Collegio di Ingegneria Gestionale e della Produzione
Corso di Laurea Magistrale in Ingegneria Gestionale

Tesi di laurea magistrale

Assessment of how I5.0 approaches and technologies influence the performance of logistics system with Delphi study

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Sessione di Laurea Aprile 2025

Fa che i tuoi sogni siano di pietra,
in modo che nessuno te li possa distruggere.

- K. Gibran

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LIST OF ACRONYMS

AGV	Automated Guided Vehicle
AI	Artificial Intelligence
AMR	Autonomous Mobile Robot
AR	Augmented Reality
CI	Computational Intelligence
DMM	Domain Mapping Matrix
DRM	Design Research Methodology
DS-I	Descriptive Study
HIRT	Human interaction and recognition technologies
I5.0	Industry 5.0
IEMS	Intelligent Energy Management Systems
IoE	Internet of Everything
IoP^2	Internet of Personalized Products
IQR	Interquartile range
ISWs	Intelligent smart wearables
LGV	Laser-Guided Vehicle
ML	Machine Learning
NGWNs	NextG wireless networks
NTaaS	Tracking-as-a-Service

PS	Prescriptive Study
PS-II	Descriptive Study II
RC	Research Clarification
SRL	Systematic Literature Review
Q1	First interquartile
Q3	Third interquartile

INTRODUCTION

The goal of this thesis is the assessment of Industry 5.0 approaches and technologies for the performance of logistic systems.
Being this thesis a research thesis it was decided to adopt the methodology suggested by Calderon (2010) the Design Research Methodology (DRM). The DRM is composed of four phases: Research Clarification (RC), Descriptive Study (DS-I), Prescriptive Study (PS) and Descriptive Study II (PS-II).

The RC phase defines the objective of the research.
The DS-I phase creates the awareness and improves the understanding of the subject matter that has been defined in the previous phase.
The result of these two phases is the definition of the framework, in which the execution in the third phase must be carried out.

In this case, the framework was defined by Bottazzi (2024) in her job "Impact of Industry 5.0 target dimensions on the performance of intra-logistic systems: a proposed assessment framework".

The current thesis instead focuses on the execution of the third phase of the Design Research the Methodology within the framework that was developed by Bottazzi (2024). Only once this phase is completed it is recommended to move to the next one Descriptive Studies II, but this is not the object of the current work.

The Prescriptive Study has been carried out by applying the Delphi study, a detailed description of this Delphi study is the object of the content of the third chapter of this thesis.

The first chapter focuses on the description of the three pillars of Industry 5.0, the description of three intra-logistic systems that are considered in this thesis and explains the methodology that was used the conduct the research of articles within current literature.

The second chapter describes the initial assessment framework that was developed by Bottazzi (2024), the Likert scale used to evaluate the relationship between approaches/technology with parameters and highlights the changes needed as a consequence of the analysis result.

The third chapter can be considered the core of this thesis. It contains the description of the Delphi study, as already mentioned, and the adopted calculation methodology of the medians and interquartile range (IQR). In addition, it contains the panel of participants and the grading sheet.

The results of the Delphi study are also discussed in this chapter. One of the outcomes, for instance, is that respondents do not fully agree on the impact of approaches and technologies on the investment and operating costs. This is particularly evident when talking about storage and material handling systems, which require more complex and expensive technological infrastructures. On the other hand, respondents agree on investments and operating cost regarding the picking systems, but do not fully agree on other aspects such as level of automation and picking operation time as far as concerned the technologies.

Finally, the fourth chapter describes the innovative contribute brought by this work to the literature but also describes its limits.

Researches on these topics are crucial because once all outcomes are combined, they can bring innovative and significant benefits to the manufacturing industry. Indeed, Industry 5.0 represents the new paradigm towards which the industry is evolving, following the established experience of Industry 4.0.

1 THEORETICAL BACKGROUND

The present chapter explains the term industry 5.0 with its pillars and the different types of internal logistic systems. Such a knowledge is crucial to understand the research work.

1.1 INDUSTRY 5.0

Industry 5.0 is a new industrial revolution, which developed gradually with technological interactions and social-economic changes.
Three important pillars characterize this revolution (Dacre et al., 2024):

1. Human-centricity: Industry 5.0 is focused on workers' well-being, in particular on improving the quality of working life by reducing repetitive tasks and reducing workload through intelligent automation.
   It aims at making the working place safe, more satisfying where the contribution of the human being is valuable and promoted.
2. Sustainability: Industry 5.0 focuses on sustainability and circular-economy, trying to minimize wastes and reduce the environmental impact of production processes. Therefore, there is a ecological and social responsibility by integrating eco-friendly practices in each phases of production.
3. Resilience: Industry 5.0 aims at the designing and manufacturing of robust and flexible production processes, which enables companies to promptly react to even traumatic changes without suffering permanent consequences.

Now, you may wonder what are the differences between Industry 5.0 and Industry 4.0? Why there was a need of creating and defining the new concepts of the industry?
Industry 4.0 principles were the automation and digitalization of industrial processes with the scope of interpreting the behaviour of the digital twin to predict the behaviour of physical twin and therefore prevent inefficiency in the real

production process. Industry 5.0, instead, completes Industry 4.0 principles bringing human beings back to the centre of the process (Jefroy et al., 2022) and considering the sustainability and the circular-economy of the production processes.
On the light on what was stated here above, we are going to explore what the applications of Industry 5.0 principals means for internal logistic systems: picking system, storage system and material handling system.

1.2 INTERNAL LOGISTIC SYSTEM

With the always increasing demand of being faster to the market, efficient and competitive, the necessity of having high performing internal logistic system became crucial.

Internal logistic system refers to the whole movements of all supplied material and to all supporting tasks within a production plant. In other words, this system allows the control of the movements of the materials within the plant, ensuring the perfect timing, quantity and position of a certain product. In this thesis we will take into consideration three different types of internal logistic systems:

a. Automated Picking System
b. Automated Storage System
c. Automated Material Handling System

1.2.1 Automated Picking Systems

With the term picking is intended the task of selection and the taking of material from storage with the scope of gathering them together and making that ready to be analysed or delivered to different places.

Picking activities can take place in various ways: from the simplest way in which the operator manually checks the amount of product units (Figure 1), to the most sophisticated one based on a fully automated system.

Figure 1: The operator manually checks the amount of product units, Source [1]

For example in the picking process, Autonomous Mobile Robots (AMRs) (Figure 2), which are intelligent robots able of moving without pre-defined paths and therefore very flexible, and Automated Guided Vehicles (AGVs) (Figure 3), which instead are able to move along pre-defined paths, increase efficiency and reduce errors by automatically picking products from their shelves and taking them to the packing or shipping areas. This not only speeds up the process, but also ensures greater accuracy in identifying and picking items.

Figure 2: Autonomous Mobile Robots, Source [2]

Figure 3: Automated Guided Vehicles, Source [3]

1.2.2 Automated Storage Systems

With the term storage is intended the aim of storing different kind of product in a warehouse so that companies ensure the availability to complete their planned production or distribution processes.

We can distinguish two main types of storages:

1. Manual storage system: it is the traditional storage mode, where there are no automatic systems and operations are carried out by operators only. In these facilities, the operator is not only responsible of the picking operation but also for packing and shipping of the product.
   In some cases, the handling of goods can be performed with the help of lifting equipment such as forklift trucks.
2. Automatic storage: while in the manual storage is the operator that picks the good, in the automated warehouses is good that moves to the operators through the automated picking system (the so called *goods-to-man approach*) (Figure 4)

Figure 4: Automatic storage system, Source [4]

In the automated warehouses of Industry 5.0, the interaction between humans and machines becomes crucial, in fact workers collaborate with robots and intelligent systems to perform tasks that require human skills, such as quality control, process optimization, and exception management. In this way, the automated warehouse of Industry 5.0 becomes an environment where human and machine capabilities complement and enhance each other [5].

1.2.3 Automated Material Handling Systems

With Material Handling System we intend not only the movement of materials and goods within a warehouse, but it also includes the protection, the storage and the control of materials from manufacturing to distribution.

Material Handling Systems can be simple pallet racking, forklift trucks, but also sophisticated handling systems such as sorters (Figure 5) and laser-guided vehicles (LGVs). In addition, this can include handling robots, various types of palletisers, packaging and wrapping systems (taping, filming, etc.).

Figure 5: Sorters, Source [6]

These more sophisticated Handling Systems can take companies through Transition 5.0 with logistics solutions that are intelligent, responsive and adaptable to the changing needs of the market as they generate greater efficiency and precision to warehouse operations, transport and inventory management.

1.3 SYSTEMATIC LITERATURE REVIEW

One of the main research methods used in this thesis is the Systematic Literature Review (SLR). This method fits whit the topic of the thesis as it focuses on the gathering on the information on papers written by experts of the field and then in the synthesise of the multiple studies to deliver a comprehensive view of the topic of interest, which in this case is how performance affects the different internal logistics systems of Industry 5.0.

The SLR is divided in 5 steps (De Lombaert et al., 2023):

1. Framing the question
2. Identifying relevant publications
3. Assessing study quality
4. Summarizing the evidence
5. Interpreting the findings

1.3.1 Methodology of the research

This paragraph describes the methodology used for the research of articles containing relevant information inherent the topic.

The ultimate goal of this research is to evaluate which Industry 5.0 approaches and technologies have the greatest impact on the design parameters and performance of intra-logistics systems. To this end, it is crucial to analyse how the three different pillars of Industry 5.0 influence the performance of intra-logistics systems according to the scientific literature.

In the first phase of the research, inclusion and exclusion criteria were defined and a list of keywords for the literature review was created. The collected papers were then analysed in three stages: preliminary title analysis, reading of the abstract and finally in-depth analysis of the full content.

From the analysis of all papers, it was possible to distinguish the pillars of Industry 5.0 and three internal logistics systems, highlighting a gap of information in both target dimensions of I5.0 and intra-logistic systems.

1.3.2 Inclusion/exclusion criteria and keywords

The multidisciplinary database chosen for the research is Scopus, which is internationally recognized. The search was carried out by using queries containing the selected keywords, combined with Boolean logical operators ('AND' and 'OR'). Queries were usually formulated as 'Keyword A AND Keyword B AND Keyword C' or 'Keyword A OR Keyword B AND Keyword C'. The papers included in Scopus were from the database that is made available to students of the Polytechnic of Turin. Table 1 summarizes the adopted inclusion criteria.

INCLUSION CRITERIA	
PUBLISHING YEAR	From 2019 to 2024
DOCUMENT TYPE	• Journal paper • Conference paper • Book chapter • Review
LANGUAGE	English
DATABASE	Scopus

Table 1: Research constraints

The initial search strings were:

- 'impact AND industry 5.0 performance AND logistics AND system';
- 'impact AND industry 5.0 resilience AND performance AND logistics AND system';
- 'impact AND industry 5.0 sustainability AND performance AND logistics AND system';
- 'impact AND industry 5.0 sustainability OR ecological AND performance AND logistics AND system';
- 'impact AND industry 5.0 human AND centricity AND logistics AND system'.

Based on the results these queries produced, the search string was refined by replacing 'logistics system' with the three types of systems: automated picking system, automated material handling system and automated storage system.

Since the results of new search were not so encouraging either, we decided to replace the operator 'AND' with 'OR' in order to increase the number of papers filtered by the queries. Many inquires were made to the database by using this setup and combining the different logistic systems and the three pillars of Industry 5.0. Unfortunately, this research didn’t generate sufficient good results, so therefore we decided to reformulate some keywords, for example:

- 'impact' was replaced by 'effect';
- 'impact' was replaced by 'industry 5.0';
- 'performance' was replaced by 'impact'/'effect';

and many other combinations (150+).

In searching for publications, we also defined the constraints listed in Table 1.

The publication period was set between 2019 and 2024 because the concept of Industry 5.0 was not introduced by research and experts before 2019. As a matter of fact before 2019, most of the publications were related to the concept of Industry 4.0 and only few of them to Industry 5.0 which, by the way, were not relevant to this study.

As a type of document, the research was extended to "journal papers", "conference papers", "book chapters" and "review" only, in order to maintain homogeneity in the definitions of the different contributions and to increase the coherence between the themes.

The third constraint, the English language, was imposed due to the fact that the author's professional knowledge is limited to English and Italian and the thesis is written in English in order to make the thesis globally understandable.

This search produced 257 papers overall (many queries did not produce any results) but only 14 of them were related to the study since they took into account the impact of the performances on the logistics systems. Of these 14 articles, only seven actually considered at least one of the three pillars of Industry 5.0 and one of the intra-logistic systems (Figure 2a, see Appendix 1A for the complete analysis). The remaining 243 articles were not taken into consideration because their content was either focused on Industry 4.0 and therefore not pertinent to the topic, or they were lacking of references on the performance of the logistics systems.

1.3.3 *“Snowballing” in Systematic Literature Review*

Snowballing is a search method used to identify relevant and fundamental articles of a particular topic of interest. This approach is based on the analysis of the references listed in a certain article, or the citations received from it, to identify other relevant papers (Wohlin, 2014).

The process starts with the definition of a small group of significant articles, called the *initial set* (Table 2a and Appendix 1A) that represents the starting point of the search.

The are two types of snowballing:

- Backward snowballing: it focuses on the bibliographic references cited in the articles of the initial set.
- Forward snowballing: it focuses on looking for subsequent articles starting from citations included in the initial set of articles.

For the research of this study we adopted both approaches: backward approach we found six papers (Table 2b, see Appendix 1B for the complete analysis), while with the forward approach we found thirteen papers (Table 2c, see Appendix 1C for the complete analysis).

1.3.4 *Articles found by snowballing*

Table 2b shows the articles founded by using the backward snowballing method and, as we can see, all articles deal with only one of the target dimensions of Industry 5.0 (human-centricity) and all related to the picking systems as a topic. There is only one exception, one article that deals with both picking and material handling systems.

Table 2c shows the articles founded by using the forward snowballing method. As we can see most of the articles deal with human-centricity, while sustainability and resilience are both covered by only two articles. On the other hand, as far as intra-logistics systems are concerned, the picking system is again the most dealt with, while the material handling system is the second most dealt with, and last is the storage systems.

The merge of Table 2a, Table 2b, and Table 2c represents the final corpus of the literature review.

As a conclusion, it is clear that the literature from 2019 to 2024 focuses on the in-depth study of human-centricity and picking systems. At the same time, it is noticeable that there are no articles that considered the three target dimensions and the three intra-logistic system simultaneously. This research gap was filled-in with the development of the framework and its application through the Delphi study.

Article number	Title	Authors	Target dimension of I5.0			Performance of Logistic System		
			Human centricity	Sustainability	Resilience	Picking system	Storage system	Material Handling system
1	Passive Exoskeletons to Enhance Workforce Sustainability: Literature Review and Future Research Agenda	Ashta, G., Finco, S., Battini, D., Persona, A.	X	X		X		X
2	In pursuit of humanised order picking planning: methodological review, literature classification and input from practice	De Lombaert, T., Braekers, K., De Koster, R., Ramaekers, K.	X			X		
3	Application of supportive and substitutive technologies in manual warehouse order picking: a content analysis	Grosse, E.H.	X			X		
4	Human-Centric Assistive Technologies in Manual Picking and Assembly Tasks: A Literature Review	Lucchese, A., Mummolo, G.	X			X		
5	Augmented Reality in a Lean Workplace at Smart Factories: A Case Study	Pereira, A.C., Alves, A.C., Arezes, P.	X			X		X
6	Collaborative Robotics Making a Difference in the Global Pandemic (abstract)	Doyle-Kent, M., Kopacek, P.	X				X	
7	An Industry 5.0 Perspective on Feeding Production Lines	Chivilò, M., Meneghetti, A.	X	X	X			X

Table 2a: The initial seven articles

			Target dimension of I5.0			Performance of Logistic System		
Article number	Title	Authors	Human centricity	Sustainability	Resilience	Picking system	Storage system	Material Handling system
8	Automated order picking systems and the links between design andperformance: a systematic literature review	Jaghbeer, Y., Hanson, R., Johansson, M.I.	X			X		X
9	Picker Routing in AGV-Assisted Order Picking Systems	Löffler, M., Boysen, N., Schneider, M.	X			X		
10	Hybrid order picking: A simulation model of a joint manual and autonomous order picking system	Winkelhaus, S., Zhang, M., Grosse, E.H., Glock, C.H.	X			X		
11	Smart lighting systems: state-of-the-art and potential applications in warehouse order picking	Füchtenhans, M., Grosse, E.H., Glock, C.H.	X			X		
12	Empirical Evidence on Human Learning and Work Characteristics in the Transition to Automated Order Picking	Loske, D.	X			X		
13	Determining the source of human-system errors in manual order picking with respect to human factors	Setayesh, A., Grosse, E.H., Glock, C.H., Neumann, W.P.	X			X		

Table 2b: Backwards snowballing articles found

			Target dimension of I5.0			Performance of Logistic System		
Article number	Title	Authors	Human centricity	Sustainability	Resilience	Picking system	Storage system	Material Handling system
14	Investigating the efficiency of a passive back-support exoskeleton in manual picking tasks	Ashta G.; Finco S.; Battini D.; Persona A.	x			x		x
15	Industrial exoskeletons for secure human–robot interaction: a review	Cheng, Dinghao; Hu, Bingtao; Feng, Yixiong; Song, Xiuju; Zhang, Zhifeng; Song, Junjie; Wang, Fei; Tan, Jianrong	x					x
16	Performance optimisation of pick and transport robot in a picker to parts order picking system: a human-centric approach	Vijayakumar, V., Sobhani, A.	x		x	x		
17	Assessments of Order-Picking Tasks Using a Paper List and Augmented Reality Glasses with Different Order Information Displays	Li, K.W., Khaday, S., Peng, L.	x			x		
18	Human–robot vs. human–manual teams: Understanding the dynamics of experience and performance variability in picker-to-parts order picking	Koreis, J.	x			x		
19	Human-and-cost-centric storage assignment optimization in picker-to-parts warehouses	Diefenbach, H., Grosse, E.H., Glock, C.H.	x			x		

			Target dimension of I5.0			Performance of Logistic System		
Article number	Title	Authors	Human centricity	Sustainability	Resilience	Picking system	Storage system	Material Handling system
20	Storage Location Assignment for Improving Human–Robot Collaborative Order-Picking Efficiency in Robotic Mobile Fulfillment Systems	Chen, Y., Li, Y.	x			x		
21	Towards human-centric warehousing: the impact of rack configuration and cognitive demands on order picking performance	Loske, D., Grosse, E.H., Glock, C.H., Klumpp, M.	x			x		
22	Machine learning in smart production logistics: a review of technological capabilities	Flores-García, E., Hoon Kwak, D., Jeong, Y., Wiktorsson, M.		x		x		x
23	Manual and robotic storage and picking systems: a literature review	Silva, A., Coelho, L.C., Darvish, M., Renaud, J.	x			x	x	x
24	Human Factors Issues in Augmented Reality-Assisted Manual Order Picking: A Systematic Literature Review	Abdullah, Md., Rahman, M.	x			x		
25	A classification approach to order picking systems and policies: Integrating automation and optimization for future research	Pinto, A.R.F., Nagano, M.S., Boz, E.	x			x	x	
26	Use of Green Industry 5.0 Technologies in Logistics Activities	Trstenjak, M., Mustapić, M., Gregurić, P., Opetuk, T.	x	x	x	x		x

Table 2c: Forwards snowballing articles found

1.4 DESIGN RESEARCH METHODOLOGY

This paragraph illustrates the methodology used for this the work: the Design Research Methodology.

This methodology is divided in 4 different parts (Blessing and Chakrabati, 2009):

1. Research Clarification (RC): the RC stage clarifies the overall research objective, establishes a research plan, and provides a focal point for the subsequent stages.
2. Descriptive Study I (DS-I): the goal of the DS-I stage is to enhance comprehension of design and the factors influencing its success through an examination of the design phenomenon, in order to inform the development of support.
3. Prescriptive Study (PS): the PS stage aims to systematically develop the support, taking into account the findings of DS-I.
4. Descriptive Study II (PS-II): the DS-II stage concentrates on assessing the usability and applicability of the actual support and its effectiveness

This thesis focuses on the Prescriptive Study phase, in which the Delphi study is used to apply the evaluation framework developed in the previous part of the research (Bottazzi, 2024). The results of the study will make possible to identify which I5.0 approaches and technologies have the greatest impact on the design and performance parameters of intra-logistics systems. This result, in turn, will allow guidelines to be drawn up for developers of intra-logistics systems so that they can make such systems compliant with I5.0 and its target dimensions, while at the same time improving their performance.

Finally, the final phase of Descriptive Study II will be a future research and it will be consist in a pilot test with intra-logistics system developers to assess the actual usability of the evaluation framework.

2 THE ASSESSMENT FRAMEWORK

This chapter illustrates Bottazzi's (2024) framework, explaining in particular the construction of the Domain Mapping Matrices (DMMs) and their changes over time.

Furthermore, this part describes the motivation of the Likert rating scale to assess the relationship between approaches and technologies of all Industry 5.0 target dimensions and the design and performance parameters of the internal logistics system.

2.1 DOMAIN MAPPING MATRIX

Domain Mapping Matrix is a tabular tool used to represent the relationship or correspondence between two collections of elements belonging to different domains (Danilovic and Browning, 2007). In particular (Table 3):

- The rows (elements of domain A) with columns (elements of domain B)
- The cells define a relationship or a rule of transformation between elements of A and B.

		Domain B		
		Element *B1*	Element *B2*	Element *B3*
Domain A	Element *A1*			
	Element *A2*			
	Element *A3*			

Table 3: Example of DDM

Just like in any other field of applications, the use of tables as is advantages and disadvantages. In our study it was decided to use this table because of the advantages of providing visual clarity, facilitating the management of dependencies, high traceability and improved communication despite the disadvantages of being complex in management, of being redundant and because of lack of dynamism.

So, in the end, the DMMs are fundamental tools for achieving ambitious goals, contributing to greater efficiency in the management and development of complex projects, but it is also important to consider their limitations for effective use.

