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The impact of supportive technologies on the human factor in warehousing: classification of assessment approaches in experimental studies

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Abstract

The increasing adoption of supportive technologies, such as exoskeletons and collaborative robots, in warehousing operations is reshaping the role of human operators. While these technologies aim to reduce physical strain and enhance efficiency, their impact on the human factor remains unclear, with diverse and fragmented assessment approaches and a lack of standardized evaluation criteria. This paper presents a PRISMA-based systematic literature review of 57 studies on supportive technologies in warehousing. The review provides a comprehensive overview of the experimental approaches used to evaluate physical, cognitive, perceptual, and psychosocial impacts In addition, it offers a structured classification of the technologies adopted, the warehouse activities they support, and the human dimensions they affect. The findings highlight current gaps in the literature and offer practical guidance for selecting appropriate assessment approaches in experimental studies. This work contributes to the development of human-centric approaches in warehousing and supports informed decision-making in both research and practice.

Keywords: Warehousing; human factor; supportive technologies; laboratory experiment

1. Introduction

The strategic importance of warehousing has recently led to renewed attention on the role of human operators in the light of the Logistics 5.0 paradigm [1]. While warehouse operations have become more complex, due to rapid e-

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commerce expansion, increased service-level expectations and the higher sustainability requirements [2], human flexibility and decision-making turn out to be crucial [3]. At the same time, the fast diffusion of automation solutions and digital tools has been transforming the warehouse environment and redefining human roles [3], [4], [5]. From voice-picking systems and wearable scanning devices to Autonomous Mobile Robots (AMRs) and Robotic Mobile Fulfilment Systems (RMFS), these innovations are reshaping how tasks are allocated between machines and people [3], [6]. Within this technological shift, supportive technologies, such as exoskeletons, and collaborative robots (cobots) have gained attention for their potential to support operators' efforts [7]. These technologies are increasingly adopted in warehouses to provide either cognitive or physical support for human operators, rather than substitute them. Hence, human factors and workers' interactions with technologies are crucial elements for operational success [3], [8]. However, the overall effects of supportive technologies on warehouse operators remain unclear. While some studies report reduced physical fatigue, findings on cognitive workload, comfort perception, and user acceptance are inconsistent, and rigorous evidence from real-world settings is still limited [9], [10]. In this context, experimental investigations are fast increasing, with the aim of systematically capturing both performance metrics and human-centric effects of the evolving warehouse operations [11], [12]. However, current approaches to measuring human factor dimensions in warehousing remain highly fragmented, with neither a consolidated overview nor established criteria to guide the optimal selection of methods in experimental research settings.

Building on these gaps, this paper aims to explore the assessment approaches used in experimental settings to measure the impact on the human factor associated with the adoption of supportive technologies in warehousing domains. The research also intends to identify which dimensions of the human operator, i.e., physical, mental, perceptual, and psychosocial, based on the classification proposed by Grosse et al. (2015) [13], can be evaluated with each of the assessment approaches identified. To this objective, a PRISMA-based systematic literature review was conducted to identify a complete and exhaustive sample of papers on supportive technologies in warehousing. A final sample of 57 has been analyzed. The analysis generated two main outputs: (1) a detailed mapping of supportive technologies deployments in warehouse operations, identifying each technology application domain and the specific human factor dimension addressed, (2) a structured taxonomy of experimental methods employed to assess impacts on physical, cognitive, perceptual, and psychosocial dimensions, supported by a comprehensive state of the art.

Several contributions arise from this work. First, the overview of prevalent supportive technologies and their adoption contexts provides a valuable resource for both researchers and practitioners. Second, the structured presentation of human factor assessment approaches establishes clear guidelines to inform approach selection in experimental studies.

The remainder of the paper is organized as follows. Section 2 describes the review methodology. Section 3 presents the results and Section 4 offers conclusions and directions for future research.

