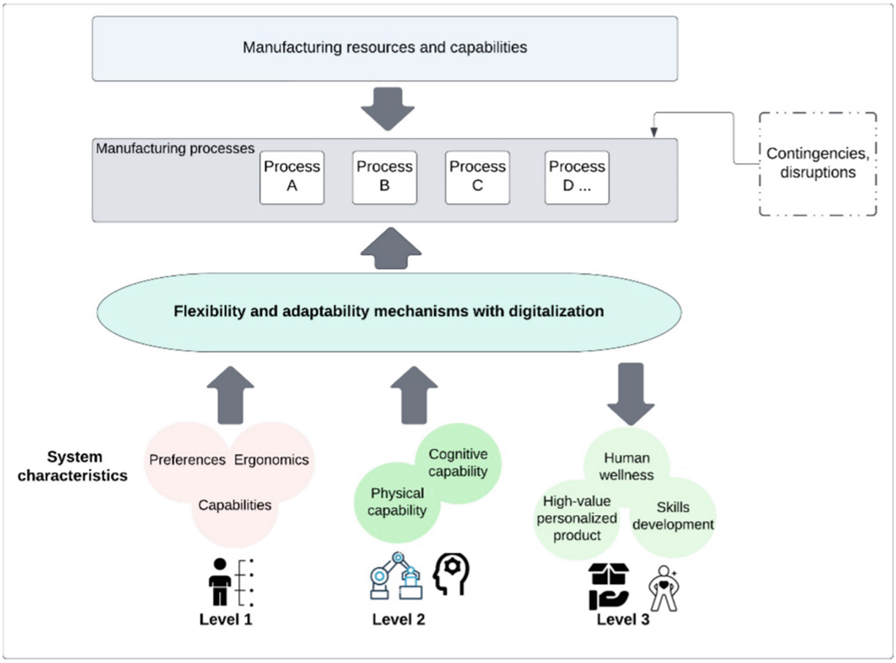

Fig. 1. A conceptual framework for flexibility in a Human-centric manufacturing system inspired by Lu et al. (2022)

convey high stress to workers. In a human-centric manufacturing system, workforce needs are taken care of from the outset, and actions hindering human wellness would ideally be avoided. In our case study, it is important to highlight that digitalization aimed at maximum support and minimum complexity, as suggested in the previous literature [18]; the aim in the case firm was increasing the employability of the workers and designing more inclusive working environments. Further, in our case, the level of digitalization and visual support was high, but the level of automation was low.

In this respect, small changes in work procedures at the case company helped accommodate people with functional variations, such as physical or hearing impairments. For example, when making protective clothing, adjustments were made to the worktable height to accommodate a volunteer who used a wheelchair, and materials were delivered to the work area to avoid contamination of the protective clothing. Another example showed how communication was adapted for a person with hearing impairment during the assembly of protective clothing, i.e., physical and cognitive variations when making changes in the workplace.

6 Conclusions and Contributions

This study adds to the existing research on production flexibility, mainly focusing on the context of SMEs and digitalization. It advances our knowledge of how human-centered digitalization can increase the adaptability and flexibility of SME production processes, leading to resilient systems both during high-impact events and normal company operations. It advises businesses on improving the flow of their production processes and dealing more skillfully with upcoming difficulties. The study utilizes a conceptual framework for comprehending the relationship between flexibility and adaptability mechanisms made possible by digital technologies and the production system features through progressively integrating human-centric characteristics in a digitalized manufacturing system.

The case study illustrates a human-centric strategy for designing a workspace where people's capabilities and interests are placed at the center of the manufacturing processes, consistent with Industry 5.0's goal. Our findings indicate that a digitalized working method considering human capabilities and needs can enable a more flexible and inclusive production process. It can help expand the production capacity by employing a more diverse workforce and enable a rapid setup of new and additional production processes. Such a method can be leveraged to quickly respond to supply chain disruptions caused by events like the pandemic, as demonstrated by the studied SME. Additionally, sales associates functioning as project managers can help provide better customer service, resulting in high-quality products with short lead times. Developing a learning culture and attitudes between colleagues can promote positive energy and skill development, resulting in better production processes and products. The findings of this study have implications for managers and practitioners interested in driving or supporting the transition of SMEs to Human-centric, resilient, and sustainable businesses.

Future work of interest is to focus on identifying other examples of I5.0 and its implication on the resilience of SMEs. There is also a need to explore employee engagement in a given environment like the one in the presented case study and investigate concepts such as job autonomy, job demands, and social support to promote job satisfaction and organizational commitment.

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Challenges in Designing and Implementing Augmented Reality-Based Decision Support Systems for Intralogistics: A Multiple Case Study

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Abstract. Numerous Augmented Reality-based prototypes and proof of concepts of assistance systems have been developed for industrial application scenarios that have not yet reached operational use. Alongside remaining technical challenges, the human-centered development of the systems and the associated improvement of the human-machine interfaces are seen as critical challenges for successful development and introduction. Therefore, this contribution addresses the challenges of designing and implementing augmented reality-based decision support systems for intralogistics work processes focusing on system users. The authors compared the qualitative results of a multiple case study conducted in ten intralogistics companies with challenges for industrial AR systems based on a literature review and the resulting focus areas regarding a human-centered design process. The view of the experts from the companies confirms the literature-based challenges on many points. However, some aspects pose particular challenges in intralogistics, such as the high-efficiency requirements for work processes. Overall, the results underscore the importance of involving operators in system development and highlight factors like usability, workload, and user acceptance, which can be evaluated through user research methods.

Keywords: Industrial Augmented Reality · Artificial Intelligence · Cognitve Assistance Systems · Human-centered design · Multiple Case Study · Intralogistics

1 Human-Centered Augmented Reality in Intralogistics

The digitalization of industrial work environments, including production environments under the term Industry 4.0, brings together information, technologies, and people in smart work environments [1]. The interaction of increasingly

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autonomous systems with human intelligence in industrial work environments from a human-centric perspective is addressed by the term Industry 5.0 [2]. For operators, the work is increasingly shifting to knowledge-based activities, decentralized decision-making, and collaborative tasks, which translates into a higher cognitive load for operators [3].

Assistance technologies are coming into use to support people in increasingly complex and dynamic industrial work environments [4]. One of the assistance technologies suitable for operator decision support in complex work environments is augmented reality (AR) [5]. For the visual processing of information on mobile devices, AR promises natural interaction between humans and technical systems and context-based information provision [6]. However, AR-based assistance systems have so far predominantly corresponded to perceptual assistance systems. Artificial intelligence (AI) techniques can provide operators with decision support for different tasks and open up new ways of collaboration with the operators [7]. In recent years, the possibilities of developing AR solutions for mobile hardware, such as smartphones, tablets, or smart glasses, have led to a strong interest in AR technology and the development of numerous mobile AR applications. This development trend can also be observed in the development of industrial AR applications [8]. In the industrial application context, a rapidly increasing number of industrial AR developments and numerous potential applications are contrasted by the fact that AR solutions have not yet been widely deployed in industrial practice [9–11]. Due to the numerous possibilities of the technology, such as the visualization of virtual information, interaction in three-dimensional space, or the design of user interfaces, no standards for the design of human-machine interaction of industrial AR systems have yet been established [12]. Therefore, the human-centered view of the technology is seen as an essential research direction [13]. The concrete structure of the human-centered design process and the associated investigation of factors contributing to the successful development and introduction of AR-based assistance systems in industrial application contexts from the user perspective have not yet been comprehensively investigated [14].