2.2 FRAMEWORK SECTIONS AND STRUCTURE

The proposed framework is divided into three parts, each representing one of the fundamental pillars of Industry 5.0: human-centricity, sustainability and resilience.

For each pillar, two tables are provided for each of the three types of intra-logistics systems considered:

- The first table puts in a relationship the approaches of the pillar with the design and performance parameters that were selected from the scientific literature (Table 4).
- The second table puts in a relationship the technologies of the pillar with the design and performance parameters that were selected from the scientific literature (Table 5).

<table>
<tr><td colspan="3" rowspan="3"></td><th colspan="8">ANALYSED INTRA-LOGISTICS SYSTEM</th></tr>
<tr><td colspan="2"></td><th colspan="3">Reliability</th><td colspan="3"></td></tr>
<tr><td>Parameter 1</td><td>…</td><td>…</td><td>…</td><td>…</td><td>…</td><td>…</td><td>Parameter n</td></tr>
<tr><th rowspan="4">A pillar of Industry 5.0</th><th rowspan="4">Approaches</th><td>Approach 1</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>…</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>…</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Approach n</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
</table>

Table 4: Pillar approaches vs Parameters

<table>
<tr><td colspan="3" rowspan="3"></td><th colspan="8">ANALYSED INTRA-LOGISTICS SYSTEM</th></tr>
<tr><td colspan="2"></td><th colspan="3">Reliability</th><td colspan="3"></td></tr>
<tr><td>Parameter 1</td><td>…</td><td>…</td><td>…</td><td>…</td><td>…</td><td>…</td><td>Parameter n</td></tr>
<tr><th rowspan="4">A pillar of Industry 5.0</th><th rowspan="4">Technologies</th><td>Technology 1</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>…</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>…</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Technology n</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
</table>

Table 5: Pillar technologies vs Parameters

2.3 LIKERT EVALUATION SCALE

With the scope of evaluating the relationship between approaches/technology and parameters the respondents are, as a matter of fact, answering the following question:

How much does the application of the approach/technology of the intra-logistics system (row) affect the design/performance parameter (column)?

Respondents should indicate the answer based on their experience by entering the appropriate number in the cell according to the following 5-point Likert scale (Table 6):

5-point Likert evaluation scale				
1	2	3	4	5
Significant decrease	Decrease	No change	Increase	Significant increase

Table 6: Likert scale

The Likert scale is an evaluation instrument used to assess attitudes, opinions or perceptions on a given topic through a series of statements to which the respondent assigns a level of agreement or disagreement.

2.3.1 Key characteristics of the Likert scale

The main characteristics of this scale, according to Göb et al. (2007), are

- It is an ordinal scale, so it measures the degree of agreement or disagreement without a precise numerical distance between options.
- It is typically used in surveys and market research, psychology, business management and industrial engineering to collect quantifiable qualitative data.

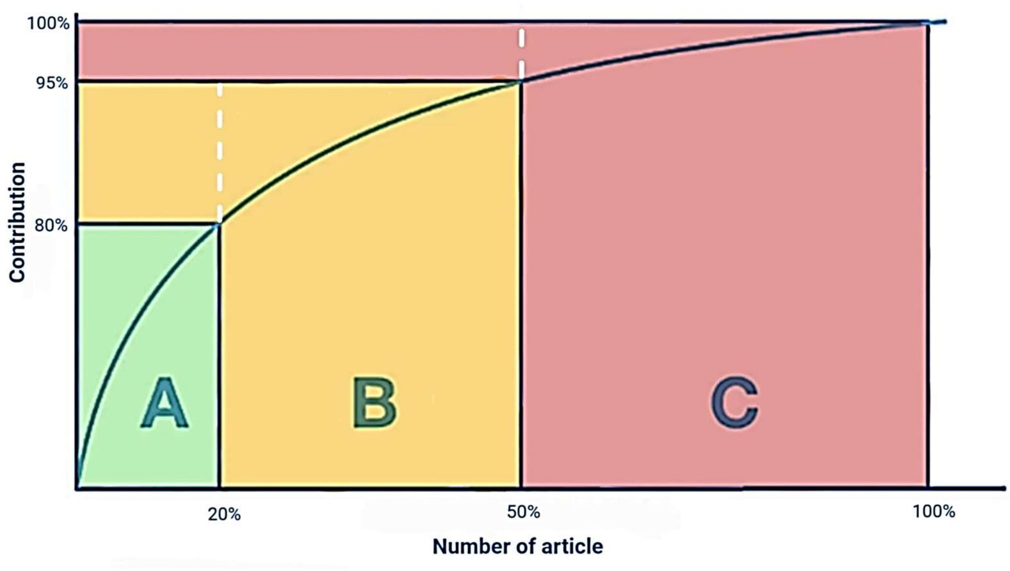
2.3.2 Advantages and disadvantages of Likert scale

Likert scale was adopted because it carries many advantages (O'Neill, 2017) with it: it is ease-of-use since it is easy to understand the content and offers a complete picture to both researchers and respondents; it allows the quantification of opinions, meaning that it is possible to transform those opinions into data that can be further analyzed; it is flexible; it facilitates the analysis of the data and it is not a yes-or-no option but it leaves room for rating.

On the other hand, just like any other tool, it also implies some disadvantages (Kusmaryono, 2022) such as a tendency towards neutrality as respondents can tend to choose options in the middle to avoid extremes, and at the same time, the ones that are perceived more socially acceptable. Plus, in some cases, the cultural and personal differences can influence the perception of the answers, and it does not always capture the intensity of the opinions. Finally, a certain bias must always be kept into account being the Likert scale a 1-to-5 scale, it does not always catch or correspond to the exact opinion of a responder.

2.4 ABC ANALYSIS

The ABC analysis is a type of statistical analysis based on the Pareto principle, which is used to divide a set of elements into three different categories (A, B and C) according to their importance (Graphic 1).



Graphic 1: ABC analysis

Its main objective is to evaluate the impact of these elements on the company, for example in terms of turnover, consumption or stock management, allowing the identification of the most strategic and the most critical elements.

In more detail:

- Class A: includes a small number of elements (about 20% of the total) that generate the majority of value (about 80%).
- Class B: includes items of medium importance (about 30% of the total) that contribute a more moderate proportion of value (about 15%). They require less rigorous control than Class A.
- Class C: comprises the majority of elements (about 50%), but with a marginal impact on total value (about 5%). These elements are less strategic and can be managed with fewer resources.

With this classification, companies can optimise resource allocation, improve inventory management and focus on the elements that are most critical to business success.

2.4.1 Applications of ABC Analysis

As affirmed by Kučera and Suk (2019), the ABC analysis can be used in a variety of business areas:

- Inventory management: identifying the most critical products to optimise purchasing and reduce inventory costs.
- Supply chain management: prioritising strategic suppliers to ensure business continuity and quality.
- Sales and Marketing: focus on the most profitable customers to maximise profits.
- Cost control: optimise resource allocation for more efficient management.

2.4.2 Steps to perform the ABC analysis

As mentioned, an ABC analysis to find the parameters of the columns of the DDMs that composed the final frameworks was carried out.

The ABC analysis consists in performing six steps:

1. Collect data: collection of the papers which contained the parameter as a keyword (Bottazzi, 2024)

2. Sort the papers in descending order according to the frequency of the keyword
3. Calculate the total of the papers

$$Total = \sum_{i=1}^{N} N.of\ papers\ including\ the\ parameter\ as\ a\ keyword_i$$

4. Calculate the percentage of the individual performance parameter

$$Percentage\ of\ individual\ perfomance\ parameter = \\ = \frac{N.of\ papers\ including\ the\ parameter\ as\ a\ keyword_i}{Total}$$

5. Calculate the cumulative percentage: the cumulative value of the first parameters is the same value of the individual performance parameter. From the second on, the value is calculated as the sum of the current value and the previous one.
6. Divide the cumulative percentage into three classes (A, B, C), but for the analysis, we considered only class A and B.

In the following tables (from Table 7 to Table 9), the parameters belonging to Class A are green coloured, the parameters belonging to Class B are coloured in orange.

We can see the cumulative percentage of Class B is a bit higher than the theoretical value (95%), but we have considered them because they are very important realistically describe the intra-logistics system under consideration. In this way, we have mixed Class A and B (high and moderate importance/value), resulting in a percentage of 40% instead of 35% and for each intra-logistic system, we considered:

- 6 out of 11 parameters or 54%, for picking systems
- 13 out of 20 parameters or 65%, for storage systems
- 11 out of 17 parameters or 64%, for material handling systems

PICKING SYSTEMS Parameters	N. of papers including the parameter as a keyword	Percentage of individual performance parameter (= percentage of total)	Cumulated percentage
Accuracy/Efficiency: getting the right product in the right quantity	141	51,8%	51,8%
Level of automation: degree of human labour required	61	22,4%	74,3%
Cycle time picking operation/picking time	28	10,3%	84,6%
Picking lines/h (picking productivity)	20	7,4%	91,9%
Operating costs: energy cost, personnel cost, cleaning cost	15	5,5%	97,4%
Investment cost/Investment cost of a new system to build	4	1,5%	98,9%
Level of physical strain required: automated picking systems reduce the physical strain on workers, leading to fewer injuries and a healthier workforce.	2	0,7%	99,6%
Ability to reduce unnecessary worker movement	1	0,4%	100,0%
Mean time to repair	0	0,0%	100,0%
Mean time between failure: up time/num failure	0	0,0%	100,0%
Mean time to failure: tot time operation/num of units	0	0,0%	100,0%
TOTAL	272		

Table 7: ABC analysis of picking systems

STORAGE SYSTEMS Parameters	N. of papers including the parameter as a keyword	Percentage of individual performance parameter (= percentage of total)	Cumulated percentage
Utilisation rate: ratio of actual working time to available working time	48	20,3%	20,3%
Operating costs: energy cost, personnel cost, cleaning cost	47	19,9%	40,3%
Storage system capacity RECEIVABILITY in udc: number of udc that can be stored in the warehouse, an indicator that gives the size of the warehouse	42	17,8%	58,1%
Level of automation: degree of human labour required	29	12,3%	70,3%
Scalability/Flexibility: the ability of a technology to handle an increase in the amount of work or workloads effectively and efficiently	24	10,2%	80,5%
System lifetime, life cycle, useful life, service life	11	4,7%	85,2%
Storage depth single/double/triple o multi deep/ depth	10	4,2%	89,4%
Storage density: ratio between the cubic metres of gross stowable goods (including the box if the goods are boxed) and the square metres of the area occupied by the automation alone.	8	3,4%	92,8%
Horizontal speed [m/s] **Vertical speed** [m/s]	4	1,7%	94,5%
Investement cost/Investment cost of a new system to build	4	1,7%	96,2%
N order lines/h (Productivity) Productivity (bubble lines/h): identifies the time required to complete picking operations and thus expresses the efficiency of the system: the different technological solutions are also defined by a range of heights in which the minimum, optimum and maximum heights are specified.	3	1,3%	97,5%
Storage height: height (minimum, optimum and maximum) [m]	2	0,8%	98,3%
Selectivity/direct access items	1	0,4%	98,7%
Mean time to repair	1	0,4%	99,2%
Mean time between failures	1	0,4%	99,6%
Mean time to failure	1	0,4%	100,0%
Accessibility (to goods in case of plant failure)	0	0,0%	100,0%
Modularity/Expandability: this means the possibility of expanding the system already implemented by lengthening its shelving or multiplying its aisles if the conditions exist to do so or if there is space to do so	0	0,0%	100,0%
Ridondanza: the capacity of the system with multiple resources or alternatives to ensure that operations can continue despite unforeseen events or technical problems	0	0,0%	100,0%
Maintenance cost	0	0,0%	100,0%
TOTAL	236		

Table 8: ABC analysis of storage systems

MATERIAL HANDLING SYSTEMS Parameters	N. of papers including the parameter as a keyword	Percentage of individual performance parameter (= percentage of total)	Cumulated percentage
Level of energy consumption	967	44,6%	44,6%
Speed	495	22,8%	67,4%
Level of automation: degree of human labour required	145	6,7%	74,1%
Utilization rate: ratio of actual working time to available working time	134	6,2%	80,3%
Battery autonomy	128	5,9%	86,2%
(System lifetime)/ life cycle, useful life, service life	82	3,8%	90,0%
Cycle time	56	2,6%	92,6%
Load capacity: maximum weight moved [kg]	52	2,4%	95,0%
Investment cost/Investment cost of a new system to build	47	2,2%	97,1%
Operation cost: energy cost, personnel cost, cleaning cost	21	1,0%	98,1%
Scalability/Flexibility: advanced material handling systems can adapt more easily to changes in order volume and product variety, making it easier for warehouses to scale operations up or down as needed.	18	0,8%	98,9%
Mean time between failures	7	0,3%	99,3%
Obstacle detection ability: minimum time and space required for the system to detect the presence of obstacles (objects or people) in its vicinity	7	0,3%	99,6%
Maintenance cost Costo di manutenzione	4	0,2%	99,8%
Mean time to repair	3	0,1%	99,9%
Degree of interaction with humans: ability of a system to cooperate with the human operator	2	0,1%	100,0%
Mean time to failure	0	0,0%	100,0%
TOTAL	2168		

Table 9: ABC analysis of material handling systems

2.5 FINAL FRAMEWORK STRUCTURE

After applying the ABC analysis, we only considered parameters belonging to classes A and B.

We can see that each intra-logistic system has two DMMs, whose columns are the same parameters but whose rows change, representing in one case approaches and in the other case technologies.

Furthermore, it is clear that for each pillar of Industry 5.0, we would have a different number of approaches and technologies for each internal logistics system, in fact, if we look at the tables, the number of rows is different. The number of rows between approaches and technologies varies, either by keeping one pillar fixed and looking at different internal logistics systems, or by keeping one internal logistics system fixed and changing pillars.

Appendix 2 contains the final framework used in the pre-test phase of the Delphi study.

3 DELPHI STUDY

This thesis uses the Delphi study which is a particularly effective method for reaching expert consensus on complex and poorly structured issues.

The main advantages of this approach are:

1. Involvement of qualified experts: the study allows for the collection of input from industry experts, ensuring a deep and informed understanding of relevant approaches, technologies and parameters.
2. Iterative methodology: based on multiple cycles (rounds), the Delphi process involves the collection and analysis of data with the exchange of internal feedback which allows participants to review and refine their responses.
3. Anonymity: the anonymity of participants reduces the risk of cross-influencing or social pressure, thus encouraging more objective and authentic responses.
4. Statistical robustness: data is analysed through the calculation of the median and interquartile range (IQR). These parameters are useful for assessing consensus, even in the presence of Likert scale responses.
5. Adaptability to complex issues: the Delphi study is ideal for addressing interdisciplinary or emerging topics, such as the integration of Industry 5.0 in intra-logistics systems, where existing knowledge may be limited or fragmented.
6. Geographical and thematic flexibility: participants can come from different geographical areas and fields of specialization, as their physical presence in the same place is not required.

This methodology is therefore a valuable tool for collecting and synthesizing knowledge that will allow the definition of common guidelines and strategies, which are essential for promoting the application of Industry 5.0 in intra-logistics systems.

3.1 DELPHI METHOD IMPLEMENTATION STEPS

The Delphi method is a structured methodology designed to gather opinions and insights from a group of experts to reach a consensus on a specific topic.

The process is generally carried out in four main steps:

1. Objective setting: the first step is to clearly identify the objectives and scopes of the study. The main questions or topics of interest that require expert input are outlined, and the key issues to be addressed are identified. This lays the foundation for the process and ensures that the overall study is focused and relevant.
2. Selection of experts: the selection of the group of experts is a key step in ensuring the success of the Delphi method. Experts need to have relevant skills, knowledge and experience in relation to the topic under analysis. These qualities may also be influenced by the geographical context in which the experts operate: as Nair et al. (2024) point out, participants may come from the same country, while van de Wijdeven et al. (2024) stress the possibility of including experts from different countries.

   In our case study, all participants are based in Italy. Although the group is composed of experts with the same geographical background, it is still important to ensure sufficient diversity to ensure a rich variety of perspectives and opinions. The number of experts involved may vary depending on the complexity and scope of the study, with a general recommendation of at least 10-15 participants.

   Specifically, 12 experts were invited, but only 8 of them agreed to participate. As stated by Dillinger et al. (2022), a Delphi study can have between 5 and 20 participants, including both academic and industry representatives.
3. Questionnaire design and launch: this phase consists of the design and distribution of questionnaires to collect input from experts. The questionnaires can be structured, semi-structured or open-ended, depending on the specific objectives of the study.

   The questionnaire could also have been completed in two different ways: Offline (Zenezini et al., 2022) or Online (Haidar et al., 2024). In the first case, participants respond individually, without direct interaction with the researchers. This approach is typical of the Delphi method, where experts receive the material via email or links to dedicated platforms and provide their assessments independently. In the second case, the questionnaire is deployed through direct interaction between researchers and experts as face-to-face meeting, video conference or live interview.

For this thesis, we used both approach in the first round, while in the second round we used only the offline approach.

Typically, the first round is an open-ended questionnaire that allows participants to freely express their opinions and insights without external influence.

- Round 1: in Round 1, the open questionnaire is sent to all experts who will express their opinions, predictions and suggestions regarding the pre-defined objectives.
- Round 2: once the responses from Round 1 have been collected, the facilitator synthesises and organises the expressed opinions while guaranteeing the anonymity of each participant. This synthesis is used to engage the same audience in a second, more targeted and structured questionnaire. Specifically, the audience will receive the outcome of the first round and the same questionnaire so that the experts can then check, rethink and, if necessary, modify the previous answers.
- Subsequent rounds (optional): if the level of consensus is still not satisfactory, additional rounds might be needed. This process continues until the predefined level of consensus is reached or the facilitator decides to out it an end.

  In this case, the process ends with the analysis of the data collected during the second round, since an optimal level of consensus has been reached.

4. Use of results: at the end of the Delphi process, the results are analysed and used to support decision making, forecasting, policy development or other purposes stated in the objectives of the study. The anonymity of the experts ensures that the final results are unbiased and reflect the collective wisdom of the group.

This thesis the four steps indicated above and illustrated in the figure below Figure 6. The only difference is that in the picture, the third step is articulated in two rounds, each one followed by the corresponding analysis. The calculation of medians and the interquartile range was executed for both analysis round.

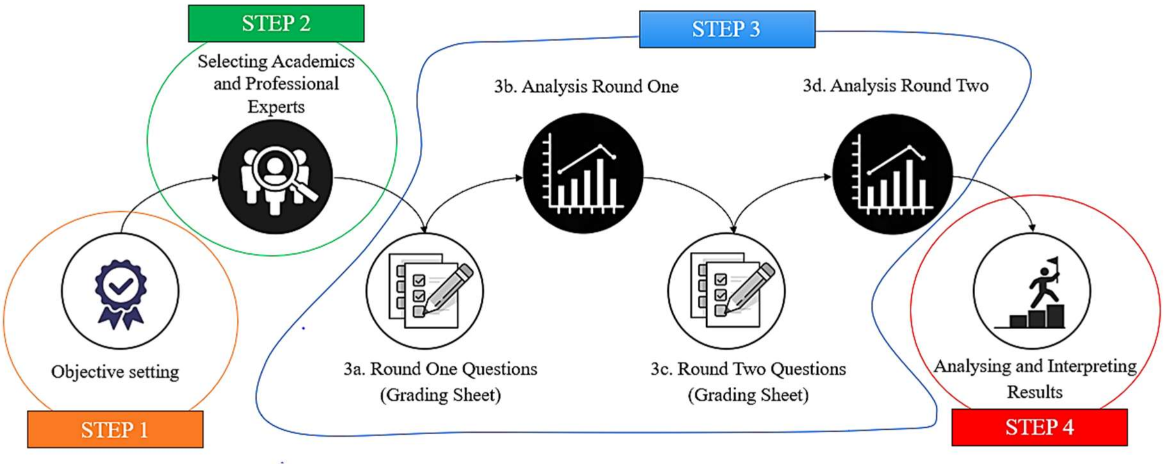


Figure 6: Steps of the Delphi study

3.1.1 The interquartile range definition

The interquartile range (IQR) measures the statistical dispersion of a set of data. It indicates the distance between the first interquartile (Q1) and the third interquartile (Q3), in other words, the length of the interval that corresponds the centred 50% of data (Wan et al., 2014).

$$IQR = Q3 - Q1$$

Where:

- Q1: the value separating the bottom 25% of the data from the rest.
- Q3: the value separating the bottom 75% of the data from the top 25%.

The IQR is calculated in three steps:

1. Sort the data in ascending order
2. Find Q1 and Q3
3. Calculate the interquartile range using the formula expressed above

Since the aim of the Delphi method is to achieve a high level of agreement between participants, we chose the interquartile range as a measure (Keeney et al, 2011).

The overall level of consensus is assessed as the percentage of matrix cells in which there is a high degree of agreement. Of the various measures of consensus available for Delphi studies, the IQR was selected because it can be calculated on ratings using a Likert scale.

3.1.2 Medians definition

The median is a statistical method for determining the central value of an ordered set of data. The median divides the data set into two equal parts, with 50% of the lower values and 50% of the upper values**.**

The calculation of the medians is executed in two steps:

1. Sort the data in ascending order.
2. Determine the central position and:
    - If the number of values is odd, the median is the central value.
    - If the number of values is even, the median is the arithmetic mean of the two central values.

We chose to use the median (Diamon et al., 2014) because our goal is the analysis of the average ratings of the respondents, i.e. the most representative rating given to each approach/technology and parameter pair. As the ratings were expressed on a Likert scale, the median was the most appropriate measure to represent the central value of the responses given for each cell of the matrices.

