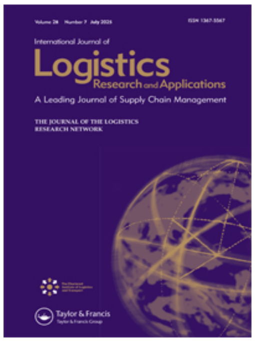

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A systems thinking framework of human–machine interactions and their impact on warehouse operations

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ABSTRACT

The emergence of warehouse automation has caused debate about the impact on human labour, highlighting the need to understand human–machine interactions in warehouse operations to assess the overall efficiency and facilitate developing appropriate intervention strategies. Many studies in the past looked at human–machine interactions in isolation e.g. in order-picking areas of warehouses ignoring the other substantial activities. This study moves away from the isolated approach and develops a comprehensive view of the system structure by using qualitative system dynamic through Causal Loop Diagrams. This research follows a Delphi-style approach and held three rounds of consultations with experts. The model developed provides new insights between human factors and warehouse operations which can be used to develop intervention strategies, recognising the level of collaboration between humans and machines, enhancing productivity, improving knowledge and promoting well-being of workers. The outcomes of this research could assist the design of future-focused Industry 4.0 warehouse operations.

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KEYWORDS
Warehouse operations; logistics; human and machine interactions; system thinking; qualitative model; industry 4.0

1. Introduction

In the complex domain of logistics, warehousing is a critical factor that directly impacts essential network metrics such as on-time rate and fill rate. The emergence of digital technologies aligned with Industry 4.0 framework e.g. Internet of Things, Cloud computing, and Artificial Intelligence, henceforth referred to as 4.0 technologies – has resulted in a new era for logistics operations. These technological advancements have pushed the evolution and improvement of logistics processes, resulting in greater efficiency and adaptability, thus giving rise to the paradigm of Warehousing 4.0 within the broader framework of Industry 4.0 (Tutam 2022). The proliferation of smart warehousing concepts has emerged as a key to the technological revolution within the supply chain (Min 2023). As of 2024, the global warehouse automation market is valued at approximately USD 21.8 billion, with industry key players such as Dematic, SSI Schaeffer, Swisslog Holding AG, TWG Logistics Group, and Daifuku (Precedence Research 2024).

At the heart of warehouse operations is the human element that will continue to play a significant role in various operational activities although technology is likely to replace many of them soon. While automated machines and robots can perform certain parts of activities, most of these tasks still require human labour within the operational settings (Govindan et al.

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2022). Regardless of the automation level, personnel possess the ability to interpret data, make strategic decisions, and anticipate challenges. According to Bureau of Labor Statistics (2024), approximately 1.77 million employees are engaged in the warehouse and storage industry in the United States alone. Similarly, the transportation and storage sector in the UK employs over 1.8 million people (Office for National Statistics 2024) and millions more work in the warehouse industry globally.

The digitalisation of warehousing has introduced human factor concerns that impact worker safety, job satisfaction and overall efficiency. Human factors is the scientific discipline that aims to improve human well-being and system performance by understanding interactions within systems, the application of theories and principles (Grosse et al. 2017). Many planning models developed to assist managerial decisions in logistics systems have frequently overlooked the characteristics of human labourers. This disregard frequently results in planning outcomes that are disjointed from real-world conditions e.g. unrealistic work schedules affecting the performance but also jeopardising the welfare of employees (Sgarbossa et al. 2020).

For example, Woolworths warehouses in Australia have adopted headsets to monitor and time workers' tasks for maximising productivity. However, employees reported that this technology imposes unrealistic demands, causing physical and emotional injury (Bogle 2024). Spencer (2023) reported that UK Amazon's automation and surveillance systems have impacted job quality, increasing workers' stress, anxiety, and monotony – leading to more accidents. This indicates how automation could turn workplaces oppressive, forcing workers to imitate robots. As seen in Amazon's case, neglecting human factors in automation can lead to significant challenges, including workers' protests and dissatisfaction (Hector and Cameron 2023; Singh and Lippert 2024). It is evidenced that humans working with machines could render them passive and monitored, limit their activities to repetitive tasks, cause fatigue, and hinder social cohesion due to reduced human interaction, potentially contracting human capabilities (Engstrom and Jebari 2023). Whereas Industry 4.0 emphasises the capabilities of humans enhanced by technology, Industry 5.0 thus focuses on the capabilities of technology deployed to support human requirements and goals (European Commission 2021).

The integration of man-machine collaboration in warehouse operations is transforming the industry to enhance efficiency while maintaining human involvement. Sgarbossa et al. (2020) indicated that most production and logistics planning models have failed or underestimated human factors in the systems. Failure to consider human factors when implementing new technologies can result in several challenges, including a lack of skilled personnel, decreased acceptance among employees, and limited collaboration within the workforce, ultimately leading to a failed implementation (Cimini et al. 2021). In the context of warehouse industry, several scholars have investigated human-related phenomena, particularly in order-picking activity (Cimini et al. 2019; Grosse et al. 2016; Setayesh et al. 2022; Winkelhaus and Grosse 2020). Pasparakis, De Vries, and De Koster (2023) highlighted that technology should assist rather than replace warehouse human operators, and that their integration into automated systems can lead to improve operation efficiency and worker well-being. Likewise, De Lombaert et al. (2024) showed that involving workers autonomy in order-picking operational decisions can lead to improvements in their job satisfaction and well-being. Therefore, de Koster (2022) stressed the need to design for a sustainable balance between human and robots, maximising joint productivity.