Therefore, this paper examines the current challenges to the industrial deployment of AR-based decision assistance systems. The article relates this state-of-the-art research to the empirical results from a multiple case study. Based on the empirical results, we discuss the implications for a human-centered design process and derive factors that need to be considered for the human-centered development of AR-based decision assistance systems from the perspective of both science and practice. Intralogistics was considered as the industry in this case, as there are many potential applications for the use of AR-based systems for process support, especially in personnel-intensive areas such as picking [15–17]. In the multiple case study, we interviewed company representatives about previous experience with digital assistance systems for process support, the requirements for AR-based decision assistance systems, and the challenges and opportunities of such systems. In addition, concrete implementation potentials were jointly identified as to which processes are suitable for AI-based AR support. These were identified in incoming goods inspection, picking and warehouse management, and packaging.

The paper is divided into the presentation of the research design in Sect. 2, the analysis of open challenges for industrial AR assistance systems from selected scientific review papers in Sect. 3, the description of the empirical results from the case study in Sect. 4, the discussion of the challenges from both science and practice and the resulting focus areas concerning a human-centered design process in Sect. 5.

2 Research Design - Literature Analysis and Multiple Case Study

As a first step, we analyzed the current challenges to industrial AR assistance systems based on 23 review papers in a scoping review following Arksey [18]. Therefore, we conducted a search Scopus database for review papers on the topic of industrial AR (76 search results). We selected the review papers according to the subject (content), the impact, and the inclusion of challenges of industrial AR. In each case, the subject is AR assistance systems for the industrial application context. Of the search results from Scopus, nine review papers met the defined criteria. We extended these results with a search in google scholar, from which an additional twelve relevant review papers were identified. By conducting forward and backward searches, we manually identified an additional two relevant review papers that also met our search criteria.

Kim [19], Dey [20] and De Souza Cardoso [9] address industrial AR use independent from the application field. Other authors analyze the state of research for specific application fields: Manufacturing [6,8,21–26], maintenance [11,27], shipbuilding [28], automotive [29], engineering services [30], construction [31–35], and logistics [17,36] To assess the article's impact on the scientific community, we determined the average number of citations using the Average Citation Score (ACC), according to [20]. The ACC is calculated by dividing the total number of citations by the time since publication in years. For this purpose, we used the current citation counts according to Google Scholar. Dey [20] set a threshold of 1.5 for the ACC in their review to ensure a moderate impact of the article on the scientific community. The reviews considered here have an ACC between 12 and 107. The consideration was limited to papers from 2012 onwards, as there have been significant technical advancements from this period ahead, especially in mobile AR.

For the case study, we selected ten companies from the intralogistics environment. The companies interviewed included four manufacturing companies: mechanical engineering (1), medical technology (2), and construction (1). In addition, we interviewed two logistics service providers, each of which operates its own logistics infrastructure. Furthermore, we interviewed experts from AR and AI software development (2), one IT security company (1), and one logistics IT consulting company (1). We surveyed the companies' previous experiences with developing and introducing cognitive assistance systems for process support, the requirements for such assistance systems, and the existing challenges for AI-based AR support with regard to a human-centered design process. To ensure a systematic qualitative approach, we created a case study protocol, preparing the objectives and background, the data collection procedure, the questionnaire, and the case study report, according to Yin [37]. Based on a catalog of questions, we interviewed 15 experts in semi-structured interviews. In addition to the expert interviews, we conducted process inspections at five companies to provide a detailed insight into the companies' intralogistics processes. All expert interviews were recorded and transcribed. The transcripts were supplemented by the records of the process inspections. A total of over 120 pages of text material were analyzed using qualitative content analysis according to [38], being an established evaluation method for expert interviews [39]. The qualitative content analysis derives categories from the texts and quantifies them according to the number of mentions in the text material [40]. To ensure scientific rigor, a systematic approach to data analysis is essential [41]. Therefore, we opted for inductive category formation, according to [38]. To ensure a systematic approach, we applied the web application QCAmap [42]. Initially, the first author of this paper conducted the text analysis for all three research questions under study and derived categories. These categories were aggregated in several iterations and assigned to each main category. The author team reviewed text coding and categorization of the text and jointly developed a summary in main categories across all three research questions.

3 Background - Current Challenges for Industrial AR Assistance Systems from a Scientific Perspective

We identified a total of 34 challenges from the analyzed 23 review papers. For structuring reasons, we first assigned the identified challenges to the categories user, technology, and interaction. Figure 4 shows this categorization, including the empirical results of the case study.

Linked to *interaction* are challenges in designing intuitive user interfaces using different forms of interaction [6,17,21,23–25,27–33,36]. Other challenges are for example the development of guidelines for AR user interfaces [22] and the standardization of interaction patterns for different forms of interaction [6].

Regarding *technology*, we could identify numerous challenges that we divided into hardware- and software-related challenges. Hardware-related challenges include the lack of ergonomics of AR hardware [6,9,11,17,19,22,24,27,28,30,32–34,36], or the so-far insufficient Field of View of head mounted displays (HMD) [6,8,9,11,19,22,28–30,36]. Furthermore, in the industrial work context the hardware must comply with occupational safety regulations [6,27,29,32,36]. In the software domain, tracking virtual objects in the real environment is one of the key challenges over the entire review period [6,8,9,11,19,21,23,24,26–28,30,32,33,35]. Furthermore, the challenges mentioned include improving rendering, i.e., embedding virtual objects into the real scene [6,9,11,19,24,26,28] or providing contextual data in real-time [22,23,25–27,31–33,36].

Concerning *users*, we could identify challenges in increasing usability and user experience [6,11,20,23,25–27,32,33,35,36]. Furthermore, gaining knowledge through user-centered evaluation is an essential prerequisite for the practicality of industrial AR solutions [8,19,20,23,33]. Other reviews name the physical strains, e.g., dizziness, nausea, or headaches, and cognitive load of the users in using an AR assistance system as a challenge [9,11,21,23–26,28,32,33,36]. Boboc [29], Egger [6], and Rejeb [36], name user acceptance of industrial AR systems as a current challenge.

The research needs we identified in analyzing the review papers concerning the users were the basis and motivation to conduct the case study. The results of the literature analysis served as a basis for the development of the case study protocol and for the classification of the case study results.

4 Empirical Results - A Practical Perspective from Intralogistics

For the case study, we interviewed the experts using an interview guide. Of the ten companies surveyed, seven each had prior experience with AR or AI-based approaches. Based on the inductive categorization, according to Mayring [38], four main categories could be derived in which we combined a total of 48 categories from the text analysis: user (17), system/technology (18), process (7), and system implementation (6). The findings for each category are described below.