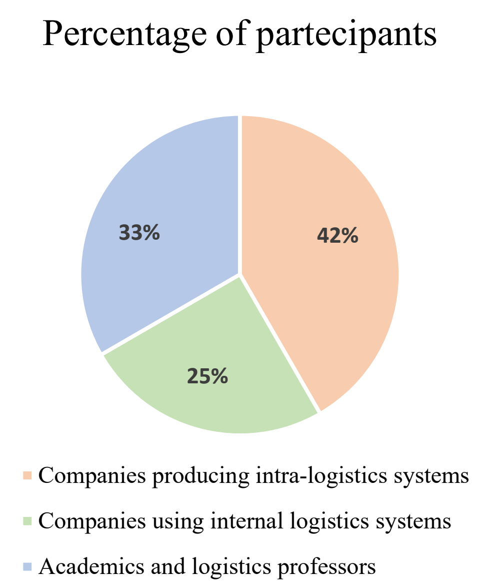
3.2 BUILDING THE PANEL OF RESPONDENTS

The selection of participants for a Delphi study is a crucial step, as it has a direct impact on the quality and validity of the results.

The Delphi method is based on the collection of expert judgements and opinions through a series of structured consultation rounds. The aim is to reach a level of consensus among the participants, which is usually around 80%.

The panel of experts was selected on the basis of the knowledge of the researchers who conducted the Delphi study, and on the authoritativeness of the participants, assessed both in terms of their professional or academic profile and in terms of the prestige of the company or university research group to which they belong.
The 12 experts (Xu et al., 2023) from three different categories were invited to participate in order to obtain a broad and diverse range of knowledge and opinions. The categories of participants are shown in Graphic 2:

1. Companies producing intra-logistics systems:
    - 1 company operating in the field of logistics, distribution and supply chain management, with applications also in the healthcare sector
    - 1 company involved in automation, electrification, robotics and renewable energy technologies.
    - 1 company specialized in warehouse automation, logistics, supply chain management and industrial robotics.
    - 2 companies active in automation and logistics management, one focused on manual and electric material handling equipment and the other on automated logistics.
2. Companies using internal logistics systems:
    - 2 companies in the food sector that use automated solutions to manage their logistics processes.
    - 1 company in the electrical equipment distribution sector that uses advanced logistics technologies for supply chain management.
3. Academics and logistics professors:
    - 4 logistics professors from different Italian universities who provided an academic and theoretical perspective on the topic.



Graphic 2: Participant categories

However, only 8 of the potential candidates from the three categories agreed to complete the questionnaire. These 8 participants represent roughly the 80% of the invited experts, a percentage that is, anyways, in line with what is recommended for a Delphi study (Sedrakyan et al., 2022).

3.2.1 Role of participants

The eight respondents to the Delphi study questionnaire had different roles depending on the companies or universities they are working for. This diversity of professional profiles enriched the comparison and provided a multidisciplinary view of the analysed topic.

In particular, both respondents from the companies producing intra-logistics systems are Sales Manager, while those from the two companies using storage systems were Chief Information Officer and Operations Manager respectively. In the academic field, the four participants were all experts in the field of logistics and operations management, covering the following positions: Full Professor of Logistics, Full Professor of Operations Management & Industrial Systems Engineering (two participants with this title) and an Assistant Professor (RTDb).

3.3 GRADING SHEET

Once the questionnaire had been developed, it was tested by having it filled-in by a professor specialized in logistic automation from the Polytechnic of Turin.

The test is a fundamental step in the research. Scope of the test is the effectiveness of the questionnaire and how much it is in line with the objectives of the study. Just like in any other application, the test represents a strategic step that will help improving the quality and the reliability of the survey.

The pre-test is carried out for several reasons:

1. Validity of the questions: ensure that the questions are understandable, relevant and aimed at eliciting the necessary information.
2. Clarity: ensure that the language is clear and easily interpreted by the recipients, avoiding ambiguity.
3. Reasonable duration: assess whether the time necessary to complete the questionnaire is reasonable and in line with expectations.
4. Reliability: assess the consistency of responses given by different participants at different times while ensuring reliable results.
5. Error detection: identify and solve any issue, such as poorly worded questions, unclear sections or format mismatch.
6. Preliminary feedback: gather useful suggestions from participants on content and structure to improve the questionnaire before large-scale distribution.
7. Optimise layout and flow: ensure that the structure and format of the questionnaire makes it easy for respondents to complete without confusion or struggle.

In the specific case of this thesis, pre-testing proved to be particularly important. In fact, the professor suggested dividing the parameters of the intra-logistics systems under consideration into two categories:

- Design parameters: these are characteristics defined during the design phase of a product or process. These parameters are chosen by the engineer to define the configuration and structure of the system, directly influencing its functionality.

- Performance parameters: these are the measures used to evaluate the effectiveness and efficiency of the system or product, often in relation to the design objectives. These parameters are not directly determined at the design stage, but result from design choices and operating conditions.

The following pages contain the templates of all tables (from Table 10 to Table 27) that were used to collect and analyse the questionnaire results.

			PICKING SYSTEMS					
			DESIGN PARAMETERS	PERFORMANCE PARAMETERS				
			Level of automation	Picking productivity (N. picking lines/h)	Picking operation time	Picking accuracy	Investment costs	Operating costs
Human centricity	Approaches	Decentralized decision making						
		Human-robot co-working						
		Tracking-as-a-Service (NTaaS)						

Table 10: Domain Mapping Matrix between human-centricity approaches and the parameters of picking systems

			PICKING SYSTEMS					
			DESIGN PARAMETERS	PERFORMANCE PARAMETERS				
			Level of automation	Picking productivity (N. picking lines/h)	Picking operation time	Picking accuracy	Investment costs	Operating costs
Human centricity	Technologies	Artificial Intelligence (AI)						
		Natural language processing for interacting with robots						
		Intelligent smart wearables (ISWs) and exoskeletons						
		Cobots						
		Natural user interfaces (NUIs)						
		Human interaction and recognition technologies (HIRT)						
		Gesture-tracking devices						
		Augmented Reality (AR)						
		Sensors						
		Internet of Everything (IoE)						
		Clothing industrial smart wearables						
		Internet of Things (IoT)						
		Edge computing						

Table 11: Domain Mapping Matrix between human-centricity technologies and the parameters of picking systems

			STORAGE SYSTEMS												
			DESIGN PARAMETERS							PERFORMANCE PARAMETERS					
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Speed	Storage density	Selectivity (direct access to items)	Storage capacity	Level of automation	Productivity (N. order lines/ h)	Scalability (Flexibility)	System lifetime (life cycle, useful life, service life)	Utilisation rate	Investement costs	Operating costs
Human centricity	Approaches	Decentralized decision making													
		Human-robot co-working													
		Tracking-as-a-Service (NTaaS)													

Table 12: Domain Mapping Matrix between human-centricity approaches and the parameters of storage systems

			STORAGE SYSTEMS												
			DESIGN PARAMETERS							PERFORMANCE PARAMETERS					
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Speed	Storage density	Selectivity (direct access to items)	Storage capacity	Level of automation	Productivity (N. order lines/ h)	Scalability (Flexibility)	System lifetime (life cycle, useful life, service life)	Utilisation rate	Investement costs	Operating costs
Human centricity	Technologies	Artificial Intelligence (AI)													
		Natural language processing for interacting with robots													
		Intelligent smart wearables (ISWs) and exoskeletons													
		Cobots													
		Natural user interfaces (NUIs)													
		Human interaction and recognition technologies (HIRT)													
		Gesture-tracking devices													
		Augmented Reality (AR)													
		Sensors													
		Internet of Everything (IoE)													
		Clothing industrial smart wearables													
		Internet of Things (IoT)													
		Edge computing													

Table 13: Domain Mapping Matrix between human-centricity technologies and the parameters of storage systems

			MATERIAL HANDLING SYSTEMS										
			DESIGN PARAMETERS					PERFORMANCE PARAMETERS					
			Load capacity	Battery autonomy	Speed	Cycle time	Level of automation	Level of energy consumption	System lifetime (life cycle, useful life, service life)	Utilization rate	Scalability (Flexibility)	Investment costs	Operating costs
Human centricity	Approaches	Decentralized decision making											
		Human-robot co-working											
		Tracking-as-a-Service (NTaaS)											

Table 14: Domain Mapping Matrix between human-centricity approaches and the parameters of material handling systems

			MATERIAL HANDLING SYSTEMS										
			DESIGN PARAMETERS					PERFORMANCE PARAMETERS					
			Load capacity	Battery autonomy	Speed	Cycle time	Level of automation	Level of energy consumption	System lifetime (life cycle, useful life, service life)	Utilization rate	Scalability (Flexibility)	Investment costs	Operating costs
Human centricity	Technologies	Artificial Intelligence (AI)											
		Natural language processing for interacting with robots											
		Intelligent smart wearables (ISWs) and exoskeletons											
		Cobots											
		Natural user interfaces (NUIs)											
		Human interaction and recognition technologies (HIRT)											
		Gesture-tracking devices											
		Augmented Reality (AR)											
		Sensors											
		Internet of Everything (IoE)											
		Clothing industrial smart wearables											
		Internet of Things (IoT)											
		Edge computing											

Table 15: Domain Mapping Matrix between human-centricity technologies and the parameters of material handling systems

			PICKING SYSTEMS					
			DESIGN PARAMETERS	PERFORMANCE PARAMETERS				
			Level of automation	Picking productivity (N. picking lines/h)	Picking operation time	Picking accuracy	Investment costs	Operating costs
Sustainability	Approaches	Circular processes						
		Reduction of climate change						
		Renewable sources						
		Remanufacturing						
		6Rs policy						
		Predictive maintenance						
		Bioeconomy						

Table 16: Domain Mapping Matrix between sustainability approaches and the parameters of picking systems

			PICKING SYSTEMS					
			DESIGN PARAMETERS	PERFORMANCE PARAMETERS				
			Level of automation	Picking productivity (N. picking lines/h)	Picking operation time	Picking accuracy	Investment costs	Operating costs
Sustainability	Technologies	Machine Learning						
		Intelligent Energy Management Systems (IEMS)						
		Big Data						
		Artificial Intelligence (AI)						
		Computational Intelligence (CI)						
		Internet of Things (IoT)						
		Internet of Personalized Products (IoP^2)						

Table 17: Domain Mapping Matrix between sustainability technologies and the parameters of picking systems

			STORAGE SYSTEMS												
			DESIGN PARAMETERS							PERFORMANCE PARAMETERS					
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Speed	Storage density	Selectivity (direct access to items)	Storage capacity	Level of automation	Productivity (N. order lines/ h)	Scalability (Flexibility)	System lifetime (life cycle, useful life, service life)	Utilisation rate	Investment costs	Operating costs
Sustainability	Approaches	Circular processes													
		Reduction of climate change													
		Renewable sources													
		Remanufacturing													
		6Rs policy													
		Predictive maintenance													
		Bioeconomy													

Table 18: Domain Mapping Matrix between sustainability approaches and the parameters of storage systems

			STORAGE SYSTEMS												
			DESIGN PARAMETERS							PERFORMANCE PARAMETERS					
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Speed	Storage density	Selectivity (direct access to items)	Storage capacity	Level of automation	Productivity (N. order lines/ h)	Scalability (Flexibility)	System lifetime (life cycle, useful life, service life)	Utilisation rate	Investment costs	Operating costs
Sustainability	Technologies	Machine Learning													
		Intelligent Energy Management Systems (IEMS)													
		Big Data													
		Artificial Intelligence (AI)													
		Computational Intelligence (CI)													
		Internet of Things (IoT)													
		Internet of Personalized Products (IoP^2)													

Table 19: Domain Mapping Matrix between sustainability technologies and the parameters of storage systems

			MATERIAL HANDLING SYSTEMS										
			DESIGN PARAMETERS					PERFORMANCE PARAMETERS					
			Load capacity	Battery autonomy	Speed	Cycle time	Level of automation	Level of energy consumption	System lifetime (life cycle, useful life, service life)	Utilization rate	Scalability (Flexibility)	Investment costs	Operating costs
Sustainability	Approaches	Circular processes											
		Reduction of climate change											
		Renewable sources											
		Remanufacturing											
		6Rs policy											
		Predictive maintenance											
		Bioeconomy											

Table 20: Domain Mapping Matrix between sustainability approaches and the parameters of material handling systems

			MATERIAL HANDLING SYSTEMS										
			DESIGN PARAMETERS					PERFORMANCE PARAMETERS					
			Load capacity	Battery autonomy	Speed	Cycle time	Level of automation	Level of energy consumption	System lifetime (life cycle, useful life, service life)	Utilization rate	Scalability (Flexibility)	Investment costs	Operating costs
Sustainability	Technologies	Machine Learning											
		Intelligent Energy Management Systems (IEMS)											
		Big Data											
		Artificial Intelligence (AI)											
		Computational Intelligence (CI)											
		Internet of Things (IoT)											
		Internet of Personalized Products (IoP^2)											

Table 21: Domain Mapping Matrix between sustainability technologies and the parameters of material handling systems

<table>
<tr><td colspan="3" rowspan="3"></td><td colspan="6">PICKING SYSTEMS</td></tr>
<tr><td>DESIGN PARAMETERS</td><td colspan="5">PERFORMANCE PARAMETERS</td></tr>
<tr><td>Level of automation</td><td>Picking productivity (N. picking lines/h)</td><td>Picking operation time</td><td>Picking accuracy</td><td>Investment costs</td><td>Operating costs</td></tr>
<tr><td rowspan="8">Resilience</td><td rowspan="8">Approaches</td><td>Organizational resilience</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Cognitive resilience</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Psycological resilience</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Operator safety strategies</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Biological resilience</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Human-machine systems resilience</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Renewable sources</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Physical resilience</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
</table>

Table 22: Domain Mapping Matrix between resilience approaches and the parameters of picking systems

<table>
<tr><td colspan="3" rowspan="3"></td><td colspan="6">PICKING SYSTEMS</td></tr>
<tr><td>DESIGN PARAMETERS</td><td colspan="5">PERFORMANCE PARAMETERS</td></tr>
<tr><td>Level of automation</td><td>Picking productivity (N. picking lines/h)</td><td>Picking operation time</td><td>Picking accuracy</td><td>Investment costs</td><td>Operating costs</td></tr>
<tr><td rowspan="8">Resilience</td><td rowspan="8">Technologies</td><td>Big Data</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Machine Learning</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Artificial Intelligence (AI)</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Internet of Things (IoT)</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Cyber-physical systems</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>NextG wireless networks (NGWNs)</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Cloud computing</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Internet of Everything (IoE)</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
</table>

Table 23: Domain Mapping Matrix between resilience technologies and the parameters of picking systems

			STORAGE SYSTEMS												
			DESIGN PARAMETERS							PERFORMANCE PARAMETERS					
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Speed	Storage density	Selectivity (direct access to items)	Storage capacity	Level of automation	Productivity (N. order lines/ h)	Scalability (Flexibility)	System lifetime (life cycle, useful life, service life)	Utilisation rate	Investement costs	Operating costs
Resilience	Approaches	Organizational resilience													
		Cognitive resilience													
		Psycological resilience													
		Operator safety strategies													
		Biological resilience													
		Human-machine systems resilience													
		Renewable sources													
		Physical resilience													

Table 24: Domain Mapping Matrix between resilience approaches and the parameters of storage systems

			STORAGE SYSTEMS												
			DESIGN PARAMETERS							PERFORMANCE PARAMETERS					
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Speed	Storage density	Selectivity (direct access to items)	Storage capacity	Level of automation	Productivity (N. order lines/ h)	Scalability (Flexibility)	System lifetime (life cycle, useful life, service life)	Utilisation rate	Investement costs	Operating costs
Resilience	Technologies	Big Data													
		Machine Learning													
		Artificial Intelligence (AI)													
		Internet of Things (IoT)													
		Cyber-physical systems													
		NextG wireless networks (NGWNs)													
		Cloud computing													
		Internet of Everything (IoE)													

Table 25: Domain Mapping Matrix between resilience technologies and the parameters of material handling systems

			MATERIAL HANDLING SYSTEMS										
			DESIGN PARAMETERS					PERFORMANCE PARAMETERS					
			Load capacity	Battery autonomy	Speed	Cycle time	Level of automation	Level of energy consumption	System lifetime (life cycle, useful life, service life)	Utilization rate	Scalability (Flexibility)	Investment costs	Operating costs
Resilience	Approaches	Organizational resilience											
		Cognitive resilience											
		Psycological resilience											
		Operator safety strategies											
		Biological resilience											
		Human-machine systems resilience											
		Renewable sources											
		Physical resilience											

Table 26: Domain Mapping Matrix between resilience approaches and the parameters of material handling systems

			MATERIAL HANDLING SYSTEMS										
			DESIGN PARAMETERS					PERFORMANCE PARAMETERS					
			Load capacity	Battery autonomy	Speed	Cycle time	Level of automation	Level of energy consumption	System lifetime (life cycle, useful life, service life)	Utilization rate	Scalability (Flexibility)	Investment costs	Operating costs
Resilience	Technologies	Big Data											
		Machine Learning											
		Artificial Intelligence (AI)											
		Internet of Things (IoT)											
		Cyber-physical systems											
		NextG wireless networks (NGWNs)											
		Cloud computing											
		Internet of Everything (IoE)											

Table 27: Domain Mapping Matrix between resilience technologies and the parameters of material handling systems

3.4 CONDUCING THE DELPHI STUDY

Once the parameters were defined, with the scope of clearly organize the information and facilitate the analysis and comparison of the different internal logistics systems, we created an Excel file consisting of six sheets. The first sheet contained the detailed instructions for filling-in the questionnaire; the second and third sheets contained the definitions of the approaches, technologies and parameters related to each intra-logistics system. The last three sheets are dedicated to the three pillars of Industry 5.0 and contain six Domain Mapping Matrices: three are related to the approaches and related to the technologies. Those matrices are replicated for each intra-logistics system.

A time frame of four weeks was given for completing the questionnaire for both rounds, with a reminder email sent to the participants at the end of the second and third week. However, in order to reach the quota of eight Delphi (Grime and Wright, 2016) participants in both rounds, a further extension of one week was required.

The difference between the first and the second round is that in the first round only the Excel file to be filled-in was sent to all participants, whereas in the second round two different files were sent out:

- A file containing the summary of the results obtained in the first round. In details they could find the medians of the evaluations expressed by the participating experts, distinguished by Industry 5.0 dimension, and the interquartile range (IQR) values calculated on these evaluations, again distinguished by Industry 5.0 dimension, with a coloured scale highlighting the level of consensus among the participants
- Another file containing the same Excel spreadsheet that they had created, where they were supposed to highlight the cells that in tier opinion should have been changed according to the results of the first round.

3.5 FIRST AND SECOND ROUND COMPARISON

Once we have collected the first and second round questionnaires responses from all eight participants, we could compare the results by analysing both the interquartile range and the medians (Von Der Gracht, 2012).

3.5.1 The interquartile range calculation

The interquartile range was calculated for each pillar in both rounds. Specifically, for each parameter, the interquartile range was determined by considering the approaches and technologies that influence it in each intra-logistics system.

Once all interquartile ranges were calculated, they were entered into the Domain Mapping Matrices of each intra-logistics system for each pillar. Conditional formatting was then applied to visually represent the degree of consensus (Table 28).

IQR	Consensus
$IQR \leq 1$	Strong consensus
$1< IQR \leq 1.5$	Moderate consensus
$IQR > 1.5$	Lack of consensus

Table 28: Interquartile range consensus

The degree of consensus in the interquartile range indicates how much the experts agree on the parameter evaluations for each pillar of the intra-logistics system. In order to understand the stability of the assessments and the reliability of the information for each analysed parameter, we have identified three degrees of consensus:

1 Strong consensus: the interquartile range is narrow, which means that the assessments are concentrated in a small range and there is a high convergence of opinions.

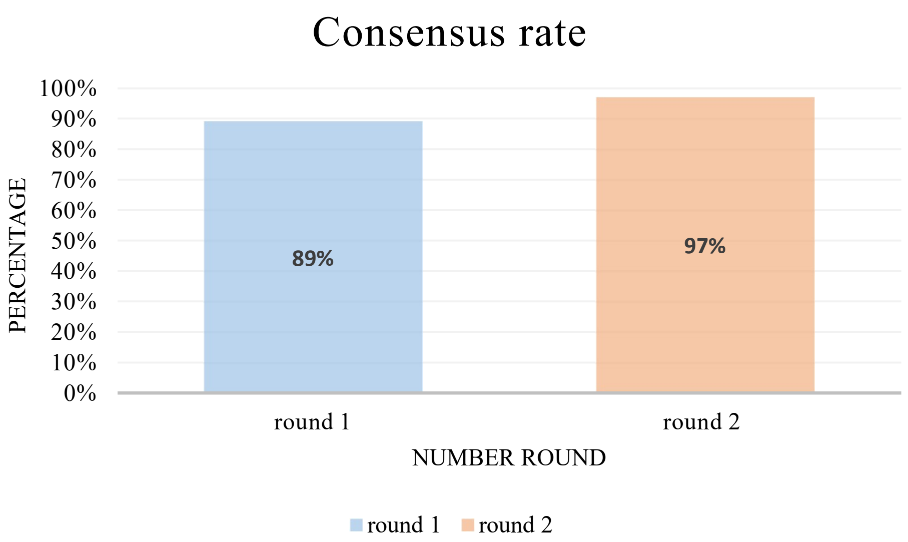
2 Moderate consensus: the interquartile range is wider, indicating greater variability in ratings, but still some consistency in responses.

3 Lack of consensus: the interquartile range is very wide or indeterminate, indicating a high degree of dispersion in the data and a lack of clear agreement between evaluations.

Then, for both rounds, the sum of the cells with strong consensus and the total sum of the cells were calculated for each DMM of each pillar. From this data, the ratio was calculated to determine the consensus percentage.

$$Consensus\ percentage = \frac{Total\ of\ cells\ with\ strong\ consensus}{Total\ of\ cells}$$

Thanks to this formula, we can see that from the first to the second round, the percentage of agreement increased by 8% (Graphic 3).



Graphic 3: Consensus percentage of the two rounds

To determine the number of rounds to be completed in the Delphi study, we use a consensus percentage of 90%, roughly. Therefore, based on the results we have obtained, we stopped after the second round, where we reached 97% of consensus against the 89% achieved after the first round.