2. Methodology

A systematic literature review (SLR) represents the most rigorous method for aggregating and synthesizing all relevant studies that address a given research question [14]. Originating in the medical sciences, the SLR methodology applies transparent and repeatable procedures to gather and evaluate evidence-based findings, with the dual objectives of expanding the scholarly knowledge base and guiding policy and practice [14], [15]. Accordingly, this study employs an SLR to produce a dependable, reproducible, and comprehensive overview of the current state of knowledge and address the defined research objective.

The methodology used, adapted from Miklautsch and Woschank (2022) [14], comprises four primary stages: database selection, keyword-string formulation, application of the PRISMA protocol for papers screening and selection, and integration of the sample with papers obtained through backwards search. In line with established SLR guidelines [15], Scopus has been chosen as the unique source of papers, since parallel searches in other repositories yielded no additional relevant records. Then, a comprehensive search string, refined through iterative adjustments to ensure completeness and precision, was defined. The keywords and search string used to identify the first sample are summarized in Table 1 and Table 2, respectively. The search string was constructed to capture three core dimensions of the review: (1) warehousing activities, (2) supportive technologies, and (3) human factors. The first group ("warehous*" OR "picking" OR "receiving" OR "storage" OR "material handling" OR "logistic*") ensures comprehensive coverage of all relevant warehousing processes. The second group ("assistive tech*" OR "assistive device" OR "supportive device" OR "exoskeleton" OR "back support*" OR "arm support*" OR "back exosuit*" OR "AMR" OR "Autonomous Mobile Robot" OR "cobot" OR "collaborative robot" OR "logistics 5.0" OR "warehouse 5.0" OR "industry 5.0") encompasses both generic and specific technologies employed to support operators. Generic terms such as “assistive tech*,” “assistive device,” and “supportive device” capture the broad spectrum of support tools, while entries like “exoskeleton,” “AMR,” and “cobot” (with their respective acronyms) target key emerging solutions, because some specific studies might refer to these technologies by name without using the umbrella term. Finally, the third group ("human-factor" OR "human-centric" OR "ergonomics" OR "well-being" OR "cognitive load" OR "fatigue" OR "age" OR "gender”) isolates studies addressing human aspects, such as ergonomic considerations, cognitive demands, demographic variables, and overall operator well-being, reflecting the human-centred objectives of the study. These three clusters are combined with logical AND operators to yield a focused yet exhaustive query.

Table 1. Keywords composing the search string.

AND	Warehouse – related	Supportive technology – related	Human factor - related
OR	"warehous*”	"assistive tech*"	"human-factor"
OR	"picking"	" assistive device"	“human-centric”
OR	"receiving"	"supportive device"	“ergonomics”
OR	"storage"	"exoskeleton"	“well-being”
OR	"material handling"	"back support*"	“cognitive load”
OR	"logistics*"	"arm support*"	“fatigue”
OR		"back exosuit*"	"age"
OR		"AMR"	"gender"
OR		“Autonomous Mobile Robot”	
OR		"cobot"	
OR		"collaborative robot"	
		"logistics 5.0"	
		"warehouse 5.0"	
		"industry 5.0"	

Table 2. Search string.

Search string
TITLE-ABS-KEY (("warehous*" OR "picking" OR "receiving" OR "storage" OR "material handling" OR "logistic*") AND ("assistive tech*" OR "assistive device" OR "supportive device" OR "exoskeleton" OR "back support*" OR "arm support*" OR "back exosuit*" OR "AMR" OR “Autonomous Mobile Robot” OR "cobot" OR "collaborative robot" OR "logistics 5.0" OR "warehouse 5.0" OR "industry 5.0") AND ("age" OR " gender" OR "human-factor" OR “human-centric” OR “ergonomics” OR “well-being” OR “cognitive load” OR “fatigue”))

Following the execution of this query, records were screened and filtered according to PRISMA criteria. Besides, the resultant sample of papers was further enriched by identifying pertinent studies cited within the selected articles, through a backward search, in line with Miklautsch and Woschank (2022) [14]. The PRISMA framework delineates a systematic protocol for identifying and selecting studies, thereby safeguarding both the rigor and reproducibility of the review process [16]. Backwards search, a key step of the snowballing technique, examines the reference lists of included articles to uncover additional pertinent studies [14]. By integrating this step, the review mitigates the risk of overlooking relevant work, including publications not captured in the initial database search. The entire methodology, reported in Fig. 1, has been performed independently by three researchers to ensure reproducibility of the whole procedure and minimize biases in the definition of criteria and in the selection of papers.