User. Concerning users, the experts emphasized the added value of an assistance system for processing the work task (see Fig. 1). Most experts stated that the introduced assistance system or an assistance function must represent added user value (13 mentions). Further, achieving user acceptance is a high priority for the companies (14 mentions). In this context, the companies mentioned the consideration of users' individual motivation for using an assistance system and a higher general acceptance of new technologies for future introduction as particularly relevant topics. Other issues often mentioned by the experts were ensuring usability (7 mentions), mainly by involving operators in technology selection and system development. In addition, the experts named the avoidance of cognitive and physical burdens as essential for AR-based decision support systems (7 mentions). For example, a mobile assistance system must not restrict operators' freedom of movement or cause dizziness or headaches during prolonged use. All identified user-related categories concerning the number of their occurrence and the context of the statement (experience, requirement, challenge, or opportunity) are depicted in Fig. 1.

System/Technology. For most companies interviewed, the effort and costs were the most critical challenge associated with system development (10 mentions). The experts focus on ensuring a short payback period and assume that

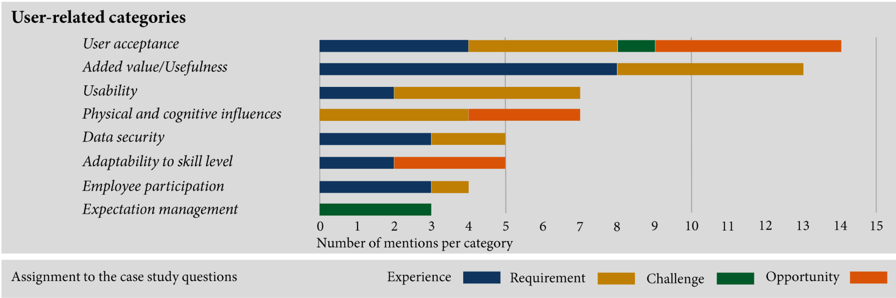

Fig. 1. Identified categories and number of mentions from the case study concerning the users

developing an AR-based decision support system might be related with a higher development effort than other solutions. In connection with the introduction of AR solutions, many experts mentioned the hardware's practicality (8 mentions). Particularly concerning the use of data glasses, the experts see a need for further development due to the current technological maturity of the hardware. For using AI-based methods for decision support in the work process, the companies see the associated effort with data preparation and maintenance as one of the most significant challenges (8). As a basis for AI-supported data evaluation, companies must digitize the work process, connect data streams, and record highly reliable data. As per previous experience, the companies stated about assistance systems and the use of new technologies that the systems must achieve a high level of reliability to be considered for practical use (6 mentions). In addition, the companies see further system-related challenges concerning data preparation for visualizing information on AR systems (5). Depending on the data basis, this involves a great deal of effort. For all other empirical results on system/technology-related categories, see Fig. 2.

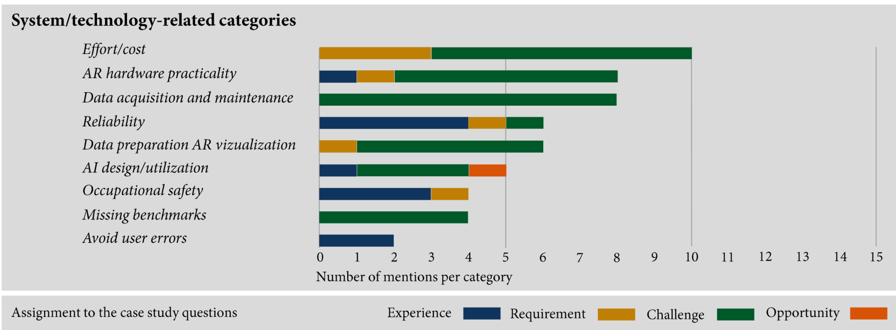

Fig. 2. Identified categories and number of mentions from the case study concerning system/technology

Process. Increasing process efficiency is essential for intralogistics processes (14 mentions). The experts are concerned with avoiding errors, increasing process quality, or increasing speed with system use. In this context, the high demands on the system's speed are seen as a central challenge since assistance must not slow down the operators by data input or related tasks. Regarding the work process, the experts also see the need to align the design of assistance functions with the work process and to increase process efficiency through the use of the assistance system, e.g., that the use of the system reduces the workload of the operators or AI-based assistance functions provide targeted support (8 mentions).

Implementation. The most important aspect mentioned from the experts concerning implementation is a gradual introduction of hardware and functionalities (6 mentions). In this context, the experts see positive effects on the acceptance of a cognitive assistance system and the requirement that assistance functions be designed to be expandable to ensure long-term usability. Analogous to the costs of developing an assistance system, companies consider it a requirement to keep the introduction costs as low as possible (3 mentions). The introduction of AI-based assistance functions, in particular, poses significant challenges in integrating the successfully tested processes into the companies' existing IT structures. All results of the main categories process and implementation are summarized in Fig. 3.

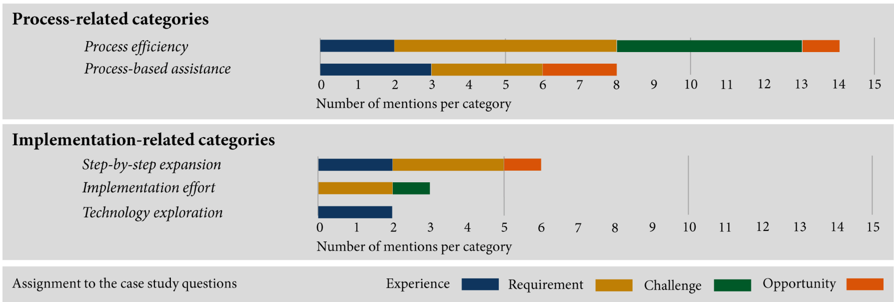

Fig. 3. Identified categories and number of mentions from the case study concerning processes and implementation

5 Discussion

In this section, we match the challenges for industrial AR assistance systems with the empirical results from the case study, which relate to AI-based process support using AR technology for intralogistics processes. Figure 4 divides the categories from the literature review into user, technology, and interaction. From the case study, we added the main categories of process and implementation. To enable a comparison between the scientific and practical views of the experts, we have expressed the individual categories in ideograms (Harvey Balls) according to the number of mentions in the literature or case study. The different scaling is explained by the number of review papers examined (23) and the aggregated mentions of the categories in the case studies.

User. Concerning users, the empirical results confirm the consideration of user-related factors, usability/user experience (UX), physical and cognitive loads, and user acceptance. Additional factors mentioned in both the review papers and the case studies are data security or the handling of personal data, and user participation in system development. The review papers additionally address the evaluation of the systems, which is expressed, e.g., in the requirement to evaluate with real users in the actual application environment [20] or the adaptation of user-oriented evaluation methods to the requirements of AR systems [19]. The companies did not explicitly name the involvement of users in the evaluation of AR assistance systems. In our opinion this is addressed by the objective to develop usable solutions and to involve users in system development. Most surveyed companies emphasized the added value of an assistance system for the users in the respective work session. This demand for efficient support of the work process is reflected, e.g., in the usability definition according to ISO 9241-11 ("extent to which specified users can use a system, product or service to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use" [43, p. 9]) or the construct of usefulness from Davis' TAM model ("The degree to which a person believes that using a particular system would enhance his or her job performance" [44, p. 320]). Another new factor, which was mentioned in particular by the companies from the software development sector, is the management of expectations concerning AR technology. From our point of view, the expectations towards the technical solution can be met by the users' participation and the decision makers' early involvement. Moreover, the companies expressed the need for different experience levels, which should offer the possibility of adjusting the level of support to operators with different qualification profiles.