Now, let's go a little bit more into the details and let's analyse each storage system individually. By looking at the results it is possible to identify the parameters that gain full acceptance in both rounds of the Delphi study by comparing the three pillars, and independently from the adopted approach and technology:

1. Picking systems: in the human-centricity pillar, there is a full agreement on the level of automation and picking productivity, while in the technology pillar there is the unanimous agreement on picking accuracy. In the sustainability pillar, there is full consensus on the level of automation, picking accuracy, picking time and picking productivity. However, the latter is not included in the technologies.

   On the other hand, in the resilience pillar, there is full consensus in both approaches and technologies for the level of automation, picking productivity and picking accuracy. There is also full agreement on operating costs, but only in the technologies side.

   The results show that some parameters, such as the level of automation, the picking accuracy and the picking productivity, maintain a stable consensus across all pillars, while others, such as the picking productivity, are recognised mainly in the approaches and rather than in the technologies. The level of automation, picking accuracy and picking productivity are considered essential for improving efficiency and reducing errors, so they find consensus in all pillars. However, picking productivity is mainly associated with the approaches, as it depends more on management and organisational strategies, such as process optimisation, rather than the adoption of specific technologies.
2. Storage systems: all three pillars, in both approaches and technologies, show some parameters that remain in full consensus in both rounds, including storage depth, storage height, speed, storage density and storage capacity. However, there are some exceptions. Productivity is only present in approaches in the resilience pillar, while it is recognised in both approaches and technologies in the sustainability and human-centricity pillars. On the other hand, scalability is present in technologies as far as concerning the resilience pillar, but in both approaches and technologies as far as concerning the human-centricity pillar. System lifetime is fully accepted in all approaches in all three pillars, while for technologies it is only recognised in the human-centricity pillar. Utilisation rate is present in both approaches and technologies in the sustainability and resilience pillars, while operating costs are fully accepted in the resilience and human-centricity approaches and in the resilience and sustainability technologies.

In general, the full consensus on these parameters reflects their crucial importance for the operational efficiency and sustainability of storage systems, regardless the pillar. However, the differences found, such as in the case of productivity, which is recognised mainly in the approaches in resilience and in both areas in sustainability and human-centricity, indicate that some parameters are influenced more by management strategies (approaches) than by technologies. On the other hand, parameters such as scalability and system lifetime, which depend heavily on technological capabilities and the durability of solutions, show divergences between the pillars according to their emphasis on technological innovation and long-term management.

3. Material Handling systems: in the material handling system, parameters with full consensus in both approaches and technologies are present in the three pillars in both rounds, including load capacity, speed and operating costs. Cycle time and system lifetime, on the other hand, are only present in the Sustainability approaches, but the latter parameter is considered with full consensus in both approaches and technologies in the resilience pillar. Other common parameters between sustainability and resilience in both approaches and technologies include level of consumption, scalability, utilisation rate and level of automation. However, these last three characteristics are also shared by technologies in the human-centricity pillar.

   These similarities between the pillars indicate that parameters such as level of consumption, scalability, utilisation rate and level of automation are considered crucial to improving the operational efficiency, sustainability and resilience of material handling systems. Their transversal presence in all three pillars suggests that these factors are considered crucial from both an operational and technological perspective to optimise processes, reduce costs and ensure flexibility to the systems. In contrast, cycle time and system lifetime are more focused on specific aspects of sustainability and resilience, and this points out the importance of time management and long-term durability to ensure an effective implementation of solutions.

In the first round of the study, there were cells with no or moderate agreement within the different storage systems for both approaches and technologies. However, following the submission of the summary, respondents reconsidered some of their assessments, and this resulted in a greater degree of agreement on several performance and design parameters. For example, in the human-centred context of order picking and material handling, investment and operating costs received strong agreement for all approaches and technologies. Similarly, in the context of storage systems, resilience-related technologies achieved full consensus on all design and performance parameters.

3.5.2 Medians calculation

To complete the analysis of Domain Mapping Matrices, we defined five different ranges of median values (Table 29) to ensure a homogeneous distribution of the data. Each range was structured so that the distance between the minimum and maximum values from the median was the same. In addition, to each range was assigned a specific colour, which was used to highlight the cells of the DMMs corresponding to each pillars.

MEDIAN VALUES	Cell color
1 - 1,5	Orange
2 - 2,5	Light Orange
3	White
3,5 - 4	Light Green
4,5 - 5	Green

Table 29: Median values colour association

The same format was applied to both rounds of the Delphi study. After calculating the medians for each relationship between approach/technology and performance/design parameter, the data were formatted by assigning different colours to the cells according to the obtained range. Specifically, in the second round, after formatting, all cells that did not reach full agreement according to the IQR of the second round, were crossed out in all DMMs of the three pillars. In this section, the comparison only concerns cells that reached full agreement in both rounds.

The following considerations emerge from an analysis of the different storage systems and a comparison of the three pillars:

1. Picking systems: in round 1, under human-centricity, neither approach nor technology had a positive impact on the design and performance parameters, with the exception of intelligent smart wearables (ISWs) and exoskeletons, which showed an increase for all parameters considered. However, in round 2, neither technology nor approach maintained a positive impact, as ISWs and exoskeletons did not gain full acceptance in relation to picking operation time.
   In terms of sustainability, the 6Rs policy and predictive maintenance approaches contributed to the reduction of operating costs in both rounds, with a more pronounced reduction in the second round for the 6Rs policy. In addition, the level of automation had a positive impact for all technologies and remained constant in both rounds. In general, the approaches did not significantly affect the benchmarks in round 2, while the technologies maintained or increased their impact relative to the benchmarks.
   Within resilience, all technologies had a positive and constant impact on the level of automation in both rounds, just like it was for the sustainability. However, the main difference between the two rounds is that in the second round, a greater number of approaches (cognitive resilience, psychological resilience and physical resilience) and technologies (Machine Learning, Artificial Intelligence, cyber-physical systems and IoT) had a positive impact by leading to a reduction on the picking time.
   These results show how the integration of advanced technologies and robust approaches in round 2 led to an improved operational performance, to a reduced picking times and optimised automation.
2. Storage systems: within human-centricity, in round 1 all approaches had a positive impact on the productivity and utilisation rate parameters. However, in round 2, while the positive impact on utilisation remained unchanged, the strong consensus shifted to the investment costs. With regard to technologies, in both rounds a positive impact was observed on the level of automation and investment costs, with the difference that

instead of reducing some operating costs, they remained unchanged or increased.

For sustainability, the approach with the greatest impact on the design and performance parameters in round 1 was the 6R policy. In round 2, however, no approach had a significant impact on the parameters. In addition, most of the operating costs associated with the approaches decreased in round 1, whereas they remained the same in round 2. In terms of technologies, a positive impact on the level of automation was confirmed in both rounds. However, as with the approaches, the operating costs decreased more in the first round than in the second.

In the area of resilience, no parameter had a positive impact on all approaches in both rounds. However, for technologies, the level of automation and scalability maintained a constant positive impact, with no major variations between the two rounds.

In conclusion, the analysis of the two rounds shows that the positive impact of the approaches tends to decrease or stabilise over time, while technologies continue to play a key role in improving automation and scalability.

3. Material Handling systems: within human-centricity, all approaches had a positive impact on utilisation rate and scalability parameters in round 1. However, in round 2, the positive impact remained only on the utilisation rate. For technologies, none of the approaches showed a positive impact on all design and performance parameters, in both rounds.

   For sustainability, no parameter was found to be positively affected by all technologies or approaches. A similar trend was observed for resilience, where in the table of approaches no parameter had a positive impact on all analysed elements. However, in the first round, all technologies in resilience had a positive impact on scalability and operating costs, by reducing them. However, this trend was not confirmed in round 2.

   The analysis shows how the positive impact of some approaches and technologies tends to mitigate in the transition between the two rounds, suggesting greater selectivity in the evaluations.

3.6 SECOND ROUND RESULTS

In this section, we focus in particular on the results obtained in the second round, which were decisive in leading us to close the process at the end of this phase of the Delphi study.

3.6.1 Interquartile range results

From the results of the interquartile range tables (from Table 30 to Table 47), we can see that by keeping the pillar fixed and by varying the intra-logistics system, a comparison of the DDMs of approaches and technologies shows a greater or smaller consensus on approaches versus technologies.

			PICKING SYSTEMS					
			DESIGN PARAMETERS	PERFORMANCE PARAMETERS				
			Level of automation	Picking productivity (N. picking lines/h)	Picking operation time	Picking accuracy	Investment costs	Operating costs
Human centricity	Approaches	Decentralized decision making	0,50	1,00	0,00	1,00	1,00	0,50
		Human-robot co-working	0,25	0,00	1,00	0,25	2,00	0,25
		Tracking-as-a-Service (NTaaS)	0,00	0,25	0,00	1,00	1,25	0,25

Table 30: DMM between human-centricity approaches and parameters IQR results of picking systems

			PICKING SYSTEMS					
			DESIGN PARAMETERS	PERFORMANCE PARAMETERS				
			Level of automation	Picking productivity (N. picking lines/h)	Picking operation time	Picking accuracy	Investment costs	Operating costs
Human centricity	Technologies	Artificial Intelligence (AI)	0,50	0,50	0,50	0,50	1,00	0,50
		Natural language processing for interacting with robots	1,25	1,00	1,25	0,25	1,25	0,00
		Intelligent smart wearables (ISWs) and exoskeletons	0,25	1,00	2,00	1,00	0,50	1,00
		Cobots	0,50	1,00	2,00	0,25	0,75	0,50
		Natural user interfaces (NUIs)	0,00	0,25	1,00	0,00	1,00	0,00
		Human interaction and recognition technologies (HIRT)	0,50	0,50	1,50	1,00	1,00	0,00
		Gesture-tracking devices	0,00	0,75	0,75	1,00	1,00	0,00
		Augmented Reality (AR)	0,00	0,00	0,25	0,00	0,50	0,25
		Sensors	0,00	0,00	1,00	1,00	0,25	0,25
		Internet of Everything (IoE)	0,50	0,00	0,00	0,75	0,50	0,50
		Clothing industrial smart wearables	0,50	0,00	0,00	1,00	0,00	0,50
		Internet of Things (IoT)	0,00	1,00	0,25	1,00	1,00	1,00
		Edge computing	0,25	0,00	0,00	0,50	0,50	0,50

Table 31: DMM between human-centricity technologies and parameters IQR results of picking systems

			STORAGE SYSTEMS												
			DESIGN PARAMETERS							PERFORMANCE PARAMETERS					
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Speed	Storage density	Selectivity (direct access to items)	Storage capacity	Level of automation	Productivity (N. order lines/h)	Scalability (Flexibility)	System lifetime (life cycle, useful life, service life)	Utilisation rate	Investement costs	Operating costs
Human centricity	Approaches	Decentralized decision making	0,50	0,00	0,50	0,00	0,50	0,00	1,50	0,75	1,00	0,50	1,00	1,00	0,75
		Human-robot co-working	0,25	1,00	0,25	1,00	0,00	0,00	1,00	1,00	1,00	1,00	0,00	0,25	1,00
		Tracking-as-a-Service (NTaaS)	0,25	0,25	1,00	1,00	0,25	0,25	1,00	1,00	1,00	1,00	0,50	1,00	0,75

Table 32: DMM between human-centricity approaches and parameters IQR results of storage systems

			STORAGE SYSTEMS												
			DESIGN PARAMETERS							PERFORMANCE PARAMETERS					
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Speed	Storage density	Selectivity (direct access to items)	Storage capacity	Level of automation	Productivity (N. order lines/h)	Scalability (Flexibility)	System lifetime (life cycle, useful life, service life)	Utilisation rate	Investement costs	Operating costs
Human centricity	Technologies	Artificial Intelligence (AI)	0,00	0,50	0,00	0,50	0,50	0,50	0,00	0,00	0,00	0,50	0,00	0,00	1,00
		Natural language processing for interacting with robots	0,00	0,00	1,00	0,25	0,00	0,00	1,00	0,00	0,50	0,50	1,00	0,00	0,50
		Intelligent smart wearables (ISWs) and exoskeletons	0,00	0,00	1,00	0,25	0,00	0,00	1,00	1,00	0,50	0,00	1,00	0,50	1,00
		Cobots	1,00	0,25	1,00	0,00	0,00	0,25	0,25	0,00	0,25	1,25	0,00	0,50	1,00
		Natural user interfaces (NUIs)	0,00	0,00	1,00	0,25	0,25	0,00	0,25	0,00	0,50	0,50	0,50	0,00	1,00
		Human interaction and recognition technologies (HIRT)	0,00	0,00	1,00	0,50	0,00	0,00	1,00	0,50	0,00	0,00	1,00	0,50	1,00
		Gesture-tracking devices	0,00	0,00	0,00	0,00	0,00	0,00	0,75	0,75	1,00	0,00	1,00	0,00	0,75
		Augmented Reality (AR)	1,00	1,00	1,00	1,00	0,25	0,00	0,00	0,00	0,00	1,00	0,00	0,00	0,25
		Sensors	1,00	1,00	1,00	1,00	0,00	0,25	0,25	1,00	0,00	1,00	0,25	0,00	0,50
		Internet of Everything (IoE)	0,00	0,50	0,50	1,00	0,50	0,50	0,50	0,50	0,75	1,00	0,75	0,00	2,00
		Clothing industrial smart wearables	0,00	0,00	0,75	0,75	0,00	0,00	1,00	0,75	0,75	0,00	0,75	0,00	0,75
		Internet of Things (IoT)	0,00	0,00	1,00	1,00	0,25	0,00	1,00	1,00	0,25	0,00	1,00	0,00	1,00
		Edge computing	0,00	0,00	0,75	0,00	0,00	0,00	1,00	0,75	0,00	0,75	0,75	0,00	0,75

Table 33: DMM between human-centricity technologies and parameters IQR results of storage systems

			MATERIAL HANDLING SYSTEMS										
			DESIGN PARAMETERS					PERFORMANCE PARAMETERS					
			Load capacity	Battery autonomy	Speed	Cycle time	Level of automation	Level of energy consumption	System lifetime (life cycle, useful life, service life)	Utilization rate	Scalability (Flexibility)	Investment costs	Operating costs
Human centricity	Approaches	Decentralized decision making	0,25	0,25	1,00	1,00	1,50	1,00	0,25	0,50	1,25	0,25	1,00
		Human-robot co-working	0,50	0,25	0,00	0,25	1,00	1,00	1,00	0,00	0,00	0,25	1,00
		Tracking-as-a-Service (NTaaS)	0,00	0,50	1,00	1,25	1,00	0,00	0,00	1,00	0,25	1,00	1,00

Table 34: DMM between human-centricity approaches and parameters IQR results of material handling systems

			MATERIAL HANDLING SYSTEMS										
			DESIGN PARAMETERS					PERFORMANCE PARAMETERS					
			Load capacity	Battery autonomy	Speed	Cycle time	Level of automation	Level of energy consumption	System lifetime (life cycle, useful life, service life)	Utilization rate	Scalability (Flexibility)	Investment costs	Operating costs
Human centricity	Technologies	Artificial Intelligence (AI)	0,50	1,00	0,50	0,50	1,00	1,00	0,00	0,00	0,00	0,00	1,00
		Natural language processing for interacting with robots	0,25	0,50	1,00	1,25	0,00	0,25	0,25	1,00	1,00	1,00	0,00
		Intelligent smart wearables (ISWs) and exoskeletons	1,00	0,25	1,00	1,25	1,00	1,25	0,00	1,00	1,00	0,25	0,25
		Cobots	1,00	0,00	0,25	1,25	0,25	0,50	0,25	0,00	1,00	1,00	0,25
		Natural user interfaces (NUIs)	0,00	1,00	1,00	1,25	1,00	1,00	1,00	0,50	0,25	1,00	0,00
		Human interaction and recognition technologies (HIRT)	1,00	1,00	0,00	0,75	0,75	0,75	0,00	0,75	0,00	0,75	0,75
		Gesture-tracking devices	0,00	0,75	1,00	0,75	0,75	0,00	0,75	1,00	1,00	0,75	0,00
		Augmented Reality (AR)	0,00	0,25	1,00	1,00	1,00	0,50	0,25	1,00	1,00	1,00	0,00
		Sensors	0,25	1,00	1,00	1,25	1,00	0,50	1,00	1,00	1,00	1,00	0,00
		Internet of Everything (IoE)	0,00	0,75	0,00	0,00	0,75	0,00	0,75	1,00	0,00	0,75	1,00
		Clothing industrial smart wearables	0,00	0,00	0,75	0,00	0,00	0,00	0,75	0,75	1,00	0,75	0,00
		Internet of Things (IoT)	0,00	1,00	0,25	2,00	1,00	0,50	0,25	1,00	1,00	1,00	1,00
		Edge computing	0,00	0,75	0,75	0,00	1,00	0,00	0,00	0,75	0,00	1,00	0,00

Table 35: DMM between human-centricity technologies and parameters IQR results of material handling systems

			PICKING SYSTEMS					
			DESIGN PARAMETERS	PERFORMANCE PARAMETERS				
			Level of automation	Picking productivity (N. picking lines/h)	Picking operation time	Picking accuracy	Investment costs	Operating costs
Sustainability	Approaches	Circular processes	0,25	0,00	0,00	0,00	0,25	0,50
		Reduction of climate change	0,25	0,00	0,00	0,00	0,25	0,00
		Renewable sources	0,00	0,00	0,00	0,00	0,50	2,00
		Remanufacturing	0,00	0,00	0,00	0,00	0,25	1,25
		6Rs policy	0,00	0,00	0,00	0,00	0,00	1,00
		Predictive maintenance	0,25	0,25	0,25	0,00	0,50	0,25
		Bioeconomy	0,00	0,00	0,00	0,00	1,00	0,25

Table 36: DMM between sustainability approaches and parameters IQR results of picking systems

			PICKING SYSTEMS					
			DESIGN PARAMETERS	PERFORMANCE PARAMETERS				
			Level of automation	Picking productivity (N. picking lines/h)	Picking operation time	Picking accuracy	Investment costs	Operating costs
Sustainability	Technologies	Machine Learning	0,00	0,00	0,50	1,00	0,50	0,50
		Intelligent Energy Management Systems (IEMS)	0,25	1,00	1,00	0,25	1,00	1,25
		Big Data	1,00	1,00	1,00	1,00	0,25	0,25
		Artificial Intelligence (AI)	0,50	0,00	0,50	1,00	0,50	0,50
		Computational Intelligence (CI)	0,50	1,00	1,00	0,50	1,00	0,00
		Internet of Things (IoT)	0,25	1,00	1,00	0,25	1,00	0,25
		Internet of Personalized Products (IoP^2)	0,00	0,75	1,00	0,75	0,00	0,00

Table 37: DMM between sustainability technologies and parameters IQR results of picking systems

			STORAGE SYSTEMS												
			DESIGN PARAMETERS							PERFORMANCE PARAMETERS					
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Speed	Storage density	Selectivity (direct access to items)	Storage capacity	Level of automation	Productivity (N. order lines/ h)	Scalability (Flexibility)	System lifetime (life cycle, useful life, service life)	Utilisation rate	Investment costs	Operating costs
Sustainability	Approaches	Circular processes	0,00	0,00	0,00	0,00	0,25	0,00	0,00	0,00	0,00	0,00	0,25	0,25	1,25
		Reduction of climate change	0,25	0,25	0,00	0,25	0,00	0,00	0,00	0,00	0,00	0,00	0,00	1,25	0,50
		Renewable sources	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,25	0,00	0,00	0,25	2,00
		Remanufacturing	0,00	0,25	0,00	0,00	0,00	0,00	0,00	0,25	0,00	0,25	0,00	1,00	1,00
		6Rs policy	0,00	0,25	1,00	0,00	0,00	0,25	0,25	0,25	0,25	0,00	0,00	0,25	0,50
		Predictive maintenance	0,00	0,00	0,25	0,00	0,00	0,25	1,00	0,00	1,00	1,00	1,00	1,25	0,25
		Bioeconomy	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,25

Table 38: DMM between sustainability approaches and parameters IQR results of storage systems

			STORAGE SYSTEMS												
			DESIGN PARAMETERS							PERFORMANCE PARAMETERS					
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Speed	Storage density	Selectivity (direct access to items)	Storage capacity	Level of automation	Productivity (N. order lines/ h)	Scalability (Flexibility)	System lifetime (life cycle, useful life, service life)	Utilisation rate	Investment costs	Operating costs
Sustainability	Technologies	Machine Learning	0,50	0,00	0,00	0,50	1,00	0,50	0,00	0,50	0,00	0,00	0,00	0,50	0,50
		Intelligent Energy Management Systems (IEMS)	0,00	0,00	1,00	0,25	0,00	0,25	0,25	1,00	1,00	1,00	0,25	1,00	1,00
		Big Data	0,00	0,00	1,00	1,00	1,00	0,25	1,00	1,00	1,25	0,25	0,25	1,00	0,25
		Artificial Intelligence (AI)	0,50	0,00	0,00	1,00	1,00	0,50	0,00	1,00	0,00	0,00	0,00	0,50	0,50
		Computational Intelligence (CI)	0,50	0,00	1,00	1,00	0,50	1,00	0,50	0,50	0,50	0,50	0,50	0,00	1,00
		Internet of Things (IoT)	0,00	0,00	0,25	0,00	0,00	0,00	1,00	1,00	1,25	0,25	1,00	1,00	0,00
		Internet of Personalized Products (IoP^2)	0,75	0,00	0,75	0,00	0,75	0,00	0,00	0,00	0,75	0,75	0,75	0,75	1,00

Table 39: DMM between sustainability technologies and parameters IQR results of storage systems

			MATERIAL HANDLING SYSTEMS										
			DESIGN PARAMETERS					PERFORMANCE PARAMETERS					
			Load capacity	Battery autonomy	Speed	Cycle time	Level of automation	Level of energy consumption	System lifetime (life cycle, useful life, service life)	Utilization rate	Scalability (Flexibility)	Investment costs	Operating costs
Sustainability	Approaches	Circular processes	0,00	0,00	0,00	0,00	0,00	0,00	1,00	1,00	0,00	1,00	0,50
		Reduction of climate change	0,00	0,25	0,00	0,00	0,00	1,00	0,50	0,50	0,00	0,50	0,50
		Renewable sources	0,00	0,25	0,00	0,00	0,00	1,00	0,25	0,25	0,00	0,00	1,00
		Remanufacturing	0,00	0,00	0,00	0,00	0,00	0,00	0,25	0,50	0,00	1,25	0,25
		6Rs policy	0,00	0,25	0,25	0,25	0,25	1,00	0,25	1,00	1,00	1,00	0,25
		Predictive maintenance	0,00	1,00	0,25	1,00	0,50	1,00	1,00	1,00	0,50	1,00	1,00
		Bioeconomy	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,25	0,25