The initial sample of papers, retrieved as of December 2024 from Scopus through the defined search Query, included 569 papers. Then the search string was further limited to reviews, articles, and conference papers, published in scientific journals or as conference proceedings, to focus on highly relevant and qualitative literature; the language was limited to English to ensure only the inclusion of internationally peer-reviewed literature; no constraints in terms of timeframe were applied to keep the sample exhaustive.

Then, a screening process was performed on the resulting samples, only considering title and abstract (screening phase), according to the following exclusion criteria:

- out of the scope of the considered industry, i.e., studies not addressing logistics or warehousing operations (e.g. those focused on production, assembly, medical, veterinary, or other unrelated domains) (e1);
- absence of focus on supportive technologies, i.e., research that does not describe or evaluate any technology intended to support or partially substitute human operators in warehousing operations (e2);
- lack of clear technology application, i.e., studies discussing supportive technologies in general terms but failing to examine their deployment in specific warehousing activities involving human operators or related movements (e3).

A second selection phase was performed based on full-text analysis (eligibility phase), based on the following inclusion criteria:

- Focus on logistics 5.0 context, i.e., studies explicitly addressing Logistics 5.0, with a particular emphasis on warehousing operations (c1);
- Focus on supportive technologies, i.e., research that describes technologies designed to support or partially substitute human operators within warehousing environments (c2);
- Focus on specific applications, i.e., studies detailing the deployment of such technologies in specific warehousing activities involving human operators or related movements, even if illustrated outside a traditional warehouse setting (c3).

The final group of papers was integrated with 5 additional papers from a backwards search, leading to a final sample of 57 peer-reviewed papers analyzed.