Technology. For companies and academia, the better adaptation of AR hardware to the industrial work environment is a crucial challenge, including the need to achieve better ergonomics of AR hardware or better protection against environmental influences. The effort associated with the development, is estimated to be an equally important factor. The companies did not mention the detailed technical challenges, e.g., the field of view and the quality of the displays of the HMD, or the improvement of tracking and rendering on the software side. In our opinion, this might relate to the lack of concretization of the AR application or the self-perception as a user and not as a developer of an AR solution. The concrete technical challenges should be considered in the context of the individual technical implementation and are addressed depending on the type of AR application. The field of view, for example, is only relevant when using an HMD;

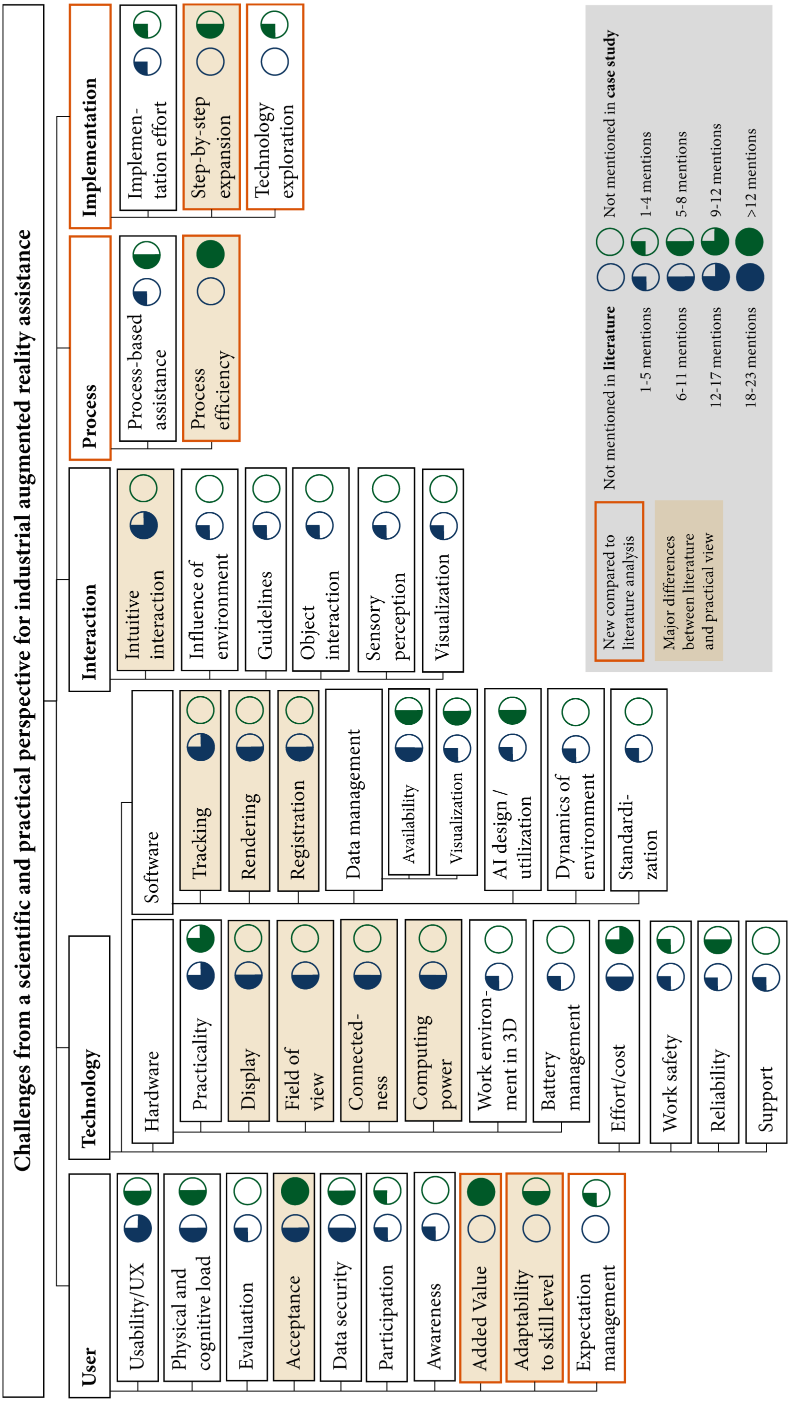

Fig. 4. Comparing the identified challenges for industrial AR-based assistance systems from literature and the intralogistics case study

the required computing power of mobile hardware also depends on the specific application. The availability and reliability of data are the foundation for the use of AI-based learning methods. In addition, data management is related to preparing data for visualization in AR systems that represented an essential part of the experience of AR-related developments of the companies. Data preparation for AR visualization can be a reason for deciding against an AR solution due to the high effort involved.

Interaction. If a smartphone or tablet is selected for process support for procedural or organizational reasons, usually more familiar interaction forms, such as touch- or voice-based interaction, are used. When selecting an HMD, hand gesture-based interaction forms and accurate three-dimensional representations can be used. This confronts most users with new interaction patterns. The AR-specific possibilities of interaction in three-dimensional space or direct interaction with virtual objects pose new challenges for science. For companies, we believe that interaction issues closely link to usability and the practicality of the AR hardware used.

Process. The review papers and the experts mentioned process-based support as an important challenge. The case study and scientific publications emphasized that an AR-based assistance system must be oriented to the work process, including hardware selection and assistance functions. In addition, many logistics processes considered place high demands on process efficiency, which is expressed in, among other things, low error rates and a high process speed. The specific requirements of the work processes in terms of speed and quality must be considered when designing assistance functions. For example, the experts expect to see an improvement in inspection results for incoming goods through image-based component inspection.

Implementation. Some companies see a big difference between the development effort of an AR- or AI-based assistance function and the actual integration into operational processes. For example, from an executable prototype of a data-based AI solution for evaluating operational enterprise data, there may still be a long way to go to a system integrated into enterprise IT. Another point for companies is the gradual introduction, both from an investment point of view and to gradually confront operators with new hardware and new software functions and thus not overstrain them. From the companies' point of view, this increases acceptance of introducing new technologies.

Limitations. Among the limitations of this paper, we count for the literature review that we limited ourselves to 23 review papers. Nevertheless, we believe that we were able to identify the fundamental challenges to industrial AR assistance systems, as the practical view from the case study confirmed many of the challenges mentioned there. The execution of the case study is limited to German companies. We assume that the results are more generalizable by interviewing other companies from different markets. The expert interviews were mainly conducted at the management level. In some cases, we could also interview operators during the process inspections. When it comes to the requirements for an AI-based AR assistance function, the requirements of operators should be considered. Despite the methodologically guided evaluation of the case study, we assume an inevitable subjectivity of the results and the category formation. We have tried to counteract this through discussions, joint revisions, and feedback within the author team. Considering the limitations mentioned above, we believe that the results from science and practice allow us to draw conclusions about which factors need special attention when designing, developing, and implementing AR decision support systems for intralogistics work processes.