Table 40: DMM between sustainability approaches and parameters IQR results of material handling systems

			MATERIAL HANDLING SYSTEMS										
			DESIGN PARAMETERS					PERFORMANCE PARAMETERS					
			Load capacity	Battery autonomy	Speed	Cycle time	Level of automation	Level of energy consumption	System lifetime (life cycle, useful life, service life)	Utilization rate	Scalability (Flexibility)	Investment costs	Operating costs
Sustainability	Technologies	Machine Learning	0,50	0,00	0,50	0,50	0,00	1,00	0,00	0,75	0,00	1,00	0,75
		Intelligent Energy Management Systems (IEMS)	0,00	1,00	1,00	0,25	0,00	1,00	0,50	0,50	0,50	1,00	1,50
		Big Data	0,00	1,00	1,00	0,00	1,00	0,25	1,00	1,00	1,00	0,25	0,00
		Artificial Intelligence (AI)	0,50	0,00	0,00	0,50	0,00	1,00	0,00	0,50	0,00	0,50	0,50
		Computational Intelligence (CI)	0,50	1,00	1,00	0,00	1,00	0,00	0,50	1,00	0,50	1,00	0,00
		Internet of Things (IoT)	0,00	1,00	1,00	0,25	1,00	0,00	1,00	1,00	1,00	1,00	0,50
		Internet of Personalized Products (IoP^2)	0,00	0,00	0,00	1,00	0,00	0,00	1,00	0,00	1,00	0,00	0,75

Table 41: DMM between sustainability technologies and parameters IQR results of material handling systems

			PICKING SYSTEMS					
			DESIGN PARAMETERS	PERFORMANCE PARAMETERS				
			Level of automation	Picking productivity (N. picking lines/h)	Picking operation time	Picking accuracy	Investment costs	Operating costs
Resilience	Approaches	Organizational resilience	0,00	0,25	0,25	0,50	0,00	1,25
		Cognitive resilience	1,00	0,00	0,25	0,25	0,00	0,25
		Psycological resilience	0,25	0,25	0,25	1,00	1,00	0,25
		Operator safety strategies	0,00	0,00	0,25	0,25	1,00	0,50
		Biological resilience	1,00	1,00	1,00	0,25	0,50	0,25
		Human-machine systems resilience	0,00	1,00	0,50	0,25	1,00	0,25
		Renewable sources	1,00	0,00	0,00	0,00	0,25	1,00
		Physical resilience	1,00	0,25	1,00	1,00	0,25	0,25

Table 42: DMM between resilience approaches and parameters IQR results of picking systems

			PICKING SYSTEMS					
			DESIGN PARAMETERS	PERFORMANCE PARAMETERS				
			Level of automation	Picking productivity (N. picking lines/h)	Picking operation time	Picking accuracy	Investment costs	Operating costs
Resilience	Technologies	Big Data	0,00	1,00	0,00	0,50	1,00	0,00
		Machine Learning	0,00	0,50	1,00	0,00	1,00	0,50
		Artificial Intelligence (AI)	0,00	0,00	1,00	0,00	1,00	1,00
		Internet of Things (IoT)	0,25	0,25	0,00	1,00	1,00	0,00
		Cyber-physical systems	0,25	1,00	1,00	0,25	1,00	0,25
		NextG wireless networks (NGWNs)	0,00	1,00	0,25	1,00	1,00	0,25
		Cloud computing	0,25	1,00	0,00	1,00	1,25	1,00
		Internet of Everything (IoE)	1,00	0,50	1,00	1,00	0,50	0,00

Table 43: DMM between resilience technologies and parameters IQR results of picking systems

			STORAGE SYSTEMS												
			DESIGN PARAMETERS							PERFORMANCE PARAMETERS					
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Speed	Storage density	Selectivity (direct access to items)	Storage capacity	Level of automation	Productivity (N. order lines/h)	Scalability (Flexibility)	System lifetime (life cycle, useful life, service life)	Utilisation rate	Investement costs	Operating costs
Resilience	Approaches	Organizational resilience	0,00	0,00	0,00	0,00	0,50	0,25	0,00	1,00	0,25	1,00	0,00	1,00	0,25
		Cognitive resilience	0,25	0,25	0,00	1,00	0,25	0,00	0,00	0,25	1,25	0,00	1,00	1,00	1,00
		Psycological resilience	0,00	0,00	0,00	0,00	0,25	0,00	0,00	1,00	1,00	0,25	0,00	0,25	0,50
		Operator safety strategies	0,00	0,00	0,00	0,00	0,50	0,00	0,00	0,25	0,25	0,25	0,00	0,50	0,25
		Biological resilience	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,50	0,00	0,00	0,00	0,50
		Human-machine systems resilience	0,25	0,25	1,00	1,00	0,25	0,00	1,00	1,00	1,00	0,25	0,25	1,25	1,00
		Renewable sources	0,00	0,50	0,00	0,00	0,00	0,00	0,25	0,00	0,25	0,25	1,00	1,25	1,25
		Physical resilience	0,00	1,00	0,00	0,00	0,25	0,00	0,00	1,00	0,25	0,00	0,50	0,00	0,50

Table 44: DMM between resilience approaches and parameters IQR results of storage systems

			STORAGE SYSTEMS												
			DESIGN PARAMETERS							PERFORMANCE PARAMETERS					
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Speed	Storage density	Selectivity (direct access to items)	Storage capacity	Level of automation	Productivity (N. order lines/h)	Scalability (Flexibility)	System lifetime (life cycle, useful life, service life)	Utilisation rate	Investement costs	Operating costs
Resilience	Technologies	Big Data	0,50	0,00	1,00	1,00	0,00	0,25	0,25	1,00	1,00	1,00	0,50	1,00	1,00
		Machine Learning	0,50	1,00	1,00	0,50	1,00	1,00	1,00	0,00	0,50	0,00	0,00	1,00	0,00
		Artificial Intelligence	1,00	1,00	0,50	1,00	1,00	1,00	0,50	0,00	0,00	0,50	0,00	1,00	0,00
		Internet of Things (IoT)	0,00	0,00	1,00	0,25	0,00	0,25	1,00	1,00	1,00	0,25	1,00	1,00	1,00
		Cyber-physical systems	0,25	1,00	0,50	1,00	1,00	1,00	1,00	1,00	1,00	0,00	1,00	1,00	0,00
		NextG wireless networks (NGWNs)	0,00	0,00	1,00	0,00	0,25	0,00	0,25	1,00	1,00	0,25	1,00	1,00	1,00
		Cloud computing	0,00	0,00	1,00	0,50	0,00	0,25	0,50	1,00	0,50	0,50	1,00	1,00	1,00
		Internet of Everything (IoE)	0,00	0,00	0,00	0,50	0,50	0,00	1,00	1,00	0,50	0,50	0,75	1,00	1,00

Table 45: DMM between resilience technologies and parameters IQR results of storage systems

			MATERIAL HANDLING SYSTEMS										
			DESIGN PARAMETERS					PERFORMANCE PARAMETERS					
			Load capacity	Battery autonomy	Speed	Cycle time	Level of automation	Level of energy consumption	System lifetime (life cycle, useful life, service life)	Utilization rate	Scalability (Flexibility)	Investment costs	Operating costs
Resilience	Approaches	Organizational resilience	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	1,00	0,25	0,25
		Cognitive resilience	0,00	0,00	0,25	0,00	1,00	0,00	0,00	0,50	0,50	0,00	0,00
		Psycological resilience	0,00	0,00	1,00	0,50	0,25	0,00	0,25	1,00	1,00	0,00	0,00
		Operator safety strategies	0,00	0,00	0,00	0,00	0,25	0,00	0,25	0,00	1,00	1,00	1,00
		Biological resilience	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,50	0,00	0,25	0,25
		Human-machine systems resilience	1,00	0,00	1,00	1,00	1,00	0,00	0,00	1,00	1,00	1,00	0,25
		Renewable sources	0,00	1,25	0,00	0,00	0,25	0,25	0,00	0,00	1,00	1,25	1,00
		Physical resilience	0,00	0,00	1,00	0,00	0,00	0,00	0,00	1,00	1,00	1,00	0,25

Table 46: DMM between resilience approaches and parameters IQR results of material handling systems

			MATERIAL HANDLING SYSTEMS										
			DESIGN PARAMETERS					PERFORMANCE PARAMETERS					
			Load capacity	Battery autonomy	Speed	Cycle time	Level of automation	Level of energy consumption	System lifetime (life cycle, useful life, service life)	Utilization rate	Scalability (Flexibility)	Investment costs	Operating costs
Resilience	Technologies	Big Data	1,00	0,25	1,00	1,00	1,00	1,00	1,00	0,50	0,25	1,00	1,25
		Machine Learning	1,00	0,00	0,50	0,00	0,00	0,50	0,00	0,00	0,00	1,00	0,00
		Artificial Intelligence	0,00	0,00	0,00	0,50	0,00	0,00	0,00	0,00	0,00	1,00	0,00
		Internet of Things (IoT)	0,00	0,00	1,00	1,00	1,00	0,25	1,00	0,50	0,25	1,00	1,25
		Cyber-physical systems	0,00	1,00	1,00	1,25	1,00	1,00	1,00	1,00	0,25	1,00	1,00
		NextG wireless networks (NGWNs)	0,00	0,50	1,00	0,50	1,00	0,00	0,25	0,25	1,00	1,00	1,25
		Cloud computing	0,00	0,00	1,00	0,25	1,00	0,00	0,25	1,00	1,00	1,25	1,50
		Internet of Everything (IoE)	0,00	0,00	0,00	1,00	1,00	1,00	0,00	0,00	0,50	0,50	0,75

Table 47: DMM between resilience technologies and parameters IQR results of material handling systems

By looking at the tables on the target dimension of human-centricity, we can see that, in the three intra-logistics systems, the relationships between the technologies and the design and performance parameters receive less acceptance than the relationships between the approaches and those same parameters (Table 48). The lower consensus on the relationship between technologies and design and performance parameters compared to approaches is due to the greater flexibility and adaptability of the approaches, which are perceived as easier to integrate into existing processes. Technologies, on the other hand, may present challenges related to their implementation, resistance to change or lack of maturity just to name few, that will result in reducing the overall consensus.

		HUMAN CENTRICITY	
	Type of intra-logistics system	Approaches/Technologies	Parameters for which no strong consensus
Approaches	Picking Systems	Human-robot co-working	Investment costs
		Tracking-as-a-Service (NTaaS)	Investment costs
	Storage Systems	Decentralized decision making	Level of automation
	Material Handling Systems	Decentralized decision making	Level of automation, Scalability
		Tracking-as-a-Service (NTaaS)	Cycle time
Technologies	Picking Systems	Natural language processing for interacting with robots	Level of automation, Picking operation time, Investment costs
		Intelligent smart wearables (ISWs) and exoskeletons	Picking operation time
		Cobots	Picking operation time
		Human interaction and recognition technologies (HIRT)	Picking operation time
	Storage Systems	Cobots	System lifetime
		Internet of Everything (IoE)	Operating costs
	Material Handling Systems	Natural language processing for interacting with robots	Cycle time
		Intelligent smart wearables (ISWs) and exoskeletons	Cycle time, Level of energy consumption
		Cobots	Cycle time
		Natural user interfaces (NUIs)	Cycle time
		Sensors	Cycle time
		Internet of Things (IoT)	Cycle time

Table 48: Relationship between human-centricity approaches/technologies and parameters that did not receive strong acceptance in the three intralogistics systems

Regarding sustainability instead, the relationships between technologies and design and performance parameters, are more strongly supported than those between approaches and design and performance parameters (Table 49). This happens because technologies provide concrete and measurable solutions to reduce the environmental impacts, while approaches often remain conceptual and generic and therefore, their effectiveness depends on organisational, regulatory and cultural factors, that makes them less immediate and standardised.

		SUSTAINABILITY	
	Type of intra-logistics system	Approaches/Technologies	Parameters for which no strong consensus
Approaches	Picking Systems	Renewable sources	Operating costs
		Remanufacturing	Operating costs
	Storage Systems	Circular processes	Operating costs
		Reduction of climate change	Investment costs
		Renewable sources	Operating costs
		Predictive maintenance	Investment costs
	Material Handling Systems	Remanufacturing	Investment costs
Technologies	Picking Systems	Intelligent Energy Management Systems (IEMS)	Operating costs
	Storage Systems	Big Data	Scalability
		Internet of Things (IoT)	Scalability
	Material Handling Systems	Intelligent Energy Management Systems (IEMS)	Operating costs

Table 49: Relationship between sustainability approaches/technologies and parameters that did not receive strong acceptance in the three intralogistics systems

With regard to resilience, a different dynamic can be observed in relation to the other pillars, as shown in the table (Table 50):

1. Picking systems: the number of reports that do not reach a strong consensus is the same for both technologies and approaches. In fact, both present an obstacle related to the evaluation of the cost-benefit ratio of implementing and managing advanced adaptive systems.
2. Storage systems: all relationships between technologies and design and performance parameters are strongly supported, unlike those related to approaches. This is because technologies allow faster and more effective responses to disturbances and variations in demand.
3. Material Handling systems: only one relationship between approaches did not receive full consensus, while technologies were more criticised. This is due to the ongoing operating costs associated with digital infrastructure, maintenance and data management. In contrast, renewable resources require a higher initial investment, but offer more stable and predictable operating costs over time.

		RESILIENCE	
	Type of intra-logistics system	**Approaches/Technologies**	**Parameters for which no strong consensus**
Approaches	Picking Systems	Organizational resilience	Operating costs
	Storage Systems	Cognitive resilience	Scalability
		Human-machine systems resilience	Investment costs
		Renewable sources	Investment costs, Operating costs
	Material Handling Systems	Renewable sources	Investment costs
Technologies	Picking Systems	Cloud computing	Operating costs
	Storage Systems	-	-
	Material Handling Systems	Big Data	Operating costs
		Internet of Things (IoT)	Operating costs
		NextG wireless networks (NGWNs)	Operating costs
		Cloud computing	Investment costs, Operating costs

Table 50: Relationship between resilience approaches/technologies and parameters that did not receive strong acceptance in the three intralogistics systems

In general, the three tables above (from Table 48 to Table 50) show that most of the moderate consensus or lack of consensus concerns investment and operating costs. This is particularly evident for storage and material handling systems, which require more complex and expensive technological infrastructures. Instead, for order picking systems, lack of full consensus results is spread across a wider range of parameters, suggesting that critical issues are not related only on costs, but also on other aspects of the technology implementation and integration.

3.6.2 Median results

We can make a more detailed analysis by considering the results of the second round, as shown in the tables (from Table 51 to Table 68).

From the defined format (Table 29), we can identify, for each dimension of Industry 5.0, the main design and performance parameters whose value has improved in picking, material handling and storage systems. We have summarised these parameters in the table (Table 69), a more detailed analysis regarding each storage system can be found in Appendices 3A, 3B and 3C.

			PICKING SYSTEMS					
			DESIGN PARAMETERS	PERFORMANCE PARAMETERS				
			Level of automation	Picking productivity (N. picking lines/h)	Picking operation time	Picking accuracy	Investment costs	Operating costs
Human centricity	Approaches	Decentralized decision making	2	3	4	2	3	3
		Human-robot co-working	4	4	2	4	4	3
		Tracking-as-a-Service (NTaaS)	4	4	3	4	3,5	3

Table 51: DMM between human-centricity approaches and parameters median results of picking systems

			PICKING SYSTEMS					
			DESIGN PARAMETERS	PERFORMANCE PARAMETERS				
			Level of automation	Picking productivity (N. picking lines/h)	Picking operation time	Picking accuracy	Investment costs	Operating costs
Human centricity	Technologies	Artificial Intelligence (AI)	4	4	2	4	3	2
		Natural language processing for interacting with robots	4	3	3	4	3,5	3
		Intelligent smart wearables (ISWs) and exoskeletons	4	4	2,5	4	4	3,5
		Cobots	4	4	4	4	4	3
		Natural user interfaces (NUIs)	4	4	2	4	4	3
		Human interaction and recognition technologies (HIRT)	4	4	3	4	4	3
		Gesture-tracking devices	4	4	2	4	3,5	3
		Augmented Reality (AR)	4	4	2	4	4	3
		Sensors	4	4	2,5	4	4	3
		Internet of Everything (IoE)	4	3	3	4	4	3
		Clothing industrial smart wearables	3	3	3	4	4	3
		Internet of Things (IoT)	4	4	3	4	3,5	3
		Edge computing	4	3	3	3	4	3

Table 52: DMM between human-centricity technologies and parameters median results of picking systems

			STORAGE SYSTEMS												
			DESIGN PARAMETERS							PERFORMANCE PARAMETERS					
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Speed	Storage density	Selectivity (direct access to items)	Storage capacity	Level of automation	Productivity (N. order lines/ h)	Scalability (Flexibility)	System lifetime (life cycle, useful life, service life)	Utilisation rate	Investement costs	Operating costs
Human centricity	Approaches	Decentralized decision making	3	3	3	3	3	3	3	3	3	3	4	3,5	3
		Human-robot co-working	3	3	3	3	3	3	4	4	4	4	4	4	3,5
		Tracking-as-a-Service (NTaaS)	3	3	4	3	3	3	3,5	4	4	3	4	3,5	3

Table 53: DMM between human-centricity approaches and parameters median results of storage systems

			STORAGE SYSTEMS												
			DESIGN PARAMETERS							PERFORMANCE PARAMETERS					
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Speed	Storage density	Selectivity (direct access to items)	Storage capacity	Level of automation	Productivity (N. order lines/ h)	Scalability (Flexibility)	System lifetime (life cycle, useful life, service life)	Utilisation rate	Investement costs	Operating costs
Human centricity	Technologies	Artificial Intelligence (AI)	4	3	4	4	4	4	4	4	4	4	4	4	3
		Natural language processing for interacting with robots	3	3	3	3	3	3	4	4	4	3	4	4	3
		Intelligent smart wearables (ISWs) and exoskeletons	3	3	3	3	3	3	3,5	4	4	3	3	4	4
		Cobots	3	3	3,5	3	3	3	4	4	4	3	4	4	3
		Natural user interfaces (NUIs)	3	3	3,5	3	3	3	4	4	4	3	4	4	3
		Human interaction and recognition technologies (HIRT)	3	3	3	3	3	3	4	4	4	3	3	4	4
		Gesture-tracking devices	3	3	3	3	3	3	4	4	4	3	3	4	3
		Augmented Reality (AR)	3,5	3	3,5	3	3	3	4	4	4	3	4	4	3
		Sensors	3	3	4	4	3	3	4	4	4	3	4	4	3
		Internet of Everything (IoE)	3	3	3	3	3	3	4	4	4	3,5	4	4	3
		Clothing industrial smart wearables	3	3	3	3	3	3	3,5	3	4	3	3	4	3
		Internet of Things (IoT)	3	3	3	3	3	3	4	4	4	3	4	4	3,5
		Edge computing	3	3	3	3	3	3	3,5	3	3	3	3	4	3

Table 54: DMM between human-centricity technologies and parameters median results of storage systems

			MATERIAL HANDLING SYSTEMS										
			DESIGN PARAMETERS					PERFORMANCE PARAMETERS					
			Load capacity	Battery autonomy	Speed	Cycle time	Level of automation	Level of energy consumption	System lifetime (life cycle, useful life, service life)	Utilization rate	Scalability (Flexibility)	Investment costs	Operating costs
Human centricity	Approaches	Decentralized decision making	3	3	4	2,5	3	3	3	4	3,5	3	2
		Human-robot co-working	4	3	4	2	4	3,5	3	4	4	4	3
		Tracking-as-a-Service (NTaaS)	3	3	3	3	3,5	3	3	4	4	4	3

Table 55: DMM between human-centricity approaches and parameters median results of material handling systems

			MATERIAL HANDLING SYSTEMS										
			DESIGN PARAMETERS					PERFORMANCE PARAMETERS					
			Load capacity	Battery autonomy	Speed	Cycle time	Level of automation	Level of energy consumption	System lifetime (life cycle, useful life, service life)	Utilization rate	Scalability (Flexibility)	Investment costs	Operating costs
Human centricity	Technologies	Artificial Intelligence (AI)	3	4	4	3	3,5	3	4	4	4	4	2
		Natural language processing for interacting with robots	3	3	3,5	3	3	3	3	4	4	3	3
		Intelligent smart wearables (ISWs) and exoskeletons	3,5	3	3	3	4	3	3	3	3,5	4	3
		Cobots	4	3	4	3	4	3	3	4	4	4	3
		Natural user interfaces (NUIs)	3	3	4	2,5	3	3	3	4	4	3	3
		Human interaction and recognition technologies (HIRT)	3,5	4	4	2	4	2	3	4	4	4	3
		Gesture-tracking devices	3	3	3	3	3	3	3	3,5	3	4	3
		Augmented Reality (AR)	3	3	3	3	3	3	3	3,5	4	3,5	3
		Sensors	3	4	3	3	3,5	3	3,5	3	3,5	3	3
		Internet of Everything (IoE)	3	3	3	3	3	3	3	4	3	4	2,5
		Clothing industrial smart wearables	3	3	3	3	3	3	3	3	3	4	3
		Internet of Things (IoT)	3	3	3	3	4	3	3	4	3	3,5	3
		Edge computing	3	3	3	3	3,5	3	3	3	3	3,5	3

Table 56: DMM between human-centricity technologies and parameters median results of material handling systems