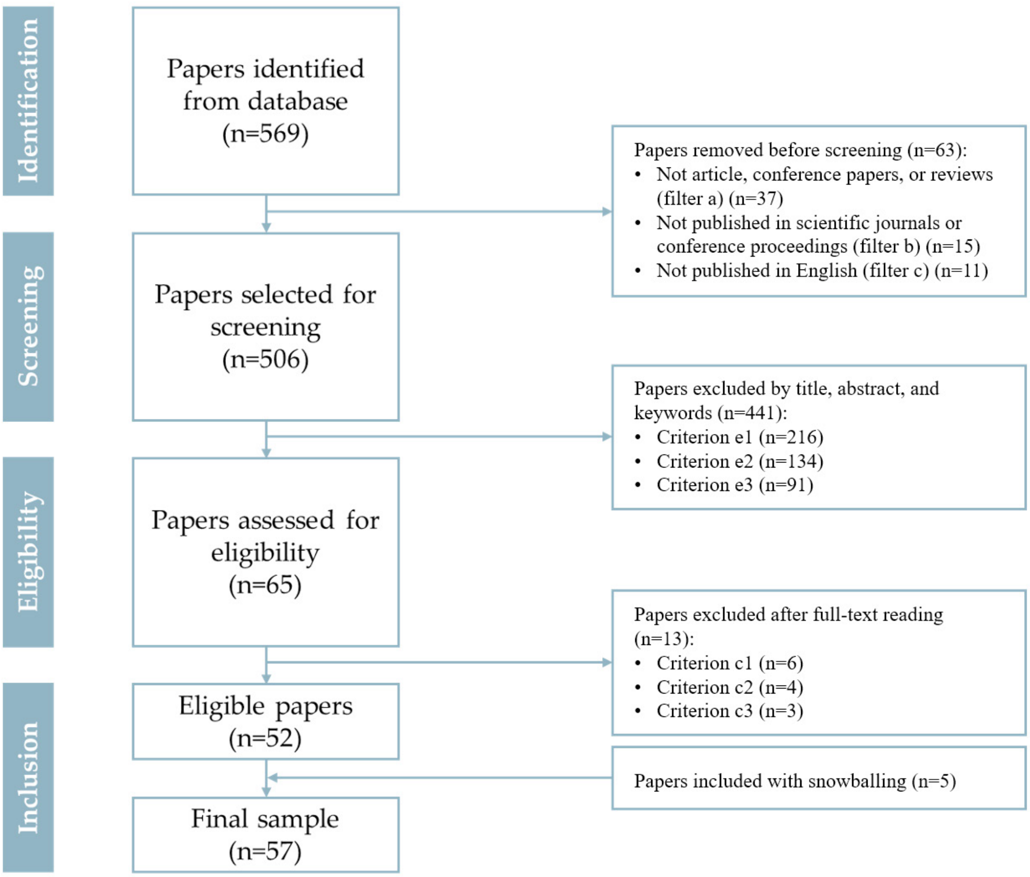

Fig. 1. Paper selection and identification procedure

3. Findings

3.1. Descriptive analysis

The 57 articles included in the review show clear methodological orientation (Fig. 2) and temporal evolution (Fig. 3).