6 Conclusion and Outlook

In this contribution, we investigated the challenges of designing, developing, and implementing AR-based decision support systems for intralogistics work processes from scientific and practical perspectives. We conducted a multiple case study in ten intralogistics companies based on a scoping review. We compared the empirical results of the case study with the challenges from science and discussed them.

For the companies, costs and efforts related to system development, implementation, and data preparation are essential for AI-based AR assistance functions for process support. Logistics processes require high efficiency, affecting the type of assistance functions and the interaction between humans and the system. Companies focus on intuitive systems that guide operators through the work process without overwhelming them with numerous setting options and new interaction patterns. Nevertheless, there should be customization options for the assistance functions to suit users' preferences and skill levels, which will determine the level of support the system provides. In terms of AR hardware, the focus for companies is on practicality. The numerous technical challenges from science, such as the field of view of HMD or improvement of the tracking of virtual objects, must be addressed in development depending on the type of assistance function. The increased involvement of users in system development, which is also intensively demanded by the scientific community, was present throughout the case study. The empirical results confirm the literature that users need to be more involved in the development process. For a human-centered design process of AR-based decision assistance systems, the work process and the work environment are crucial for selecting assistance functions and the hardware used. Compliance with occupational health and safety and data security guidelines are fundamental prerequisites for implementing process-related assistance functions. Involving users ensures their early contact with new technology. It enables drawing conclusions about the design of an assistance function and adapting the solution to the users' requirements in the respective application context. In this context, the needs of different user groups must also be taken into account, e.g. with regard to age or experience with new technologies. This was not explicitly addressed by the experts in the case study, but should be taken into account in the design and development of AR assistance functions. In addition to collecting quantitative data, such as throughput times or error rates, user-related factors can be evaluated, e.g., usability/UX, workload, or user acceptance. Questionnaire-based methods can be used for user-based evaluation, such as System Usability Scale (SUS) for usability assessment [45], the User Experience Questionnaire (UEQ) for UX assessment [46], NASA TLX for workload assessment [47], or the Technology Acceptance Model for user acceptance prognosis [44]. This contrasts with the efficiency requirements and high effort of user-based evaluation. Therefore, by prioritizing the factors for the specific use case of intralogistics, we strive to develop a requirements-based evaluation method that enables the assessment of the most critical factors while considering the limited resources. Therefore, the concrete method selection and adaptation for the human-centered design process will be the subject of our further research work. In this context, we aim to adapt user acceptance models for industrial AR assistance systems, which have not yet been investigated in detail [48]. Therefore, through further cooperation with experts from the application field, we aim to narrow down the factors to be investigated and adapt established evaluation methods to the needs.

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Data at the Heart of the Industry of the Future: New Information Issues from an Information and Communication Sciences Perspective

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Abstract. In this article, we propose to take a forward-looking look at the issue of data and information systems in industrial companies, in the context of the industry of the future. Indeed, if, as many claim, we are to take advantage of this industrial revolution to reaffirm the central role of human beings in industrial organizations, it is essential to involve the social and human sciences, and particularly the information and communication sciences, in current research on the subject. The aim of this paper is therefore to identify themes where the contribution of this discipline would be major. To this end, after tracing the major stages in the evolution of ERP (Enterprise Resources Planning) type information systems and positioning the major challenges of the industry of the future in this respect, we raise four main questions. The first concerns the need to develop a new enterprise information system model, taking into account global communication, IoT and CPS. The second concerns the coverage of this information system, and the need to take account of the company's ecosystem. The third concerns the need to integrate the informal aspect of the organization into this model. Finally, the fourth question relates to the need for a new decision model in a context of distributed intelligence and decision-making. Ultimately, these questions lead to the definition of a roadmap for the evolution of information and decision systems in industrial companies, which deeply involves information and communication sciences.

Keywords: Data · ERP · industrial engineering · industry of the future · information and communication sciences · information systems

1 Introduction and Purpose

In this paper, we propose to set out a reflective framework on the issue of data, information and its systems in the context of Industry 4.0, also known as the *industry of the future*. This perspective of the industry of the future lies at the crossroads of reaffirmed human issues and strong technological innovations - new manufacturing processes (additive manufacturing, 3D printing), principles of collaborative robotics (cobotics), advanced simulations (digital twins), massive production of data (big data) and interconnection of these data (IOT - internet of things) (PWC 2016; Barneveld and Jansson 2017).

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The problem of multiple, heterogeneous data, coming from automatic sources (sensors) as well as from human or organisational sources, is therefore an important facet of these new industrial environments, marked by a strong digitalisation and technicalisation of processes and activities. The development of sensors, recording different types of human activities (production, design, manufacturing, etc.) within the company or in connection with external actors (suppliers, customers) produces a colossal quantity of data, requiring automatic (algorithmic) processing. These modalities, characteristic of the new industrialised environments, therefore coexist with more structured info-documentary modalities, linked to the information system of the organisation concerned.

This quick overview shows that the industry of the future is an opportunity to rethink the place of people in industrial systems. Indeed, much of the literature on the industry of the future puts forward the principle of "people at the heart of the system". If we now want this principle to go beyond the mere stage of argument to become a reality, we need to analyse how disciplines stamped as Social Sciences and Humanities (SSH) can fully participate in the debate. One of these disciplines, the Information and Communication Sciences, seems to be very close to the issues of the industry of the future (particularly the data and information issue). However, an analysis of this discipline's fields of application shows that it generally focuses on areas with which it feels naturally close (education systems, libraries, etc.), and only very rarely takes an interest in industrial systems. Consequently, the aim of this paper is not to present precise results, but rather to launch a forward-looking reflection aimed at identifying scientific themes linked to the industry of the future, in which information and communication sciences can play a major role. In this sense, the proposals made in this paper contribute to the development of industry 5.0, as defined by (Müller 2020).

To this end, based on problems identified by industrial engineering but viewed from an information and communication science perspective, this paper explores several questions. How do these different types of data make up information and can they be integrated into information systems (ERP type) but also into documented and structured systems (metadata, knowledge organisation systems)? What new modes of aid to action, decision-making and governance are emerging, in connection with artificial intelligence (*algorithmic governance* – Henman 2020; Rieder 2020)? What ethical questions arise in these working contexts? What new mediations, data literacies and information cultures should be developed in these so-called *industries of the future*?

The paper is organized as follows. We will review the evolution of information systems in companies focusing on ERP (Enterprise Resources Planning) solutions. Secondly, we will focus on the key points of the so-called industry of the future, in order to confront them with ERP. From this confrontation, we will open up on four major industrial issues of interest to the information and communication sciences.

2 Enterprise Information Systems and ERP

The first element of context concerns information systems in companies and ERP (Magal and Word 2012; Ganesh et al. 2014; Sagegg and Alfnes 2020). At the time when management information systems began to be used in industrial companies, their information systems were developed in line with their organisation. Thus, each function, each department in the company built its own information system to meet its own needs and uses.

The result was to improve the functioning of these departments, but at the same time to increase the balkanisation of the company, which was already very often the rule. The overall functioning of the company gained nothing from this situation, which reflected a cruel lack of integration.

Faced with this situation, new approaches were developed, all with the aim of breaking down the walls erected between departments. The first aspect concerned data. The aim was to bring them all together in a single system, thereby avoiding the same data being found in several places in the company under different names and with different values. This approach was based on the development of large databases and was described as integration by data.