			PICKING SYSTEMS					
			DESIGN PARAMETERS	PERFORMANCE PARAMETERS				
			Level of automation	Picking productivity (N. picking lines/h)	Picking operation time	Picking accuracy	Investment costs	Operating costs
Sustainability	Approaches	Circular processes	3	3	3	3	3	3
		Reduction of climate change	3	3	3	3	3	3
		Renewable sources	3	3	3	3	3	3
		Remanufacturing	3	3	3	3	3	2,5
		6Rs policy	3	3	3	3	3	2,5
		Predictive maintenance	3	3	3	3	3	2
		Bioeconomy	3	3	3	3	3	3

Table 57: DMM between sustainability approaches and parameters median results of picking systems

			PICKING SYSTEMS					
			DESIGN PARAMETERS	PERFORMANCE PARAMETERS				
			Level of automation	Picking productivity (N. picking lines/h)	Picking operation time	Picking accuracy	Investment costs	Operating costs
Sustainability	Technologies	Machine Learning	4	4	2	4	4	3
		Intelligent Energy Management Systems (IEMS)	4	3	3	3	4	2,5
		Big Data	4	3	3	4	3	3
		Artificial Intelligence (AI)	4	4	2	3	4	3
		Computational Intelligence (CI)	4	4	2	3	4	3
		Internet of Things (IoT)	4	3	3	4	3,5	3
		Internet of Personalized Products (IoP^2)	4	4	2,5	3	4	3

Table 58: DMM between sustainability technologies and parameters median results of picking systems

			STORAGE SYSTEMS												
			DESIGN PARAMETERS							PERFORMANCE PARAMETERS					
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Speed	Storage density	Selectivity (direct access to items)	Storage capacity	Level of automation	Productivity (N. order lines/ h)	Scalability (Flexibility)	System lifetime (life cycle, useful life, service life)	Utilisation rate	Investment costs	Operating costs
Sustainability	Approaches	Circular processes	3	3	3	3	3	3	3	3	3	3	3	3	3
		Reduction of climate change	3	3	3	3	3	3	3	3	3	3	3	3	3
		Renewable sources	3	3	3	3	3	3	3	3	3	3	3	3	3
		Remanufacturing	3	3	3	3	3	3	3	3	3	3	3	3	3
		6Rs policy	3	3	3	3	3	3	3	3	3	3	3	3	3
		Predictive maintenance	3	3	3	3	3	3	3	3	3	3	3,5	2,5	2
		Bioeconomy	3	3	3	3	3	3	3	3	3	3	3	3	3

Table 59: DMM between sustainability approaches and parameters median results of storage systems

			STORAGE SYSTEMS												
			DESIGN PARAMETERS							PERFORMANCE PARAMETERS					
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Speed	Storage density	Selectivity (direct access to items)	Storage capacity	Level of automation	Productivity (N. order lines/ h)	Scalability (Flexibility)	System lifetime (life cycle, useful life, service life)	Utilisation rate	Investment costs	Operating costs
Sustainability	Technologies	Machine Learning	4	3	4	4	3	4	4	4	4	4	4	4	2
		Intelligent Energy Management Systems (IEMS)	3	3	3,5	3	3	3	4	3	3	4	4	3,5	2
		Big Data	3	3	3	3,5	3	3	4	3,5	4	3	4	3	3
		Artificial Intelligence (AI)	4	3	4	4	3,5	4	4	4	4	4	4	4	2
		Computational Intelligence (CI)	3	3	3	3	3	3	4	3	3	3	4	4	3
		Internet of Things (IoT)	3	3	3	3	3	3	4	4	4	3	3	3,5	3
		Internet of Personalized Products (IoP^2)	4	3	4	3	3	3	4	3	4	3	3	3	2,5

Table 60: DMM between sustainability technologies and parameters median results of storage systems

			MATERIAL HANDLING SYSTEMS										
			DESIGN PARAMETERS					PERFORMANCE PARAMETERS					
			Load capacity	Battery autonomy	Speed	Cycle time	Level of automation	Level of energy consumption	System lifetime (life cycle, useful life, service life)	Utilization rate	Scalability (Flexibility)	Investment costs	Operating costs
Sustainability	Approaches	Circular processes	3	3	3	3	3	3	3	3	3	3	3
		Reduction of climate change	3	3	3	3	3	2,5	4	3	3	3	3
		Renewable sources	3	3	3	3	3	3	3	3	3	3	3
		Remanufacturing	3	3	3	3	3	3	4	3	3	3	3
		6Rs policy	3	3	3	3	3	2,5	4	3	3	3	3
		Predictive maintenance	3	3,5	3	3	3	3	4	4	3	3	3
		Bioeconomy	3	3	3	3	3	3	3	3	3	3	3

Table 61: DMM between sustainability approaches and parameters median results of material handling systems

			MATERIAL HANDLING SYSTEMS										
			DESIGN PARAMETERS					PERFORMANCE PARAMETERS					
			Load capacity	Battery autonomy	Speed	Cycle time	Level of automation	Level of energy consumption	System lifetime (life cycle, useful life, service life)	Utilization rate	Scalability (Flexibility)	Investment costs	Operating costs
Sustainability	Technologies	Machine Learning	3	4	4	3	4	2,5	4	4	4	3	2
		Intelligent Energy Management Systems (IEMS)	3	4	4	3	4	2	4	4	4	3	2
		Big Data	3	3	4	3	3,5	3	3	3,5	4	3	3
		Artificial Intelligence (AI)	3	4	4	3	4	2	4	4	4	4	2
		Computational Intelligence (CI)	3	3	4	3	4	3	3	3	3	3	3
		Internet of Things (IoT)	3	3	4	3	3	3	3	3	4	3,5	3
		Internet of Personalized Products (IoP^2)	3	4	3	3	4	3	3	3	3,5	4	3

Table 62: DMM between sustainability technologies and parameters median results of material handling systems

			PICKING SYSTEMS					
			DESIGN PARAMETERS	PERFORMANCE PARAMETERS				
			Level of automation	Picking productivity (N. picking lines/h)	Picking operation time	Picking accuracy	Investment costs	Operating costs
Resilience	Approaches	Organizational resilience	4	4	3	3	4	3
		Cognitive resilience	3,5	4	2	4	4	3
		Psycological resilience	3	4	3	4	3,5	3
		Operator safety strategies	4	4	3	4	3,5	3
		Biological resilience	3	4	3	3	3	3
		Human-machine systems resilience	4	4	3	4	3,5	3
		Renewable sources	3	3	3	3	3	3
		Physical resilience	3	4	2	3	3	3

Table 63: DMM between resilience approaches and parameters median results of picking systems

			PICKING SYSTEMS					
			DESIGN PARAMETERS	PERFORMANCE PARAMETERS				
			Level of automation	Picking productivity (N. picking lines/h)	Picking operation time	Picking accuracy	Investment costs	Operating costs
Resilience	Technologies	Big Data	4	4	3	3	3	3
		Machine Learning	4	4	2	4	3	2
		Artificial Intelligence	4	4	2	4	3	2
		Internet of Things (IoT)	4	3	3	4	3	3
		Cyber-physical systems	4	4	3	4	3,5	3
		NextG wireless networks (NGWNs)	4	4	3	3	3	3
		Cloud computing	4	3	3	4	3	2
		Internet of Everything (IoE)	4	4	2	3,5	3	3

Table 64: DMM between resilience technologies and parameters median results of picking systems

			STORAGE SYSTEMS												
			DESIGN PARAMETERS							PERFORMANCE PARAMETERS					
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Speed	Storage density	Selectivity (direct access to items)	Storage capacity	Level of automation	Productivity (N. order lines/ h)	Scalability (Flexibility)	System lifetime (life cycle, useful life, service life)	Utilisation rate	Investement costs	Operating costs
Resilience	Approaches	Organizational resilience	3	3	3	3	3	3	3	3	4	3	3	3	3
		Cognitive resilience	3	3	3	3	3	3	3	3	4	3	4	3	3
		Psycological resilience	3	3	3	3	3	3	3	3	3,5	3	3	3	3
		Operator safety strategies	3	3	3	3	3	3	3	3	3	3	3	3	3
		Biological resilience	3	3	3	3	3	3	3	3	3	3	3	3	3
		Human-machine systems resilience	3	3	3	3	3	3	3,5	4	3	3	3	3	3
		Renewable sources	3	3	3	3	3	3	3	3	3	3	3	3	3
		Physical resilience	3	3	3	3	3	3	3	3	3	3	3	3	3

Table 65: DMM between resilience approaches and parameters median results of storage systems

			STORAGE SYSTEMS												
			DESIGN PARAMETERS							PERFORMANCE PARAMETERS					
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Speed	Storage density	Selectivity (direct access to items)	Storage capacity	Level of automation	Productivity (N. order lines/ h)	Scalability (Flexibility)	System lifetime (life cycle, useful life, service life)	Utilisation rate	Investement costs	Operating costs
Resilience	Technologies	Big Data	3	3	3,5	3	3	3	4	3,5	4	3	4	3	2,5
		Machine Learning	4	3	4	4	4	4	4	4	4	4	4	3	2
		Artificial Intelligence	4	3	4	4	4	3	4	4	4	4	4	3	2
		Internet of Things (IoT)	3	3	3	3	3	3	4	3	4	3	4	3,5	2,5
		Cyber-physical	3	3	3	3	4	3	4	4	4	3	4	3,5	3
		NextG wireless networks (NGWNs)	3	3	4	3	3	3	4	4	4	3	4	3,5	2,5
		Cloud computing	3	3	3	3	3	3	4	3	4	3	3	3	2
		Internet of Everything (IoE)	3	3	3	3	3	3	4	3	4	3	3	4	2,5

Table 66: DMM between resilience technologies and parameters median results of storage systems

			MATERIAL HANDLING SYSTEMS										
			DESIGN PARAMETERS					PERFORMANCE PARAMETERS					
			Load capacity	Battery autonomy	Speed	Cycle time	Level of automation	Level of energy consumption	System lifetime (life cycle, useful life, service life)	Utilization rate	Scalability (Flexibility)	Investment costs	Operating costs
Resilience	Approaches	Organizational resilience	3	3	3	3	3	3	3	3	4	4	3
		Cognitive resilience	3	3	3	3	3	3	3	4	3	3	3
		Psycological resilience	3	3	3	3	3	3	3	3	3	3	3
		Operator safety strategies	3	3	3	3	3	3	3	3	3	3	3
		Biological resilience	3	3	3	3	3	3	3	3	3	3	3
		Human-machine systems resilience	3	3	4	3	3,5	3	3	4	3	3	3
		Renewable sources	3	3	3	3	3	3	3	3	3	3,5	3
		Physical resilience	3	3	3	3	3	3	3	4	3,5	3	3

Table 67: DMM between resilience approaches and parameters median results of material handling systems

			MATERIAL HANDLING SYSTEMS										
			DESIGN PARAMETERS					PERFORMANCE PARAMETERS					
			Load capacity	Battery autonomy	Speed	Cycle time	Level of automation	Level of energy consumption	System lifetime (life cycle, useful life, service life)	Utilization rate	Scalability (Flexibility)	Investment costs	Operating costs
Resilience	Technologies	Big Data	3	3	3	2	4	2	3,5	4	4	3	2
		Machine Learning	4	4	4	2	4	2	4	4	4	3	2
		Artificial Intelligence	3	4	4	2	4	2	4	4	4	3	2
		Internet of Things (IoT)	3	3	3,5	3	3	3	3	4	4	3	2,5
		Cyber-physical	3	3	3	3	4	3	3	4	4	3	2
		NextG wireless networks (NGWNs)	3	3	4	3	4	3	3	4	4	3	3
		Cloud computing	3	3	3,5	3	3,5	3	3	4	4	3	2
		Internet of Everything (IoE)	3	3	3	2	3	2	3	3	4	4	2

Table 68: DMM between resilience technologies and parameters median results of material handling systems

Target dimension	Type of intra-logistics system	Parameters improved by both approaches and technologies
Human centricity	Picking Systems	- Picking productivity - Picking accuracy - Level of automation - Picking operation time
	Storage Systems	- Utilisation rate - Level of automation - Productivity - Scalability - Speed
	Material Handling Systems	- Scalability - Speed - Cycle time - Level of automation - Level of energy consumption - Operating costs - Utilisation rate
Sustainability	Picking Systems	- Level of automation - Picking productivity - Picking operation time - Picking accuracy - Operating costs
	Storage Systems	- Utilisation rate - Operating costs - Speed - Storage depth - Scalability - Level of automation
	Material Handling Systems	- Battery life - System lifetime - Utilisation rate - Level of energy consumption - Level of automation - Scalability - Speed - Operating costs
Resilience	Picking Systems	- Picking productivity - Picking accuracy - Level of automation - Picking operation time - Operating costs
	Storage Systems	- Scalability - Level of automation - Productivity - Utilisation rate - Operating costs
	Material Handling Systems	- Level of automation - Speed - Utilisation rate - Scalability - Operating costs

Table 69: Improved parameters of both approaches and technologies for each storage system considering all pillars of Industry 5.0

3.7 PRATICAL SUGGESTIONS FOR DEVELOPERS AND USERS

Some practical suggestions for storage system developers, based on the analysis, could relate to human-centric technologies. In particular, it is recommended to focus on Artificial Intelligence (AI), which not only enables the development of more sophisticated warehouse systems, but also improves fundamental parameters such as the level of automation and speed. Indeed, AI makes it possible to automate complex decisions such as resource allocation and material flow management, reducing human intervention and speeding up the entire process.

Next, the most relevant technologies for warehouse systems that emerged from the study are augmented reality (AR) and sensors. AR can provide operators with real-time information about warehouse operations, improving efficiency and reducing errors. Sensors, on the other hand, allow continuous monitoring of conditions and movements within the warehouse, gathering critical data to optimise space management and material flow.

A suggestion for users the human-centric approach to adopt picking systems is essential to ensure a more efficient and intuitive user experience. By integrating collaborative robots with human operators, operations can be streamlined by increasing accuracy and decrease operation time. Cobots assist operators with the most tiring and repetitive tasks, allowing them to focus on more complex and value-added tasks. This will not only increase efficiency, but also reduces the margin for errors and improves the overall working conditions. Another important aspect for the users, is the traceability of products during picking. Real-time tracking of picked items ensures more accurate inventory management, minimises errors and provides a clear and transparent view of the workflow. Thanks to these innovations, users can work in a more organised, safe and efficient environment, with greater control over operations.

A proposal for the developers, concerning sustainable technologies, could be the use of the Internet of Personalized Products (IoP^2), which is based on the exchange of information via the Internet and connected systems, and that can bring numerous benefits. By linking the three intra-logistics systems, design and

performance parameters are optimised, and therefore improving the overall efficiency of the system.
A proposal for users of intra-logistic systems concerning sustainability, is the use of predictive maintenance and the 6R policy since they directly contribute to operational efficiency by reducing wastes, consumptions and mitigate the impact on the environment of the three intra-logistic system.

It is critical for storage system designers to invest in technologies based on Machine Learning and Artificial Intelligence, the pillars of resilience. These solutions improve operational efficiency, increase accuracy and enhance process automation, making storage systems more adaptable and efficient.
Finally, a resilience-related suggestion for users is the adoption of the human-machine systems resilience approach. This approach aims to develop a production system that can quickly react to failures, variations and unforeseen events, resulting in reducing downtime and optimising the use of resources. By implementing this model, developers could create more robust and responsive internal intralogistics systems.

4 CONCLUSIONS

This final chapter illustrates the innovative contribution and limitations of this work, and it also outlines future research developments.

4.1 INNOVATIVE CONTRIBUTION

The innovative contribution of this work lies in the fact that, in the current literature can be found researches mainly focused on a single (Yu and Sun, 2024) or multiple (Passalacqua et al., 2024) target dimension of Industry 5.0 without including intra-logistics systems. Some research associates one, or at most two, target dimensions with one (Chivilò and Meneghetti, 2023) or two intra-logistics systems (Ashta et al, 2023 a) but there are no articles in literature that simultaneously address all Industry 5.0 target dimensions and the three considered intra-logistics systems. Therefore, the integration of these elements in this paper represents a significant contribution to the current state of the art.

In addition to that, it provides insights of what characteristics internal logistics systems should have in order to effectively implement the target dimensions of Industry 5.0. It can also help to define guidelines for the implementation of approaches and technologies in the design and implementation of future internal logistics systems, by integrating features in line with the target dimensions and key concepts of this industrial evolution.

4.2 LIMITS

This thesis has some limitations that it is important to highlight.

The first limitation concerns the number of intra-logistics systems that were analysed. We only considered automated systems, excluding manual systems, which are still widely used in several sectors. This limitation makes it difficult to apply the results to all manufacturing companies, as many still rely on manual solutions.

Another limitation is related to the Delphi method that was used to conduct the questionnaire. The sample consisted of only eight participants (Kumar and Anbanandam, 2019), which is a small number. The small number of participants increased the risk that the opinions of a few individuals would significantly influence the results. If the sample had been larger and included more users and producers of intra-logistics systems, the results would have been more balanced. In addition, the variety of roles played by the participants could have contributed to a more comprehensive view, as each role may bring a different perspective to the topic.

Another critical aspect is the composition of the sample. Although the participants belonged to different categories, there was a numerical imbalance between them. This imbalance could have influenced the final consensus and reduced impartiality and fairness in the processing of the results. A more balanced representation of the different categories would have ensured greater fairness in the processing of opinions.

The results of the two rounds of the Delphi study confirm what emerged from the literature review at the beginning of the thesis. The three target dimensions are indeed understood differently. Human-centricity, being a more tangible concept, is easier to apply to order picking processes rather than material handling and storage processes.

The last limitation concerns the information available at the time of writing this thesis. This work focuses exclusively on the current knowledge related to Industry 5.0 and internal intra-logistics systems. However, Industry 5.0 is still developing and evolving, and as technologies and practices advance, new information that has not been considered in this research, might emerge. Therefore, as the understanding of the topic and future developments increase, the results of this thesis may be incomplete or partial in the short term, as the evolution of the industry may lead to significant changes in the models and practices analysed.

4.3 NEXT STEPS

The next steps should focus on the fourth and final stage of the DRM: the evaluation of the usability, applicability and effectiveness of the developed framework. This evaluation will be based on the results obtained in this thesis.

The most efficient way to evaluate the impact of the developed framework is its implementation in reality. This means that it needs to test the framework on an appropriate number of developers and users companies. In particular, the developers of intra-logistics system should apply the developed framework to identify, evaluate and adopt the technologies that may make their systems more consistent with Industry 5.0 principles. In addition, by applying the proposed framework, they could and should understand which design and performance parameters will benefit the most from the implementation of those technologies. On the side, the company-users of the intra-logistics system should apply the framework to understand which managerial approaches could complement their picking, storage, or material handling systems in order to be coherent with Industry 5.0 target dimensions and principles. Plus, the application of the framework might suggest them what technologies they should invest in and integrate in their intra-logistics systems. The guide-line will drive both developers and users in the accomplishment of these tasks. The outcome of the test campaign so performed, will help evaluate the usability and the effectiveness of the proposed framework as well as its capability to be adapted to different business environments

Finally, although Industry 5.0 is still an evolving field and future research could explore aspects that are not yet fully understood or addressed, this work represents anyway a comprehensive and useful base when applied to real-world contexts.

REFERENCES

Abdullah, M., & Rahman, M. (2024). Human Factors Issues in Augmented Reality-Assisted Manual Order Picking: A Systematic Literature Review. In *IISE Annual Conference. Proceedings* (pp. 1-6). Institute of Industrial and Systems Engineers (IISE).

Ashta, G., Finco, S., Battini, D., & Persona, A. (2023 a). Investigating the efficiency of a passive back-support exoskeleton in manual picking tasks. In *Proocedings Summer School Francesco Turco*.

Ashta, G., Finco, S., Battini, D., & Persona, A. (2023 b). Passive exoskeletons to enhance workforce sustainability: Literature review and future research agenda. *Sustainability*, *15*(9), 7339.

Blessing, L. T., & Chakrabarti, A. (2009). *DRM: A design reseach methodology* (pp. 13-42). Springer London.

Bottazzi, R. (2024). *Impact of Industry 5.0 target dimensions on the performance of intra-logistic systems: A proposed assessment framework* (Master's thesis). Master program in Management Engineering, Politecnico di Torino. Retrieved from https://webthesis.biblio.polito.it/32825/1/tesi.pdf

Calderon M.L. (2010). The Design Research Methodology as a framework for the development of a tool for engineering design education", *DS 62: Proceedings of E and PDE 2010, the 12th International Conference on Engineering and Product Design Education - When Design Education and Design Research Meet*, Trondheim, Norway, 02.-03.09. 2010.

Chen, Y., & Li, Y. (2024). Storage Location Assignment for Improving Human–Robot Collaborative Order-Picking Efficiency in Robotic Mobile Fulfillment Systems. *Sustainability*, *16*(5), 1742.

Cheng, D., Hu, B., Feng, Y., Song, X., Zhang, Z., Song, J., ... & Tan, J. (2024). Industrial exoskeletons for secure human–robot interaction: a review. *International Journal of Intelligent Robotics and Applications*, 1-28.

Chivilò, M., & Meneghetti, A. (2023). An industry 5.0 perspective on feeding production lines. *Sustainability*, *15*(22), 16088.

Dacre, N., Yan, J., Frei, R., Al-Mhdawi, M. K. S., & Dong, H. (2024). Advancing sustainable manufacturing: a systematic exploration of industry 5.0 supply chains for sustainability, human-centricity, and resilience. *Production Planning & Control*, 1-30.

Danilovic, M., & Browning, T. R. (2007). Managing complex product development projects with design structure matrices and domain mapping matrices. *International journal of project management*, *25*(3), 300-314.

De Lombaert, T., Braekers, K., De Koster, R., & Ramaekers, K. (2023). In pursuit of humanised order picking planning: methodological review, literature classification and input from practice. *International Journal of Production Research*, *61*(10), 3300-3330.

Diamond, I. R., Grant, R. C., Feldman, B. M., Pencharz, P. B., Ling, S. C., Moore, A. M., & Wales, P. W. (2014). Defining consensus: a systematic review recommends methodologic criteria for reporting of Delphi studies. *Journal of clinical epidemiology*, *67*(4), 401-409.