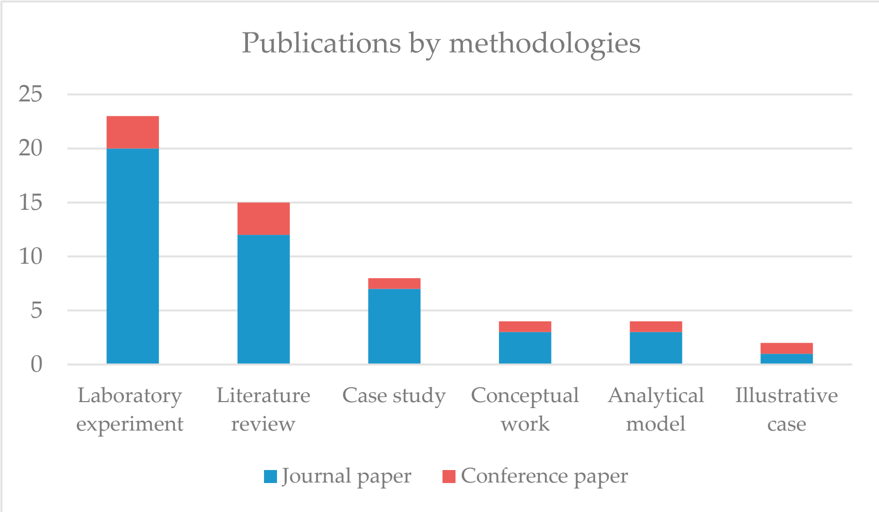

Fig. 2: Papers distributed by methodology

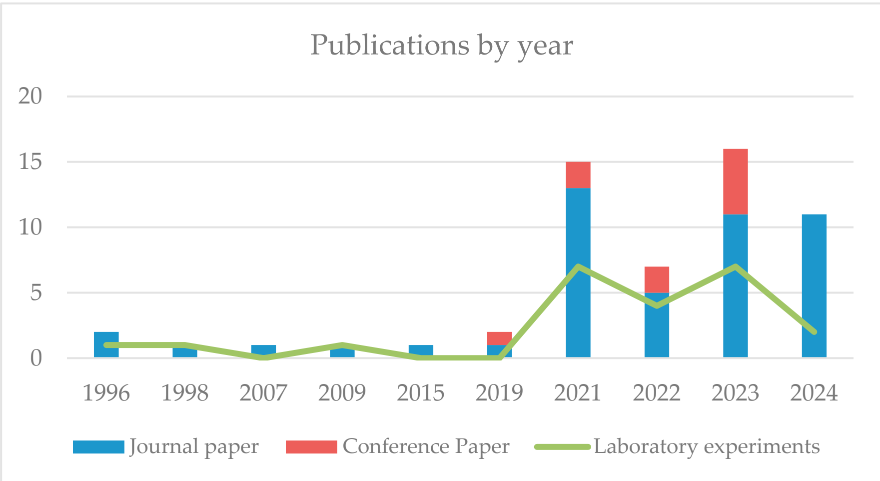

Fig. 3: Papers distributed by year

The most adopted methodology is the laboratory experiment, used in 23 studies, followed by literature reviews (15), case studies (8), conceptual works (4), analytical models (4), illustrative cases (2), and only one survey-based paper. The number of laboratory experiments has increased in parallel with this recent surge in publications in this domain. Specifically, in terms of temporal distribution, the first paper dates back to 1996, then only 7 papers were published between 1996 and 2019, while a sharp increase in research activity is observed from 2021 onwards. This surge aligns with the release of the European Union document conceptualizing the Industry 5.0 paradigm, which outlines a vision for a future European Industry pursuing societal and environmental sustainability goals through a human-centric approach [17]. This result reflects a growing interest in the topic, while the predominance of experimental methodology highlights the need for generating measurable, quantitative evidence to validate findings.

3.2. Content-wise analysis

3.2.1 The impact of supportive technologies on the human factor

There is a broad consensus in the literature that system design choices in logistics, including the degree of automation and the nature of warehousing activities, significantly influence the human factor and, consequently, the overall system performance [4], [18]. The human factor comprises multiple dimensions, i.e., physical, mental, perceptual, and psychosocial, which are affected by interactions between operators and warehouse systems [13]. Although automation is advancing, human labor remains predominant in warehouse operations, particularly in tasks such as order picking, which continues to be highly reliant on human flexibility and adaptability [6], [19], [20]. Human operators continue to play a central role in warehouse activities, although the adoption of automation and supportive technologies is steadily increasing [6], [19]. Order picking requires rapid responses and task customization, making full automation challenging [6], [20]. Its importance is reflected by the high number of papers investigating this activity among the sample analyzed. Material handling, characterized by a low level of automation due to the diversity of handled goods [7], [10], is also very frequently studied.

The current literature predominantly addresses the physical dimension of human work, especially the risks of fatigue and work-related musculoskeletal disorders (WMSDs) associated with repetitive tasks, awkward postures, and frequent lifting characterizing picking and material handling activities [21], [22]. However, they can also impact the mental dimension. In this regard, material handling is found to affect cognitive and psychosocial dimensions, contributing to mental fatigue, visual strain, and emotional stress [7]. Grosse et al. (2023) [6] emphasizes that, in order-picking, cognitive and psychosocial aspects, such as stress, motivation, and workload, play a critical role in operator performance and satisfaction. Repetitive tasks contribute to cognitive overload, although experience and task familiarity can mitigate these effects [23].

In response, supportive technologies are increasingly adopted to support human operators across different dimensions. Table 3 categorizes these technologies by task and human factor(s) addressed. Most studies focus on physical support technologies, such as exoskeletons that reduce lower-back strain during picking and material handling, and collaborative robots (cobots), including autonomous mobile robots (AMRs), which aid in task execution and reduce travel distances. Material handling is further supported by traditional mechanical aids like hoists, cranes, and lifters. Although cobots and AMRs show benefits in reducing physical workload, challenges remain regarding task allocation and user acceptance [20][23], while exoskeletons still raise concerns related to comfort and long-term impacts [12]. Cognitive and perceptual support is provided through technologies such as pick-to-light, pick-to-voice, pick-by-vision, and, more recently, augmented/virtual reality (AR/VR) systems, although research on cognitive assistance is less mature compared to physical support. For AR/VR, open issues include integration into existing workflows and risk of cognitive overload [7]. While supportive technologies hold considerable potential, a comprehensive and deeper understanding of their implications is still needed.

Table 3:Relevant paper categorized based on supportive technology studied categorized, human dimension and activity addressed.