The second step was to build business processes which use and produce the data we have just mentioned and which have the characteristic of not being adjusted to the perimeter of the company's services but of following a functional logic. For example, a process could be envisaged that goes from the customer (order) to the customer (delivery), crossing and relying on as many of the company's departments as necessary. This approach, largely inspired by Business Process Reengineering (Hammer and Champy 1993), also ignores the boundaries between departments.

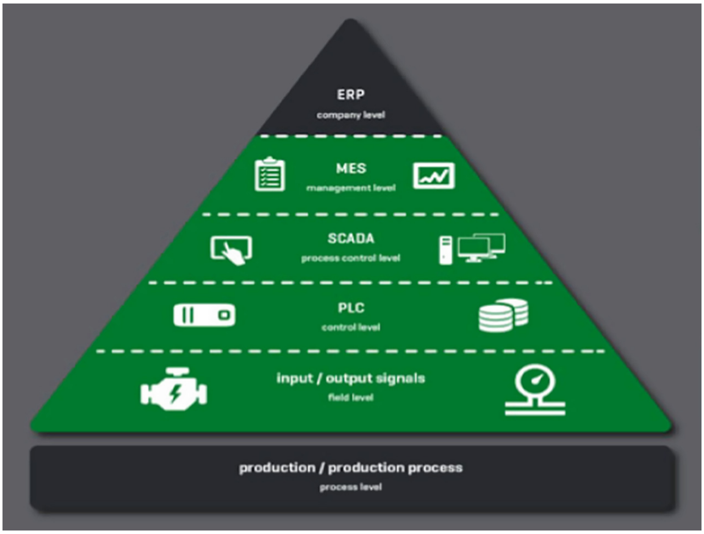

Fig. 1. Position of ERP in the CIM pyramid (Invilution)

This approach, with a single database to which business processes implemented on the basis of workflow technology are connected, has gradually become the standard and is the basic principle of ERP. In this sense, ERPs play a major role in the CIM (Computer Integrated Manufacturing) perspective (Waldner 1992), which was particularly popular in the 1980s, promoting the integration of the enterprise through computerisation. Figure 1 presents a revised view of this concept.

Thus, an ERP has many advantages (integration of data, formalisation and transparency of business processes) which effectively contribute to the integration of the company as long as it covers all the functions of the company (Fig. 2).

However, this integration is achieved at the cost of many defects and criticisms (Herr 2013; Dorobat and Nastase 2012): cumbersome implementation and use; complexity; monolithic nature; lack of ergonomics; rigidity and inability to integrate new uses. A survey carried out in 2013 (Cegid 2019) also showed that the main requests for change concerned mobility (working anywhere and on different media) and modularity (business-oriented solutions). The study concluded that: *"The ERP of tomorrow [...] will be social, will process external data and will be used on the move and in the cloud"*.

The ensuing evolution can be structured in two main stages. The first stage, which is still in progress, is based on migration to the cloud with several expected impacts (Dorobat and Nastase 2012): mobility; reduction of investments (CXP 2018), improvement of the user experience (ease of use and adaptation to new mobile and collaborative uses). The second, more forward-looking stage aims to move towards agile and scalable ERPs, less monolithic and rigid architectures with better handling and more reliable deployment projects (Dorobat and Nastase 2012), and finally, an evolution of the solution (thanks to a marketplace operation).

Fig. 2. Functional coverage of traditional ERP systems (I-scoop 2023)

As part of this trend, we can also note the I-scoop's vision (2023) concerning intelligent ERPs (i-ERPs): *"[...] you can see the intelligent ERP on the most basic level as the ERP becoming a system of engagement, system of insight and intelligence, system of decisions and system of integration and connectivity instead of just a system of records"*.

To conclude, while ERP is a salient variation of information systems in companies, it is important to emphasise that it does not encompass all information-related approaches. In particular, the design of the offer (products/services, research departments), the improvement and evolution of the company (organisational innovation) or data linked to social media and digital networks do not fall within the scope of ERP.

3 The Industry of the Future

The very strong current developments in information and communication technologies are leading to a new technological offer which has many applications in the industrial sector. It is in this context that the concept of the industry of the future has been flourishing for the last ten years. Whatever the terms used ("factory of the future", "industry 4.0", "industry of the future", etc.), it refers to the technological and organisational changes that will impact the world of work following the emergence and implementation of a new generation of IT solutions.

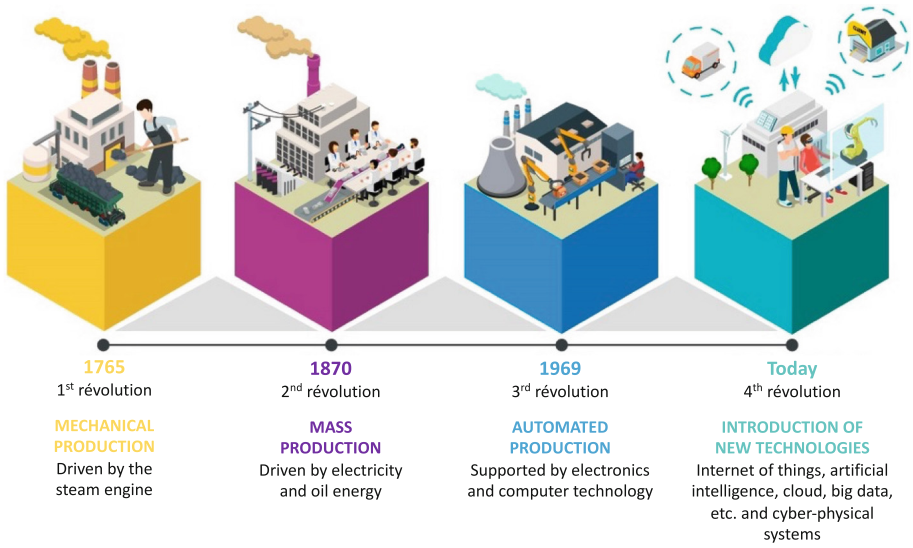

Fig. 3. The four industrial revolutions (translated from Geandarme, 2018)

It is clear that these components are only facilitators of transformation. Technological developments are only of interest if they lead to new services, new uses, new organisations or new business models. Therefore, talking about the industry of the future is not limited to considering these changes in terms of technology, but integrates the entire current transformation. This is why the factory of the future can be understood in a more general way by integrating all current trends. Beyond the trivial observation that things are changing and that trends are emerging, it is the speed of change that is taking place today that is most characteristic, a speed that leads to talk of an industrial revolution (hence the term Industry 4.0 in reference to the three previous industrial revolutions, Fig. 3).