Diefenbach, H., Grosse, E. H., & Glock, C. H. (2024). Human-and-cost-centric storage assignment optimization in picker-to-parts warehouses. *European Journal of Operational Research*, *315*(3), 1049-1068.

Dillinger, F., Bernhard, O., Kagerer, M., & Reinhart, G. (2022). Industry 4.0 implementation sequence for manufacturing companies. *Production Engineering*, *16*(5), 705-718.

Doyle-Kent, M., & Kopacek, P. (2022). Collaborative robotics making a difference in the global pandemic. In *Digitizing Production Systems: Selected Papers from ISPR2021, October 07-09, 2021 Online, Turkey* (pp. 161-169). Springer International Publishing.

Flores-García, E., Hoon Kwak, D., Jeong, Y., & Wiktorsson, M. (2025). Machine learning in smart production logistics: a review of technological capabilities. *International Journal of Production Research*, *63*(5), 1898-1932.

Füchtenhans, M., Grosse, E. H., & Glock, C. H. (2021). Smart lighting systems: state-of-the-art and potential applications in warehouse order picking. *International Journal of Production Research*, *59*(12), 3817-3839.

Göb, R., McCollin, C., & Ramalhoto, M. F. (2007). Ordinal methodology in the analysis of Likert scales. *Quality & Quantity*, *41*, 601-626.

Grime, M. M., & Wright, G. (2016). Delphi Method. Wiley StatsRef: Statistics Reference Online,© 2014–2016.

Grosse, E. H. (2024). Application of supportive and substitutive technologies in manual warehouse order picking: a content analysis. *International Journal of Production Research*, *62*(3), 685-704.

Haidar, A., Guimón, J., & Alon, I. (2024). Can graphene fuel a transformative change in energy storage technologies? A scenario analysis for the next two decades. *Technological Forecasting and Social Change*, *202*, 123278.

Keeney, S., McKenna, H. A., & Hasson, F. (2011). *The Delphi technique in nursing and health research*. John Wiley & Sons.

Koreis, J. (2025). Human–robot vs. human–manual teams: Understanding the dynamics of experience and performance variability in picker-to-parts order picking. *Computers & Industrial Engineering*, *200*, 110750.

Kučera, T., & Suk, A. (2019). The application of ABC analysis in the logistic warehousing processes.

Kumar, S., & Anbanandam, R. (2019). An integrated Delphi–fuzzy logic approach for measuring supply chain resilience: an illustrative case from manufacturing industry. *Measuring Business Excellence*, *23*(3), 350-375.

Kusmaryono, I., Wijayanti, D., & Maharani, H. R. (2022). Number of Response Options, Reliability, Validity, and Potential Bias in the Use of the Likert Scale Education and Social Science Research: A Literature Review. *International Journal of Educational Methodology*, *8*(4), 625-637.

Jaghbeer, Y., Hanson, R., & Johansson, M. I. (2020). Automated order picking systems and the links between design and performance: a systematic literature review. *International Journal of Production Research*, *58*(15), 4489-4505.

Jefroy, N., Azarian, M., & Yu, H. (2022). Moving from Industry 4.0 to Industry 5.0: what are the implications for smart logistics?. *Logistics*, *6*(2), 26.

Li, K. W., Khaday, S., & Peng, L. (2023). Assessments of Order-Picking Tasks Using a Paper List and Augmented Reality Glasses with Different Order Information Displays. *Applied Sciences*, *13*(22), 12222.

Löffler, M., Boysen, N., & Schneider, M. (2022). Picker routing in AGV-assisted order picking systems. *INFORMS Journal on Computing*, *34*(1), 440-462.

Loske, D. (2022). Empirical evidence on human learning and work characteristics in the transition to automated order picking. *Journal of Business Logistics*, *43*(3), 302-342.

Loske, D., Grosse, E. H., Glock, C. H., & Klumpp, M. (2024). Towards human-centric warehousing: the impact of rack configuration and cognitive demands on order picking performance. *International Journal of Production Research*, 1-17.

Nair, S., Viri, R., Mäkinen, J., Pöllänen, M., Liimatainen, H., & O'Hern, S. (2024). Effect of Policies to Accelerate the Adoption of Battery Electric Vehicles in Finland—A Delphi Study. *Future Transportation*, *4*(1), 67-91.

O'Neill, T. A. (2017). An overview of interrater agreement on Likert scales for researchers and practitioners. *Frontiers in psychology*, *8*, 777.

Passalacqua, M., Pellerin, R., Magnani, F., Doyon-Poulin, P., Del-Aguila, L., Boasen, J., & Léger, P. M. (2024). Human-centred AI in industry 5.0: a systematic review. *International Journal of Production Research*, 1-32.

Pereira, A. C., Alves, A. C., & Arezes, P. (2023). Augmented reality in a lean workplace at smart factories: a case study. *Applied sciences*, *13*(16), 9120.

Pinto, A. R. F., Nagano, M. S., & Boz, E. (2023). A classification approach to order picking systems and policies: Integrating automation and optimization for future research. *Results in Control and Optimization*, *12*, 100281.

Sedrakyan, A., Marinac-Dabic, D., Campbell, B., Aryal, S., Baird, C. E., Goodney, P., ... & Pappas, G. (2022). Advancing the real-world evidence for medical devices through coordinated registry networks. *BMJ surgery, interventions, & health technologies*, *4*(Suppl 1), e000123.

Setayesh, A., Grosse, E. H., Glock, C. H., & Neumann, W. P. (2022). Determining the source of human-system errors in manual order picking with respect to human factors. *International journal of production research*, *60*(20), 6350-6372.

Silva, A., Coelho, L. C., Darvish, M., & Renaud, J. (2024). Manual and robotic storage and picking systems: a literature review. *INFOR: Information Systems and Operational Research*, *62*(3), 313-343.

Trstenjak, M., Mustapić, M., Gregurić, P., & Opetuk, T. (2023). Use of green industry 5.0 technologies in logistics activities. *Tehnički glasnik*, *17*(3), 471-477.

van de Wijdeven, B., Visser, B., & Kuijer, P. P. F. (2024). Evaluating the categorisation of interventions in individual working practice aimed at preventing work-related musculoskeletal disorders: An international experts consultation. *Applied Ergonomics*, *120*, 104338.

Vijayakumar, V., & Sobhani, A. (2023). Performance optimisation of pick and transport robot in a picker to parts order picking system: a human-centric approach. *International Journal of Production Research*, *61*(22), 7791-7808.

Von Der Gracht, H. A. (2012). Consensus measurement in Delphi studies: review and implications for future quality assurance. *Technological forecasting and social change*, *79*(8), 1525-1536.

Wan, X., Wang, W., Liu, J., & Tong, T. (2014). Estimating the sample mean and standard deviation from the sample size, median, range and/or interquartile range. *BMC medical research methodology*, *14*, 1-13.

Winkelhaus, S., Zhang, M., Grosse, E. H., & Glock, C. H. (2022). Hybrid order picking: A simulation model of a joint manual and autonomous order picking system. *Computers & Industrial Engineering*, *167*, 107981.

Wohlin, C. (2014, May). Guidelines for snowballing in systematic literature studies and a replication in software engineering. In *Proceedings of the 18th international conference on evaluation and assessment in software engineering* (pp. 1-10).

Xu, J., Cheung, C., Manu, P., Ejohwomu, O., & Too, J. (2023). Implementing safety leading indicators in construction: Toward a proactive approach to safety management. *Safety science*, *157*, 105929.

Yu, H., & Sun, X. (2024). Uncertain remanufacturing reverse logistics network design in industry 5.0: Opportunities and challenges of digitalization. *Engineering Applications of Artificial Intelligence*, *133*, 108578.

Zenezini, G., Mangano, G., & De Marco, A. (2022). Experts' opinions about lasting innovative technologies in City Logistics. *Research in Transportation Business & Management*, *45*, 100865.

LIST OF VISITED WEBSITES

[1] https://toppy.it/it/picking/picking-di-magazzino/

[2] https://warehouseoptimizers.com/pallet-racking/amr-warehouse-robots-the-labor-shortage-solution/

[3] https://www.therobotreport.com/the-future-is-agv/

[4] https://www.mecalux.it/blog/aziende-magazzini-automatici

[5] https://www.linkedin.com/pulse/industria-40-vs-50-fabrizio-da-ronch-yfqaf/

[6] https://www.logisticamente.it/articoli/13056/sorter-logistici-cosa-sono-e-come-funzionano/

ACKNOWLEDGMENTS

I would like to express my sincere gratitude to Professor Anna Corinna Cagliano for giving me the opportunity to develop this thesis under her guidance over the past few months. Her support, advice and availability have been crucial to the success of this project and I am deeply grateful to her for always ensuring that everything went smoothly. My sincere thanks also go to Olivia Bernhard for her valuable suggestions during our meetings, which made a significant contribution to this work.

Special thanks to my parents, whose unconditional support has enabled me to face every challenge of the past years with determination and serenity. Without them, none of this would have been possible.

My heartfelt thanks also go to my younger brother, whose lightness and affection made even the most difficult moments more bearable, always reminding me of the importance of smiling and never losing sight of what really matters.

Finally, I would like to dedicate a thought to myself. For the perseverance, determination and passion that have accompanied me on this journey. For the sleepless nights, the moments of doubt overcome and the goals achieved. For always believing in my abilities and for never stopping working hard. This achievement is also the result of my willpower and I am proud of it.

APPENDIX 1A

					Target dimension of I5.0			Performance of Logistic System		
Article number	Title	Authors	Keyword	Aim of the paper	Human centricity	Sustainability	Resilience	Picking system	Storage system	Material Handling system
1	Passive Exoskeletons to Enhance Workforce Sustainability: Literature Review and Future Research Agenda	Ashta, G., Finco, S., Battini, D., Persona, A.	exoskeletons; human factor; manufacturing; logistics systems; social sustainability;	The article discusses the potential of passive exoskeletons to improve performance in manufacturing and logistics settings	x	x		x		x
2	In pursuit of humanised order picking planning: methodological review, literature classification and input from practice	De Lombaert, T., Braekers, K., De Koster, R., Ramaekers, K.	human factors; Industry 4.0 and 5.0; literature review; Logistics; multimethod approach; warehouse operations management	The primary aim of the article is to enhance the understanding and integration of human factors in order picking planning within warehouse operations	x			x		
3	Application of supportive and substitutive technologies in manual warehouse order picking: a content analysis	Grosse, E.H.	assistive devices; human-centricity; human–technology interaction; Order picking; technologies; warehousing	The primary aim is to explore the integration and impact of various technologies on manual order picking processes in warehouses considering also human factors, literature content analysis, future research opportunities	x			x		
4	Human-Centric Assistive Technologies in Manual Picking and Assembly Tasks: A Literature Review	Lucchese, A., Mummolo, G.	Order Picking Tasks, Assembly Tasks, Industry 5.0, Human-centric, Assistive Technologies, Literature Review	The article aims to provide insights into the role of assistive technologies in manual tasks, focusing on their human-centric design, impact on operator well-being, and the identification of potential drawbacks	x			x		
5	Augmented Reality in a Lean Workplace at Smart Factories: A Case Study	Pereira, A.C., Alves, A.C., Arezes, P.	augmented reality; ergonomics; human augmentation; human factors; human-centric systems; Industry 4.0; Industry 5.0; lean thinking; musculoskeletal disorders; occupational safety and health	The main aim was to reduce human effort during task performance. Furthermore, the potential for creating waste-free and more efficient workspaces was explored, as well as the possibility of Human Augmentation to enhance workers' capabilities and senses.	x			x		x
6	Collaborative Robotics Making a Difference in the Global Pandemic (abstract)	Doyle-Kent, M., Kopacek, P.	Collaborative Robotics; Covid-19; Global pandemic; Human centred systems; Industry 4.0; Industry 5.0	This paper look at these flexible robots and discuss the benefits they brought to manufacturing in a time of global crisis.	x				x	
7	An Industry 5.0 Perspective on Feeding Production Lines	Chivilò, M., Meneghetti, A.	AMR; assembly lines; human centricity; Industry 5.0; resilience; sustainability	the study aims to provide a comprehensive approach for companies to adopt Industry 5.0 principles in their production lines, focusing on human-centricity, sustainability, and resilience through a structured framework and practical checklists.	x	x	x			x

APPENDIX 1B

Article number	Title	Authors	Keyword	Aim of the paper	Target dimension of I5.0			Performance of Logistic System		
					Human centricity	Sustainability	Resilience	Picking system	Storage system	Material Handling system
8	Automated order picking systems and the links between design andperformance: a systematic literature review	Jaghbeer, Y., Hanson, R., Johansson, M.I.	automation; logistics; materials handling; Order picking; warehouse operations	The aims to bridge the gap between design and performance in automated order picking systems, offering valuable insights for both researchers and industry practitioners.	X			X		X
9	Picker Routing in AGV-Assisted Order Picking Systems	Löffler, M., Boysen, N., Schneider, M.	AGV; automated guided vehicles; order picking; routing; Warehousing	The aim is to enhance the efficiency of order-picking systems through the strategic use of AGVs, thereby reducing unproductive walking and improving overall productivity in warehousing operations.	X			X		
10	Hybrid order picking: A simulation model of a joint manual and autonomous order picking system	Winkelhaus, S., Zhang, M., Grosse, E.H., Glock, C.H.	Agent-based simulation; Autonomous picking robot; Collaborative order picking; Picker blocking; Warehousing	This study presents a simulation model that considers various system characteristics and parameters of hybrid order picking systems	X			X		
11	Smart lighting systems: state-of-the-art and potential applications in warehouse order picking	Füchtenhans, M., Grosse, E.H., Glock, C.H.	Intelligent lighting; light; order picking; systematic literature review; warehousing	the paper aims to provide a comprehensive overview of smart lighting systems, focusing on their current state, potential applications in warehouse order picking, and their overall impact on work environments	X			X		
12	Empirical Evidence on Human Learning and Work Characteristics in the Transition to Automated Order Picking	Loske, D.	data envelopment analysis; efficiency; human factors; learning progress; order picking	the study aims to bridge the gap in empirical research regarding the interplay between human learning and work characteristics in the context of automated order picking, with a focus on improving outcomes for both workers and organizations.	X			X		
13	Determining the source of human-system errors in manual order picking with respect to human factors	Setayesh, A., Grosse, E.H., Glock, C.H., Neumann, W.P.	ergonomics; Human system error; order picking systems; pick errors; qualitative interviews; quality	the study aims to systematically identify human factors that contribute to errors in manual order picking, with the ultimate goal of improving operational quality and efficiency in this critical area of logistics.	X			X		

APPENDIX 1C

					Target dimension of I5.0			Performance of Logistic System		
Article number	Title	Authors	Keyword	Aim of the paper	Human centricity	Sustainability	Resilience	Picking system	Storage system	Material Handling system
14	Investigating the efficiency of a passive back-support exoskeleton in manual picking tasks	Ashta G.; Finco S.; Battini D.; Persona A.	Exoskeletons; Industry 5.0; Picking; Rest Allowance	this paper, it proposes a methodological approach for evaluating the time effectiveness of exoskeleton deployment for picking tasks based on its effects on picking times and rest allowance (RA)	x			x		x
15	Industrial exoskeletons for secure human–robot interaction: a review	Cheng, Dinghao; Hu, Bingtao; Feng, Yixiong; Song, Xiuju; Zhang, Zhifeng; Song, Junjie; Wang, Fei; Tan, Jianrong	Human-centric; Human–robot interaction; Industrial exoskeleton; Industry 5.0; Research progress	the key factors and challenges affecting industrial exoskeletons are analyzed, and the research progress is summarized. It also analyzes the industrial exoskeleton technology in five aspects: mechanism design, control system design, interactive information perception, variable stiffness drive and interactive interface design.	x					x
16	Performance optimisation of pick and transport robot in a picker to parts order picking system: a human-centric approach	Vijayakumar, V., Sobhani, A.	human factors; optimisation; Order picking; pick and transport robot; warehouse zoning	This research develops a mathematical model to optimise the performance of a picker to parts OP (order picking) system using PTRs (pick and transport robots)in terms of productivity, quality, and the well-being of the order pickers.	x		x	x		
17	Assessments of Order-Picking Tasks Using a Paper List and Augmented Reality Glasses with Different Order Information Displays	Li, K.W., Khaday, S., Peng, L.	augmented reality; comfort/discomfort; order information display; warehousing management	the study aimed to enhance the understanding of how AR technology can be optimized for order-picking tasks by focusing on both performance outcomes and user comfort, ultimately contributing to the design of more effective and user-friendly AR systems.	x			x		
18	Human–robot vs. human–manual teams: Understanding the dynamics of experience and performance variability in picker-to-parts order picking	Koreis, J.	Automation technologies; Human factors; Human–robot collaboration; Intralogistics operations; Learning; Order picking; Picking performance	This study analyzed a pilot test of a novel industrial cart deployed as an AGV that automatically follows order pickers as they move through a brick-and-mortar grocery retailer's warehouse.	x			x		
19	Human-and-cost-centric storage assignment optimization in picker-to-parts warehouses	Diefenbach, H., Grosse, E.H., Glock, C.H.	Efficiency; Ergonomics; Order picking; Routing; Storage assignment	the aim of the paper is to develop strategies that improve warehouse operations by balancing efficiency with the health and safety of workers, thereby contributing to a more sustainable and effective warehousing environment.	x			x		

					Target dimension of I5.0			Performance of Logistic System		
Article number	Title	Authors	Keyword	Aim of the paper	Human centricity	Sustainability	Resilience	Picking system	Storage system	Material Handling system
20	Storage Location Assignment for Improving Human–Robot Collaborative Order-Picking Efficiency in Robotic Mobile Fulfillment Systems	Chen, Y., Li, Y.	behavioral factors; human–robot collaboration; order picking; parts-to-picker warehousing system; robotic mobile fulfillment (RMF) system; storage location assignment; sustainable technology	the study aims to optimize storage location assignments in robotic mobile fulfillment (RMF) systems to improve the collaborative efficiency of human and robot order picking, while also considering the behavioral aspects of human workers.	X			X		
21	Towards human-centric warehousing: the impact of rack configuration and cognitive demands on order picking performance	Loske, D., Grosse, E.H., Glock, C.H., Klumpp, M.	cognitive human demands; Human factors; order picking performance; order picking system design; writing system direction	The article aims to explore how warehouse design and cognitive demands affect the efficiency of order pickers	X			X		
22	Machine learning in smart production logistics: a review of technological capabilities	Flores-García, E., Hoon Kwak, D., Jeong, Y., Wiktorsson, M.	dynamic environments; machine learning; manufacturing; Smart production logistics; technological capabilities	The aim of the systematic literature review is to explore and describe the technological capabilities of smart production logistics (SPL) when applying machine learning (ML)		X		X		X
23	Manual and robotic storage and picking systems: a literature review	Silva, A., Coelho, L.C., Darvish, M., Renaud, J.	integrated warehousing problems; manual; research directions; robotic; Warehousing	the paper aims to provide a comprehensive overview of the challenges and advancements in warehousing systems, particularly in the context of e-commerce, while also suggesting future research avenues to enhance these systems' efficiency and effectiveness	X			X	X	X
24	Human Factors Issues in Augmented Reality-Assisted Manual Order Picking: A Systematic Literature Review	Abdullah, Md., Rahman, M.	Augmented Reality; Human Factors; Order Picking	The aim is to investigate and analyze the human factors involved in augmented reality (AR)-assisted manual order picking.	X			X		
25	A classification approach to order picking systems and policies: Integrating automation and optimization for future research	Pinto, A.R.F., Nagano, M.S., Boz, E.	-	the aim of the paper is to create a structured approach to classifying picking systems, which will ultimately lead to improved practices in warehouse management and picking efficiency.	X			X	X	
26	Use of Green Industry 5.0 Technologies in Logistics Activities	Trstenjak, M., Mustapić, M., Gregurić, P., Opetuk, T.	ergonomics; green industry; green logistics; Industry 4.0; Industry 5.0; logistics 4.0; sustainability	the paper's aim is to investigate the current state of awareness and implementation of Industry 5.0 technologies in logistics among Croatian manufacturing companies, focusing on their openness to adopting green practices over digital ones.	X	X	X	X		X

APPENDIX 2

			PICKING SYSTEMS					
			Picking productivity (N. picking lines/h)	Cycle time for picking operation (picking time)	Picking accuracy	Level of automation	Investment costs	Operating costs
Human centricity	Approaches	Decentralized decision making						
		Human-robot co-working						
		Tracking-as-a-Service (NTaaS)						

			PICKING SYSTEMS					
			Picking productivity (N. picking lines/h)	Cycle time for picking operation (picking time)	Picking accuracy	Level of automation	Investment costs	Operating costs
Human centricity	Technologies	Artificial Intelligence (AI)						
		Natural language processing for interacting with robots						
		Intelligent smart wearables (ISWs) and exoskeletons						
		Cobots						
		Natural user interfaces (NUIs)						
		Human interaction and recognition technologies (HIRT)						
		Gesture-tracking devices						
		Augmented Reality (AR)						
		Sensors						
		Internet of Everything (IoE)						
		Clothing industrial smart wearables						
		Internet of Things (IoT)						
		Edge computing						

			STORAGE SYSTEMS												
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Productivity (N. order lines/ h)	Speed	Storage density	Selectivity (direct access to items)	Scalability (Flexibility)	Storage capacity	Investement costs	Operating costs	System lifetime (life cycle, useful life, service life)	Utilisation rate	Level of automation
Human centricity	Approaches	Decentralized decision making													
		Human-robot co-working													
		Tracking-as-a-Service (NTaaS)													

			STORAGE SYSTEMS												
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Productivity (N. order lines/ h)	Speed	Storage density	Selectivity (direct access to items)	Scalability (Flexibility)	Storage capacity	Investement costs	Operating costs	System lifetime (life cycle, useful life, service life)	Utilisation rate	Level of automation
Human centricity	Technologies	Artificial Intelligence (AI)													
		Natural language processing for interacting with robots													
		Intelligent smart wearables (ISWs) and exoskeletons													
		Cobots													
		Natural user interfaces (NUIs)													
		Human interaction and recognition technologies (HIRT)													
		Gesture-tracking devices													
		Augmented Reality (AR)													
		Sensors													
		Internet of Everything (IoE)													
		Clothing industrial smart wearables													
		Internet of Things (IoT)													
		Edge computing													