Warehousing activity	Human factor(s) impacted	Supportive technology	Main reference(s)
Picking	Mental and perceptual factor	Information technologies	[3]
		Augmented Reality	[3], [19], [21]
	Physical factor	Exoskeleton	[3], [12], [24], [25], [26], [27], [28], [29], [30]
		Cobot, AMR, AGV, transport equipment	[1], [3], [20], [23], [31], [32], [33]
Material handling	Physical factor	Exoskeleton	[7], [9], [10], [27], [34], [35]
		Operator-to-stock retrieval equipment	[7]
		Hoists, cranes and lifter	[7], [22]
		Pallet orientation devices	[7]
	Mental and perceptual factor	Barcoding, RFID, Voice headsets and Light system, Projection, AV/VR	[7]

3.2.2 The assessment of the impact on the human factor

In this context, assessing the impact of supportive technologies on the human factor is essential. However, diverse approaches are employed in the literature. This section summarizes how these impacts are evaluated in experimental-based research, following the classification of human factor dimensions proposed by Helm et al. (2024) [19] and Grosse et al. (2015) [13], i.e. physical, mental, perceptual, and psychosocial. Results, summarized in Table 4, show that the dimensions of the human factor are typically measured through different approaches, including questionnaires, bio-signals, and observation, involving motion capture or performance proxies.

Table 4: Relevant papers categorized based on human dimension assessed, measurement instrument and metrics observed.

Human dimension(s)	Object of measurement	Measurement instrument	Metrics	Technology			Main Reference(s)
				Exo	AR	Cobot	
Physical	Perceived physical effort	Questionnaire	Borg-Score	X			[10], [27], [28], [36]
	Fatigue	Biosensor (ECG)	HRV; Oxygen consumption	X			[9], [27]
	Fatigue, WMSDs risk	Biosensor (EMG)	Muscular activation	X			[9], [10], [12], [26], [27], [34], [36]
	Ergonomics	Motion capture system	Range of motion	X			[10], [27], [37]
	Ergonomics	REBA, RULA, NIOSH	Ergonomic value		X		[22], [28]
Mental	Perceived mental fatigue	Questionnaire	M-VAS	X			[28]
	Mental fatigue	Observation	Reaction time; Task execution accuracy	X			[28]
Physical and mental	Perceived workload	Questionnaire	NASA-TLX Index	X			[27], [28]
Psychosocial	Perceived effectiveness or capability	Questionnaire	TSSE	X			[29]
	Job satisfaction	Questionnaire	Job diagnostic survey - Job satisfaction			X	[20]
	Self-Esteem	Questionnaire	Rosenberg Self-Esteem scale			X	[20]
	Self-Efficacy	Questionnaire	General Self-Efficacy Scale			X	[20]
	Self-Efficacy in HRI	Questionnaire	Human–Robot Interaction Scale			X	[20]

The physical dimension is the most frequently investigated in the literature, especially in the context of exoskeletons, where laboratory and simulated industrial tasks are implemented to compare different support conditions. In this context, several studies adopt biosensors to measure biosignals and physiological responses. Electromyography (EMG) is often used to measure muscle activation, which quantifies the biomechanical load on the body during tasks ([9], [10], [12], [27]). EMG is particularly suited for controlled environments due to its technical complexity. Other biosignals, such as heart rate variability (HRV) and oxygen consumption, measured through Echocardiography (ECG), are used to assess fatigue [9], [27]. These heart-related physiological metrics can provide insight into the energy expenditure and cardiovascular response of operators. Additionally, perceived physical effort is frequently evaluated via questionnaires, such as the Borg CR-10 Scale, which is simple to implement and offers subjective insight into task demands [28], [36]. Last, as per the physical dimension, ergonomics can be assessed via observation-based methods, such as motion capture systems that provide kinematic data [10], [37], and standardized observational tools like REBA, RULA, and the National Institute for Occupational Safety and Health (NIOSH) Lifting Index, which are used particularly to evaluate posture-related risk [22]. Among these methods, the NIOSH lifting equation is the most widely used, as it considers multiple task-related factors such as posture and load frequency. However, a major limitation is its reliance on the evaluator's judgment, which can introduce subjectivity.