In a report presenting the main results of an international survey conducted in 26 countries with 2,000 respondents (**PWC, 2016**), Industry 4.0 is identified on the basis of a set of tools (mobile media, Internet of Things (IoT)-oriented platforms, intelligent sensors, 3D printing, Big Data-type approaches, augmented reality, cloud computing, advanced human-machine interfaces, etc.) but also on the basis of a number of transformations (improved performance through digitalisation, the crucial role of data, the changing role of the customer, who is more autonomous and more closely connected to the company, etc.). A particularly interesting element of the report is the observation that the pivotal point of the industry of the future is not, in the end, a technological one, but rather linked to the human element and a new digital culture in the company. The role of data, and in particular big data, in the industry of the future is nevertheless crucial. In this respect, we can recall the words of Menger and Paye (2017) concerning the five key developments superimposed through Big data:

- scientific and technical innovations;
- multiplication of data-generating sources and connectivity;
- expansion of the market for tools and uses of mass data exploitation;
- placing of exploited informational imbalances in ethical and political controversy and legal and legislative regulation;
- formation of new service markets transforming privacy into a gradable and negotiable utility or “disutility”.

An analysis carried out in 2018 (Vallespir 2018) sought to define the content of the industry of the future field on the basis of sources of various kinds (industrial announcements, policy documents of public institutions involved in innovation - regional councils, technology transfer platforms, competitiveness clusters, etc.). This analysis is, of course, indicative, firstly because the set of sources compiled is small and, secondly, because this classification is necessarily debatable. if we now seek to isolate from this set of themes those that correspond to the subject of this paper, we can obtain the following classification:

a. **The data.** This first set concerns the data itself, from its generation (sensors and actuators) to its storage and analysis (Analytics).
b. **Connectivity.** Here we find everything that corresponds to the exchange of data between players, whether it be technical solutions (Internet of Things) or the possible perimeters and scales of exchange: between machines (connected machine), within the framework of collaboration between companies (digital supply chain) or with the customer (adaptation to demand, customisation, integration from order to delivery). An important point is the speed of connection (fast connection, adaptation to demand in real time).
c. **Management and Control.** Here We Find Levels of Control Traditionally Devolved to Control Layers External to the Resources and Requiring Human Intervention Which Are Now Found Implanted into the Technical Resources. This Concerns Supervision (Automatic Control and Supervision), Optimisation (Self-Optimising Systems, Product/process Optimisation) or Quality (Automatic Quality Control).
d. **Intelligence.** This Concerns the Intelligence and Learning Capabilities (Machine Learning) Now Attributed to Technical Resources (Decentralised Intelligence, Intelligent Mechatronic Systems).

e. **The Convergence of Information Technology and Operational Technology.** All the Points We Have just Seen Can Be Encapsulated in a General Principle of Convergence Between Physical and Information Transformation Technology. This Principle is Embodied in the Concept of Cyber-Physical Systems (CPS) or, Even More Generally, Cyber-Physical and Human Systems (Poursoltan et al. 2021).

If we compare the evolution of ERPs, as presented above, with the new paradigm represented by the industry of the future, understood as a human society, a place of behaviour and informal exchanges, it appears that this evolution of ERPs remains far from the proposals of the industry of the future (Haddara and Elragal 2015). This is why a number of scientific studies have focused on this subject (Majstorovic et al., 2020; Akyurt et al., 2020; Bytniewski et al., 2020).

Anyway, a fundamental question emerges: how can these systems adapt to an organisation where all the players communicate, supply data, demonstrate intelligence and decision-making capabilities? Indeed, one may wonder about the capacity of these systems to meet the needs of complex industrial systems composed solely of CPSs.

4 Main Questioning From an Information and Communication Sciences Point of View

On the basis of these two contextual elements (ERP-type information systems and the industry of the future), we can identify four main questions. these stem from info-communication issues and are enriched here with industrial engineering issues.

4.1 Question 1: What is the *Enterprise Information System Model* in the Age of Global Communication, IoT and CPS?

This questioning comes from the point of view of data: how can the integrative logic of current information systems (based on a single central data model) accommodate an organisation where all the players communicate and supply heterogeneous data, in mass and in real time (characteristic of big data)?

More specifically, the problem concerns the vertical integration of data, i.e. across the hierarchical levels of the company. the central and unique model solves the problem *de facto* since only one level of data is proposed. however, if the human actor continues to be a producer and user of data, in relation to his activity, the production of automatic data via sensors is intensifying and will become dominant in the near future. Several types of data thus coexist at the heart of the organisation's functioning: formal/informal data; raw/structured data; automatic/socio-personal data. It should be noted that the intensification of data production through sensors is not without risks, whether this concerns health (interweaving of the body and technology, implanted sensors), ethical issues surrounding the data collected or asymmetrical relations between users and technological systems (for example, forms of opacity concerning the conditions of capture, storage and exploitation).

If we now want to take advantage of the emerging wealth of information, it is undoubtedly necessary to envisage local information systems, on the scale of autonomous resources (CPSs?) which would be responsible for their own data, in terms of updating values and model evolution. How then can we ensure that all these local information systems are interoperable and can be aggregated in order to ensure coherence and integration and thus avoid returning to the previous situation of silos? At the information-documentary level, the stakes and challenges are also high. They concern the processes of transforming these heterogeneous data into information / documents / knowledge and raise the question of metadata and knowledge organisation systems to be deployed.

4.2 Question 2. What is the Coverage of This Information System (Integration of Suppliers, Customers, Innovation Ecosystem, Etc.)?

Even though enterprise information systems necessarily integrate information relating to their environment, they are still very much focused on their own company. However, the expected information enrichment suggests that this environment will be the source of information of major interest to the company in question. the injunction to refocus on one's core business, which has been at work for several decades, also pushes in this direction: having outsourced essential functions, the company cannot function alone. This is all the especially true in the context of the industry of the future, where the boundaries of the company, between endogenous and exogenous, are becoming more porous, with the user/customer playing a growing role in industrial processes, whether through feedback and satisfaction, or through new forms of collaborative production/innovation (Morrar et al. 2017).

Also, its performance is linked to the knowledge it has of its environment and the diversification of useful/usable data sources. The first point concerns the value chain and therefore relates to horizontal integration: the company's information system must integrate its suppliers and customers. This raises many questions: what information is needed? what information is accessible? Should we stay at the first level or extend the approach to suppliers of suppliers and customers of customers? What level of integration of "external" social data (for example from digital social networks or CRM tools)? How should it be linked to more flexible working and data production tools, in connection with collaborative innovations (within or outside the company)? In other words, how can we articulate, within what could be considered as a meta-information system, data from substitutive (automation of a certain number of tasks), rationalising (ERP type) and enabling technologies (more flexible and cooperation-oriented technologies) (Bobillier Chaumon 2021, Martine et al. 2016). The second point concerns the rest of the environment: competitors, innovation ecosystems, etc. here too, questions arise about the need for and accessibility of information.

The main challenge relating to this questioning therefore concerns the development of information ecosystems, horizontal and open to the environment, but according to perimeters and with data accessibility/utility/usability criteria to be defined.

4.3 Question 3. How Can the Informal Aspect of the Organisation Be Integrated into This Model?

The shortcomings of ERPs with regard to "human" aspects were very often noted. In response, it has been proposed that digital social networks-type approaches be integrated, that ergonomics be worked on, etc. At the same time, one of the main slogans of the industry of the future is the repositioning of people at the centre of the system. If the industry of the future aims for this aspect to go beyond the rank of slogan, it must be an opportunity to remember that a company is above all a human society and that, beyond the engineering and managerial vision (of which the ERP is the result), a company is a place of behaviour and informal exchanges. This debate is not new and has already been discussed many times (Roethlisberger and Dickinson 1939; Maslow 1943; Mayo 1971).