			MATERIAL HANDLING SYSTEMS										
			Load capacity	Level of energy consumption	Battery autonomy	Speed	Cycle time	System lifetime (life cycle, useful life, service life)	Investment costs	Operating costs	Utilization rate	Level of automation	Scalability (Flexibility)
Human centricity	Approaches	Decentralized decision making											
		Human-robot co-working											
		Tracking-as-a-Service (NTaaS)											

			MATERIAL HANDLING SYSTEMS										
			Load capacity	Level of energy consumption	Battery autonomy	Speed	Cycle time	System lifetime (life cycle, useful life, service life)	Investment costs	Operating costs	Utilization rate	Level of automation	Scalability (Flexibility)
Human centricity	Technologies	Artificial Intelligence (AI)											
		Natural language processing for interacting with robots											
		Intelligent smart wearables (ISWs) and exoskeletons											
		Cobots											
		Natural user interfaces (NUIs)											
		Human interaction and recognition technologies (HIRT)											
		Gesture-tracking devices											
		Augmented Reality (AR)											
		Sensors											
		Internet of Everything (IoE)											
		Clothing industrial smart wearables											
		Internet of Things (IoT)											
		Edge computing											

			PICKING SYSTEMS					
			Picking productivity (N. picking lines/h)	Cycle time for picking operation (picking time)	Picking accuracy	Level of automation	Investment costs	Operating costs
Sustainability	Approaches	Circular processes						
		Reduction of climate change						
		Renewable sources						
		Remanufacturing						
		6Rs policy						
		Predictive maintenance						
		Bioeconomy						

			PICKING SYSTEMS					
			Picking productivity (N. picking lines/h)	Cycle time for picking operation (picking time)	Picking accuracy	Level of automation	Investment costs	Operating costs
Sustainability	Technologies	Machine Learning						
		Intelligent Energy Management Systems (IEMS)						
		Big Data						
		Artificial Intelligence (AI)						
		Computational Intelligence (CI)						
		Internet of Things (IoT)						
		Internet of Personalized Products (IoP^2)						

			STORAGE SYSTEMS												
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Productivity (N. order lines/ h)	Speed	Storage density	Selectivity (direct access to items)	Scalability (Flexibility)	Storage capacity	Investment costs	Operating costs	System lifetime (life cycle, useful life, service life)	Utilisation rate	Level of automation
Sustainability	Approaches	Circular processes													
		Reduction of climate change													
		Renewable sources													
		Remanufacturing													
		6Rs policy													
		Predictive maintenance													
		Bioeconomy													

			STORAGE SYSTEMS												
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Productivity (N. order lines/ h)	Speed	Storage density	Selectivity (direct access to items)	Scalability (Flexibility)	Storage capacity	Investment costs	Operating costs	System lifetime (life cycle, useful life, service life)	Utilisation rate	Level of automation
Sustainability	Technologies	Machine Learning													
		Intelligent Energy Management Systems (IEMS)													
		Big Data													
		Artificial Intelligence (AI)													
		Computational Intelligence (CI)													
		Internet of Things (IoT)													
		Internet of Personalized Products (IoP^2)													

			MATERIAL HANDLING SYSTEMS										
			Load capacity	Level of energy consumption	Battery autonomy	Speed	Cycle time	System lifetime (life cycle, useful life, service life)	Investment costs	Operating costs	Utilization rate	Level of automation	Scalability (Flexibility)
Sustainability	Approaches	Circular processes											
		Reduction of climate change											
		Renewable sources											
		Remanufacturing											
		6Rs policy											
		Predictive maintenance											
		Bioeconomy											

			MATERIAL HANDLING SYSTEMS										
			Load capacity	Level of energy consumption	Battery autonomy	Speed	Cycle time	System lifetime (life cycle, useful life, service life)	Investment costs	Operating costs	Utilization rate	Level of automation	Scalability (Flexibility)
Sustainability	Technologies	Machine Learning											
		Intelligent Energy Management Systems (IEMS)											
		Big Data											
		Artificial Intelligence (AI)											
		Computational Intelligence (CI)											
		Internet of Things (IoT)											
		Internet of Personalized Products (IoP^2)											

			PICKING SYSTEMS					
			Picking lines/h (N. picking productivity)	Cycle time for picking operation (picking time)	Picking accuracy	Level of automation	Investment costs	Operating costs
Resilience	Approaches	Organizational resilience						
		Cognitive resilience						
		Psycological resilience						
		Operator safety strategies						
		Biological resilience						
		Human-machine systems resilience						
		Renewable sources						
		Physical resilience						

			PICKING SYSTEMS					
			Picking lines/h (N. picking productivity)	Cycle time for picking operation (picking time)	Picking accuracy	Level of automation	Investment costs	Operating costs
Resilience	Technologies	Big Data						
		Machine Learning						
		Artificial Intelligence (AI)						
		Internet of Things (IoT)						
		Cyber-physical systems						
		NextG wireless networks (NGWNs)						
		Cloud computing						
		Internet of Everything (IoE)						

			STORAGE SYSTEMS												
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Productivity (N. order lines/ h)	Speed	Storage density	Selectivity (direct access to items)	Scalability (Flexibility)	Storage capacity	Investement costs	Operating costs	System lifetime (life cycle, useful life, service	Utilisation rate	Level of automation
Resilience	Approaches	Organizational resilience													
		Cognitive resilience													
		Psycological resilience													
		Operator safety strategies													
		Biological resilience													
		Human-machine systems resilience													
		Renewable sources													
		Physical resilience													

			STORAGE SYSTEMS												
			Storage depth (single, double, triple, or multi-deep systems)	Storage height	Productivity (N. order lines/ h)	Speed	Storage density	Selectivity (direct access to items)	Scalability (Flexibility)	Storage capacity	Investement costs	Operating costs	System lifetime (life cycle, useful life, service	Utilisation rate	Level of automation
Resilience	Technologies	Big Data													
		Machine Learning													
		Artificial Intelligence (AI)													
		Internet of Things (IoT)													
		Cyber-physical systems													
		NextG wireless networks (NGWNs)													
		Cloud computing													
		Internet of Everything (IoE)													

			MATERIAL HANDLING SYSTEMS										
			Load capacity	Level of energy consumption	Battery autonomy	Speed	Cycle time	System lifetime (life cycle, useful life, service life)	Investment costs	Operating costs	Utilization rate	Level of automation	Scalability (Flexibility)
Resilience	Approaches	Organizational resilience											
		Cognitive resilience											
		Psycological resilience											
		Operator safety strategies											
		Biological resilience											
		Human-machine systems resilience											
		Renewable sources											
		Physical resilience											

			MATERIAL HANDLING SYSTEMS										
			Load capacity	Level of energy consumption	Battery autonomy	Speed	Cycle time	System lifetime (life cycle, useful life, service life)	Investment costs	Operating costs	Utilization rate	Level of automation	Scalability (Flexibility)
Resilience	Technologies	Big Data											
		Machine Learning											
		Artificial Intelligence											
		Internet of Things (IoT)											
		Cyber-physical											
		NextG wireless networks (NGWNs)											
		Cloud computing											
		Internet of Everything (IoE)											

APPENDIX 3A

	PICKING SYSTEMS	
Target dimension	Approaches	Technologies
Human centricity	**Human-robot co-working** results in an **increase** in **picking productivity, picking accuracy,** and the **level of automation**, as it combines elements of automation with human work, improving the automation of the overall picking process. **Picking time** tends to **decrease:** a partial process automation makes it possible to optimise picking operations, thus **improving** overall **efficiency.** **Decentralised control decreases picking accuracy**. In the absence of a centralised coordination, communication errors and information mismatches can occur, affecting the accuracy of picking operations. **Investment and operational costs** do **not change significantly** with the selected human centric approaches.	**Almost all technologies improve design and operational performance parameters** (e.g. reduce picking time), with the exception of **industrial smart wearables,** which by their nature have **no impact,** especially on: 1. **Level of automation**, as they do not automate the picking process. 2. **Picking productivity**, as they do not directly increase the speed of picking. 3. **Picking operation time**, since, while they help reduce the risk of errors and improve information management, they have no direct impact on the time required to complete a picking operation. Exoskeletons help to improve all operational and economic parameters, optimising operator performance and reducing physical fatigue. In addition to exoskeletons, other technologies bring significant benefits: **Augmented Reality (AR)**: **improves picking accuracy and speed** by providing real-time visual instructions for locating products, reducing errors and **increasing productivity**. **Sensors**: monitor the location and status of products in real time, optimising the workflow and reducing the risk of errors. **Gesture-tracking devices**: allow intuitive interaction with picking systems, improving the **speed** and efficiency of operations without the need for manual commands.
Sustainability	Only the 6Rs policy and predictive maintenance impact design and performance parameters The **6Rs policy** helps to **reduce operating costs** because, by definition, it 1. Reduces waste by optimising the use of resources. 2. Maximises the use of available resources, improving efficiency. 3. Increases safety, reducing operational risk. **Predictive maintenance reduces operating costs** by reducing the likelihood of system faults, preventing unexpected failures and optimising maintenance.	All sustainability technologies aim to combine technological innovation with social and environmental responsibility, creating more efficient, safer and environmentally friendly processes. These technologies help to **increase the level of automation** in picking systems because automation optimises the use of resources, reduces waste and improves energy efficiency, and, and most of them **improve productivity** and **reduce picking times**, optimising operations in a sustainable way. **Machine Learning (ML**) is the technology that **optimises the most parameters in picking systems**, as it analyses data and predicts inefficiencies, improving accuracy and reducing waste. This is **followed by Artificial Intelligence (AI)**, which is more comprehensive than ML, and **Computational Intelligence (CI)**, which has less impact on operational optimisation. In general, the integration of these technologies into order picking systems leads to greater business efficiency, reducing waste and improving overall performance. According to the experts, the integration of into picking systems leads to an **increase in investment costs**, but this is compensated by the fact that **in the medium to long term, operating costs do not increase** compared to the situation where Industry 5.0 was not integrated into the systems.

	PICKING SYSTEMS	
Target dimension	Approaches	Technologies
Resilience	**Resilience approaches** first **improve picking productivity** and then **increase the level of automation** and **picking accuracy** by allowing the system to effectively adapt to unforeseen events and operate autonomously,-accurately and productively. The only approach that does not affect operational parameters is the use of renewable sources, as it has no direct impact on the design and performance parameters of picking The main impacting approaches are 1. **Operator Safety Strategies**, which improve worker safety and promote greater flexibility and reliability in human-robot interaction. 2. **Human-Machine Systems Resilience**, which represents the ability of human and mechanical systems to adapt the level of autonomy to ensure practicality, comfort and continuity of operations. **Organisational resilience does not directly affect order picking**, as it focuses on the ability of the organisation to adapt to unforeseen events by reorganising resources, processes and strategies. Increasing the resilience of picking systems leads to **higher investment costs**, but **operating costs remain the same** as resilience approaches improve the efficiency of day-by-day activities, does not increasing the related costs.	**All technologies increase the level of automation and most increase picking productivity and accuracy by reducing picking time.** The technology that has the **greatest impact** on performance and design parameters is the **cyber-physical system,** as it effectively integrates the physical and digital worlds to optimise picking operations. For example, if a robot is about to malfunction or deviate from its path, the cyber-physical system can predict the problem and activate predictive maintenance or automatically redefine the robot's path without interrupting operations. This level of integration between the physical and the digital significantly improves system efficiency and reliability, optimising operations in real time. Subsequently, technologies such as **Machine Learning (ML), Artificial Intelligence (AI) and Internet of Everything (IoE)** make it possible to adapt, predict and optimise resources in real time by analysing data. These tools ensure business continuity and **improve all the design and performance parameters** In terms of costs, we can say that - The **only investment cost** that **increases** is the technology for **cyber-physical systems**, as these systems require complex infrastructure and greater integration between physical and digital technology, while other investment costs remain unchanged. - **Operating costs** will **remain the same or decrease** due to efficiency improvements and resource optimisation resulting from the use of advanced technologies.

APPENDIX 3B

	STORAGE SYSTEMS	
Target dimension	Approaches	Technologies
Human centricity	For many parameters, such as **storage density and capacity, human centricity approaches do not have a significant impact.** However, for other aspects, most approaches favour a direct **increase in utilisation, scalability, productivity and level of automation.** **Speed only increases with NTaaS**, as greater product traceability speeds up the system, eliminating delays associated with manual searches and improving the overall efficiency of the process. **Investment costs tend to increase** because the approaches considered for storage systems are generally expensive. An obvious example is the impact of human-robot collaboration: e.g. a vertical storage system with a cobot integrated into the picking station is more expensive than a vertical storage system without a cobot. However, this increase in capital cost is partly offset by **operating costs**, which experts say **do not change significantly** with the integration of human-centric approaches.	**All technologies improve:** 1. **Level of automation**, with the aim of increasing the speed of operations within the storage system. 2. **Productivity**, allowing more products per hour to be taken from the storage system. 3. **Scalability**, to efficiently and effectively manage variations in workload, adapting quickly to operational needs. The **impact of the technologies on the utilisation rate is limited,** as the improvement in this parameter is only from the impact of certain technologies, such as Artificial Intelligence (AI) is mainly influenced by natural language processing, which improves interaction with robots. . Similarly, the design parameters are only marginally affected by these technologies. However, despite the small impact, it is clear that **Artificial Intelligence (AI)** contributes to the **improvement of all design and performance parameters, with the exception of the height of the storage system.** This is because AI, by its very nature, focuses on information acquisition and processing processes and is particularly effective in improving design and performance parameters closely related to information processes.
Sustainability	**All approaches have no impact on the parameters considered**, with the **exception of predictive maintenance.** Predictive maintenance contributes to **increased uptime and reduced operating costs**, because it - Reduces the need for urgent and costly repairs. - Improves equipment longevity, optimising utilisation over time. - Reduces unplanned downtime, ensuring greater operational continuity.	Sustainability technologies **increase the level of automation**, **speed and utilisation** of warehouse systems by optimising the use of resources and improving operational efficiency. For example, intelligent monitoring of environmental conditions reduces waste, minimises errors and optimises material flow. In the storage system, **AI and machine learning** improve sustainability by optimising space, reducing waste and predicting demand. Machine learning analyses data to optimise allocations and movements, while AI automates decisions by using intelligent algorithms to analyse real-time data from operating systems, improving resource management. In addition, the **Internet of Personalised Products (IoP^2) technology** has an impact on several parameters **(storage depth, speed, level of automation and scalability)** because it enables the of products through efficient data exchange that considers customer needs and specific product requirements. **Investment costs increase while operating costs decrease**, with a more pronounced effect compared to order picking systems. This is due to the greater complexity and scope of the technologies implemented, which require a higher initial investment but generate greater operational savings in the long term.
Resilience	The **scalability** of a system is **improved by** a combination of **organisational and psychological resilience** because both contribute to making the system more adaptable to change and challenges without compromising efficiency. **Human-machine system resilience** improves both the **level of automation and productivity**, because it enables more effective integration between operators and advanced technologies, thus allowing warehouse systems to be more automous and processes to be optimised for greater efficiency and reliability. **Cognitive resilience** has a **positive impact on uptime** in particular. Operators' mental clarity in times of high stress enables them to maintain high operational efficiency, significantly reducing errors and downtime. Storage system resilience delivers long-term benefits **without increasing investmnent and operational costs.**	All resilience technologies in storage systems **increase the level of automation and scalability** by enabling systems to quickly adapt to unexpected changes, such as changes in workload or failures. As a result, **utilisation rates** increase as the system is able to better manage available resources, optimising efficiency and reducing downtime. The technology with the **greatest impact** on operational parameters is **machine learning**, as it improves operational efficiency. This is followed by **AI**, which makes the storage system more adaptable and responsive to operational conditions. Cost side: - Only half of the resilience technologies **(Internet of Things (IoT), Cyber-physical systems, NextG wireless networks (NGWNs) and Internet of Everything (IoE))** involve an **increase in investment costs**, as they require the purchase and implementation of advanced solutions. The other half, however, keep costs flat because they rely on optimising existing processes or less expensive technologies that do not require large up-front investments. - **The majority of operational costs are reduced** by optimising workflows, automating processes and proactively managing resources, all of which help to reduce inefficiencies, downtime and waste and improve overall system efficiency.

APPENDIX 3C

	MATERIAL HANDLING SYSTEMS	
Target dimension	**Approaches**	**Technologies**
Human centricity	Human centricity approaches (such as **decentralised decision making and human-robot co-working)** helps to **increase utilisation rates**, optimise the use of resources and **improve overall productivity**. The **human-robot co-working** approach brings several benefits, including 1. **Increased scalability** as it allows operations to easily adapt to changes in demand. 2. Greater speed and **reduced cycle time,** optimising workflow and making the whole process faster and more efficient. 3. Increased **level of automation**, enabling more automated management of operations, reducing human intervention and improving system efficiency and reliability. 4. **Reducing the level of consumption** by using more efficient and optimised robots that minimise the waste of resources (for example the use of intelligent conveyors that can adjust speed according to load and demand contributes to more efficient energy use) compared to manual or less automated solutions. While: - **Tracking-as-a-Service (NTaaS)** increases the level of automation as it allows companies to monitor and manage their assets, in real time, reducing the need for manual intervention in material handling systems. - **Decentralised decision making** improves material handling systems This reduces cycle times and minimises bottlenecks. However, these positive effects are offset by **increased investment costs,** which must be compensated for by **reducing or maintaining operating costs**.	**Human interaction and recognition technologies (HIRT)** support the material handling system by integrating digital elements that simplify the transfer of commands and information. This allows the material handling system to operate more efficiently and perform assigned tasks with greater precision and responsiveness. Another key technology is **AI**, which improves system efficiency, **flexibility** and **utilisation rate** through advanced data processing. Most technologies contribute to **increasing utilisation**, as solutions such as **AI** enable smarter management of workflows, optimising the use of resources. They also **improve scalability**, as AI enables companies to flexibly adapt to changes in demand by dynamically adjusting operations as needed.
Sustainability	**Most approaches do not affect design and performance parameters, with the exception of predictive maintenance,** which makes it possible to predict the future condition of equipment and determine the optimal time to perform maintenance. This approach allows. 1. **Increase battery autonomy** through more efficient energy use. 2. **Extended life of the equipment,** as continuous monitoring optimises the performance and life of the equipment by assessing its condition in real time. 3. **Improve uptime** by increasing the ratio of actual system uptime to available uptime. Some approaches influence the level of **energy consumption** and contribute to its **reduction**. This is done through - **Climate change mitigation,** which encourages a more responsible and reduced overall energy consumption. - The **6Rs policy**, which aims to minimise waste, including energy waste, by promoting more efficient use of resources. **System lifetime is extended through** a number of approaches, including climate change mitigation and remanufacturing. - **Remanufacturing regenerates components** that can be used for replacement, thus extending the life of the system. - **Reduction of Climate Change** limits the wear and degradation of materials.	**Most of the technologies increase:** 1. **Level of automation**, as reducing errors and increasing efficiency improves operational sustainability. 2. **Scalability**, because the integration of sustainable technologies allows companies to flexibly adapt to changes in demand and workflows, dynamically reducing resource consumption. 3. **Speed**, because they (for example **Machine Learning, Big Data e IoT**) improve operational speed while minimising waste of time and resources. The **key sustainable technologies** for material handling systems are **Machine Learning, AI, Intelligent Energy Management Systems (IEMS) and the Internet of Personalised Products (IoP^2)**, as they all aim to optimise operational efficiency while reducing environmental impact. Machine Learning and AI analyse and predict workflows, improving automation, resource management and energy efficiency. IEMS optimise energy use, reducing consumption and emissions. Sustainable technologies for materials handling systems **increase initial investment costs** due to the purchase and implementation of advanced technologies. However, **operating costs remain the same or decrease** as these technologies improve efficiency, optimise resource use and reduce energy consumption, downtime and waste, leading to savings in the long term.

	MATERIAL HANDLING SYSTEMS	
Target dimension	**Approaches**	**Technologies**
Resilience	**Human-machine system resilience** allows system autonomy to be adapted to ensure operational continuity even in unforeseen situations. It therefore has a positive impact on 1. **Speed**, because it allows the operational speed to be kept high 2. **Level of automation**, because it allows the system to dynamically change the level of automation according to the specific situation. 3. **Utilisation rate**, because it promotes optimal utilisation of resources, both human and automated, avoiding waste and ensuring that all resources are used efficiently to maintain high productivity. The performance parameter that **changes the most is the utilisation rate** due to: 1. **Cognitive resilience**, as it affects the mental clarity of the operator 2. **Human-machine system resilience**, as it ensures the operational continuity of the system 3. **Physical resilience**, as it affects the ability to maintain consistent performance under variable working conditions. The parameter that follows the utilisation rate is **scalability**, which is mainly affected by organisational resilience, as it relates to the flexibility of the system, and physical resilience, as operators must be able to adapt and respond effectively depending on demand. All **investment costs for material handling systems remain unchanged**, except for those related to organisational resilience, which involve an initial increase to improve organisational flexibility. However, this increase has no impact on operating costs, as organisational resilience optimises resources and reduces inefficiencies, leaving o**perating costs unchanged** in the long term.	The performance parameter that **changes the most is scalability**, followed by **utilisation**. This is because resilience allows the intra-logistics system to dynamically adapt to fluctuations in demand. As a result, the ability to flexibly scale operations increases, while the utilisation rate adapts according to the resources deployed, i.e. it is dynamically adjusted to maximise operational efficiency by adapting to the needs of the moment. Again, as with the storage system, the **technologies that have the greatest impact on operational parameters are machine learning, followed by AI**, as they enable material handling systems to be more responsive through the use of advanced algorithms. These algorithms optimise processes, allowing the system to adapt quickly to changes and improving the overall resilience of the system. On the cost side: 1. **investment costs**: the situation is similar to that of the picking system, in fact **only the IoE investment increases, while the others remain unchanged.** 2. **operating costs: all of them decrease**