Mental human dimension can be measured through both behavioral performance metrics, derived from observation and taken as proxies of mental fatigue, and subjective assessments, derived from questionnaires. Behavioral performance metrics involve the adoption of indicators computed on an observational basis and used as proxies of mental fatigue. Some examples can be reaction time, accuracy, task completion time, as a decline in these performances could be associated with an increased mental workload [28]. Subjective assessments are the most commonly used methods due to their ease of administration and scalability. One widely adopted tool is the Mental Visual Analogue Scale (M-VAS), which asks participants to rate their perceived level of mental fatigue on a continuous scale [28]. This scale is often paired with other dimensions, such as boredom (B-VAS), to capture mental fatigue globally. Another frequently employed instrument is the NASA Task Load Index (NASA-TLX), which includes "mental demand" among its six dimensions [27]. NASA-TLX provides a multidimensional profile of task load, including frustration, temporal demand, and physical effort.

Studies on collaborative robots (cobots) employ multiple validated questionnaires to gauge user acceptance and well-being: job satisfaction via an adapted Job Diagnostic Survey [20]; self-esteem using the Rosenberg Self-Esteem Scale; general self-efficacy via the General Self-Efficacy Scale; and task-specific efficacy in human–robot interaction (HRI) through the HRI Scale [20], [29]. In the context of exoskeletons, the Task-Specific Self-Efficacy (TSSE) scale is used to measure the perceived capability of users in completing specific tasks [29].

4. Conclusions

This paper investigates the role of supportive technologies in warehousing activities, analyzing their application field and their impact on the human factor and its various dimensions, thereby placing the study within the domain of Logistics 5.0 and human-centric warehousing. The paper, based on a systematic literature review, proposes an overview of supportive technologies deployments in warehouse activities, highlighting each technology application domain and the specific human factor dimension addressed. Moreover, a structured classification of assessment approaches employed in experimental studies to quantify impacts on physical, cognitive, perceptual, and psychosocial human dimensions is provided, supported by a comprehensive state of the art.

Results show a predominant focus on supportive technologies applications in picking and material handling activities, consistent with the human-intensive nature of these activities [3], [5]. The most studied technologies in this context, such as exoskeleton [24], [27] and Cobots [11], [20], offer physical support, while a narrower part of the literature tackles information technologies or AR/VR, providing mental support [7]. Moreover, several experimental studies aim to measure the impact of these technologies on human operators by adopting diverse approaches. Impacts on the physical human dimension result to be the most frequently measured, and with the highest variety of approaches. Specifically, questionnaires can be adopted to assess the perceived physical effort, while ergonomics can be assessed via observation-based methods, such as motion capture systems [10]and standardized observational tools, however, this method strongly relies on the evaluator's judgment, which can introduce subjectivity. Last, several studies adopt biosensors to measure physiological response, particularly, Electromyography (EMG) is often used in controlled environments to measure muscular activation. The impact on mental and psychosocial dimensions, instead, is less common, and it is often measured through both behavioral performance metrics, derived from observation and taken as proxies of workload, and subjective assessments, derived from questionnaires, which is the most used method due to ease of application and scalability.

Despite the relevance of the results, there could be limitations linked to the methodology followed to conduct the SLR, specifically, relying on a single database, and on a specific set of keywords and selection criteria could have led to eliminate relevant contributions, despite the effort to be complete. Still several contributions arise from this work. First, the overview of prevalent supportive technologies and their adoption contexts provides a valuable resource for both researchers and practitioners. Second, the structured presentation of human factor assessment techniques establishes clear guidelines to inform approach selection in experimental studies. Future research should expand the scope of investigation, analyzing human factor assessment approaches in a broader context, for example, focusing on warehousing activities regardless of the technology adoption, or going beyond warehousing to include manufacturing and assembly systems.

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