Also, this *hidden* side of the company's information system contributes to its overall performance and must therefore be studied and taken into account: it is necessary to know how to analyse the two sides, formal and informal (Morega 2008). The problem is not easy to solve: we stand in an intermediate space between a mechanistic and explicit approach to information (data model, business process model) and an informal and therefore invisible part. What is the limit, what is the balance between, in one hand, a ERP-type extreme formalisation and, in another hand, the consideration of the generation of activities, exchanges and communication situations in a start-up, non-formalised way? The question is therefore how to *represent* what cannot be represented (because it is informal), or in other words, how to make the *intangible tangible* (information-as-thing, Buckland 1991). In this respect, knowledge management, the documentation of innovative projects, and investigative approaches are some of the methods that can be used to transform the informal into the formal, useful for the company. Of course, not everything has to be formalised, recorded and documented, and the public/private boundary within the company, based on the law and the protection of personal data, has to be drawn.

4.4 Question 4. What is the Decision Model for Analysing the Distribution of Intelligence and Decision Making?

A simple way of representing the production activity is to consider an operational level and a management level. At the operational level, we find operators who interfere with technical resources which, in turn, act on products. At the management level, we find managers who rely on IT resources to make their decisions.

If we now think in terms of intelligence and decision-making capacity, we can distinguish between the current situation (a) and that which can be envisaged in the context of the industry of the future (b).

Current situation (a)

Operational level:

1. The operator has intelligence and decision-making capacity, both of which can be described as operational,
2. The technical resources do not have these capabilities, they respond either to orders given by the operator or directly sent by the control system,
3. The products also have none of these capabilities and simply undergo the transformations.

Management level:

4. The manager has intelligence and decision-making capability,

5. The IT resources can be described as decision support, but at a sufficiently primitive level to consider that they do not have these capabilities.

New situation (b).
Operational level:

1. The operator keeps intelligence and decision-making capability,
2. The technical resources still respond to the orders given by the operator or by the control system but have new capabilities: supervision, optimisation, adaptation, diagnosis, learning,
3. Products continue to undergo transformations but get smart capabilities. From the simple data-carrying product to the product capable of deciding on its routing or triggering actions necessary to preserve its integrity or quality for example, the notion of "intelligent product" (Trentesaux et al. 2013) covers a wide range of situations.

Management level:

4. The manager always has intelligence and decision-making capability,
5. IT resources now have data analysis and learning capabilities that allow them to become much higher-level decision aids with undoubted intelligence and decision-making capacity.

Figure 4 summarises this evolution.

The problem that then arises concerns the development of a new decision model that takes this evolution into account. Beyond this model, many questions arise: how to represent in this model all the possible solutions, from the traditional centralised system to the system where all the actors have a significant decision-making capability? How to choose the best configuration for each industrial case? Behind this question, another one emerges: how to evaluate these configurations in order to choose the best one according to the performances expected by the company? Finally, the last important

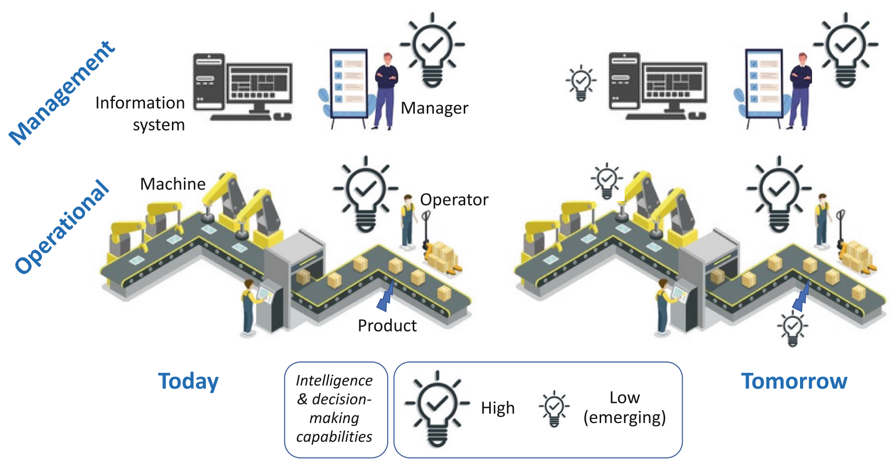

Fig. 4. Evolution of the distribution of intelligence and decision-making capabilities between actors

question is: how does the place of the human actor evolve in these new configurations? In connection with artificial intelligence and big data, questions of governance and 'algorithmic governmentality' (Henman 2020) arise with acuity, between control and *authority* of digital devices and processes of negotiation/contestation by human actors, such as proximity managers (Jemine 2021).

From the point of view of information and communication sciences, it therefore seems necessary to develop the issue of digital literacies and to bring a critical look at data culture (social, ethical, communicational, informational issues) in training courses (especially technological) and in companies. A *data mediation* perspective is also a promising area of development (see in particular the model of Human-Data mediation proposed in (Nesvijevskaia 2019). Finally, in connection with these emerging models of decision making, it is important to also alert to the new vulnerabilities and new techno-digital fractures that may emerge.

5 Conclusion

We can attempt to summarise our thoughts in Fig. 5.

Many questions are thus open, of a fundamentally interdisciplinary nature. In particular, what may interest information and communication sciences, in connection with industrial engineering issues, is the place of the user, of the informal, of 'human' data and activities as well as of document and knowledge processing operations in these new industrial company contexts and these informational environments tending to be dominated by massive, heterogeneous data, used independently of any human authority. To put it differently, it is a question, through the context of the industry of the future, of considering information systems, no longer from a strictly technological point of view but as situated anthropo-technical systems. To move in this direction, it is clear that SSH disciplines need to be involved at the forefront, particularly information and communication sciences. The aim of this paper was to identify the main themes that would benefit

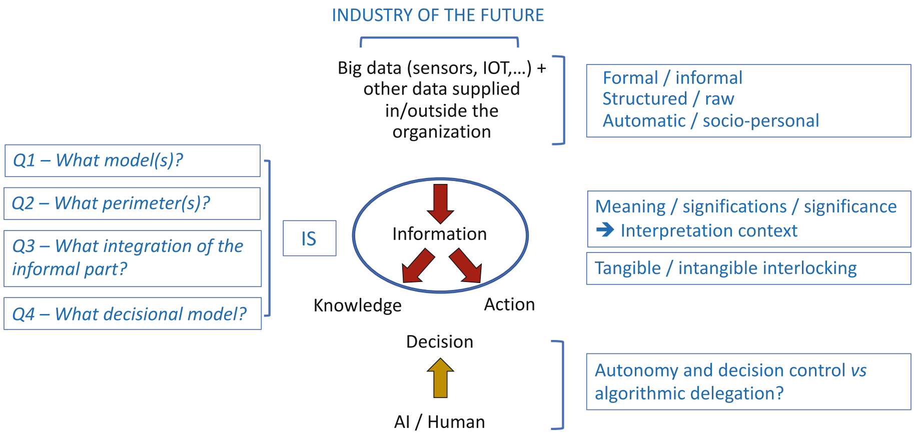

Fig. 5. Synthesis

from such involvement and it now remains to translate these themes into operational research projects.

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