This research responds to the need of the industry and aims to develop a comprehensive approach to examine the integration of human factors in warehouse operations. While several frameworks have been put forth in the literature to incorporate human factor into logistics and production systems (Klumpp and Zijm 2019; Lagorio et al. 2023; Neumann et al. 2021; Vijayakumar et al. 2022), within the context of warehouse operations, it is incomplete in terms of inattention to dynamic interconnections among warehouse activities, resources, and human factors determinants within a broader system. The objective of this paper is, thus, *to conceptually model and analyse the dynamics of human–machine interactions affecting material flows in warehouse operations within the context of Warehousing 4.0.* Driven by the significance of comprehending human involvement in the warehouse system loops within the Industry 4.0 context, the following are the research questions to be investigated:

- What are the variables to integrate human factors in the warehousing system?
- How do human factors dynamically interact and impact on operational performance in warehouse operations?

This paper is divided into six sections including this one. The next section reviews literature, followed by Section 3 describing research methodology and the approach adopted. Section 4 summarises the dynamic relationships between human factors and other variables in warehouse operations. The main findings from the integrated model are discussed in Section 5. Finally, Section 6 concludes the paper.

2. Literature review

Human factors are determined by a set of factors that shape how individuals behave in a warehouse, significantly impacting the overall performance (Bendoly, Donohue, and Schultz 2006). Grosse et al. (2015) differentiate human factors in a warehouse working conditions, namely *cognitive* (e.g. learning, forgetting), *physical* (e.g. posture, fatigue), *perceptual* (e.g. visual, auditory), and *psychosocial* (e.g. motivation, stress), as these aspects directly impact the warehouse performance. Within the scope of warehousing systems, human factors pertain to the personnel tasked with operating or monitoring the devices that facilitate the flow of goods throughout the warehouse environment. This results in increased productive use of the human workers. While the robots take over simpler, repetitive and demanding jobs, humans may concentrate on the more complex and less standardised tasks of fulfilling customer demands (Azadeh, De Koster, and Roy 2019).

The potential contribution of human factors to warehousing has been discussed since the late 1990s (Van den Berg and Zijm 1999) and it has become a bigger concern over time with further automation (Nasir, Venkitasubramony, and Jakhar 2025). Various authors have investigated human factors in warehouse operations, and one of the most discussed areas of investigation is the order picking due to its most labour intensive nature incurring a large proportion of total warehouse costs (de Koster, Le-Duc, and Roodbergen 2007). While several articles deal with benefits of automated systems in reducing pick errors (Berger and Ludwig 2007; Gong and De Koster 2011; Prause, Jentsch, and Eisenhauer 2011; Setayesh et al. 2022), inaccurate data entry (Barratt, Kull, and Sodero 2018; Dewa, Pujawan, and Vanany 2017), and lowering physical stress (Lee, Chang, and Karwowski 2020), the challenge indeed lies in maintaining the balance between workers and automated systems. Table 1 summarises relevant literature on human factors being investigated using various approaches in warehouse operations.

Considering the above-mentioned research in Table 1, we conclude that the most discussed topic of human factors research in warehousing largely focused on order picking. Table 1 also indicates that other substantial activities within warehousing such as receiving, putaway, shipping, and freight carrying, loading and unloading were ignored. While extensive research has been focused on the application of technologies and improvements in optimising warehouse operations, there remains a gap in understanding how human factors are integrated and affect the warehousing system and human well-being (de Koster 2022). The framework proposed by Lorson, Fügener, and Hübner (2022) focuses on human behavioural factors but is context-specific and primarily apply to early stages of warehouse technological development. However, current theoretical frameworks do not fully address the dynamic and interactive nature of human factors within warehouse operations. These gaps limit our understanding of human–machine interaction within warehousing system design and also of the practical implications, which may impede optimal working condition and efficiency.

Table 1. Relevant literature on human factors in warehouse operations.

Author	Research method	Warehouse activity	Human factors impact
Barratt, Kull, and Sodero (2018)	System dynamics	Inventory management	Employee behaviour such as error in data entry, misplacement of items and non-compliance inventory protocol leading to challenges in inventory management, affecting order fulfilment and overall operations
Falkenberg and Spinler (2023)	Machine learning algorithms	Picking and packing	Enhanced workforce planning by considering training, motivation, employee characteristics and operational condition to match with incoming workload
Giusti et al. (2019)	Probabilistic risk assessment, discrete event simulation, Monte Carlo simulation	Six phases of air cargo handler's warehouse	RFID implementation not only enhances operational efficiency but also substantially reduces the probability of human errors in logistics management
Herzog et al. (2018)	Laboratory experiment	Order picking	The effects of using smart glasses for 4 h during order-picking process can cause visual impairment and scotomas
Hosseini et al. (2024)	Laboratory experiment	Order picking	No significant difference of boredom and performance between low workload high autonomy and high workload high autonomy conditions
Kajiwara, Shimauchi, and Kimura (2019)	Experimental approach	Order picking	Psychosocial demand on order picker's work can reduce job satisfaction, highlighting motivation and stress in work demand
Kim, Nussbaum, and Gabbard (2019)	Simulated mock warehouse setting, statistical analysis (Anova)	Order picking and part assembly	(i) Head worn displays had positive impacts on job performance and user perception (ii) Graphic (vs. text based) user interface reduced job completion time and errors
Koreis et al. (2025)	Experimental approach	Order picking	System-level robot shares affect order-picking time in shared workspace with humans, increasing order-picking time and exposing worker safety
Kudelska and Pawłowski (2020)	Simulation	Allocation, order picking	Implemented an optimised system for assortment allocation, demonstrating reduces physical strain and improved work quality
Larco et al. (2017)	Bi-objective assignment method, empirical evidence	Picker-to-part order-picking systems	Prioritising worker well-being (reducing workers' discomfort) can impact operational speed, increasing cycle times
Lee, Kim, and Chang (2016)	electromyograph test, descriptive surveys	order picking	Most affected body regions for ergonomic risk factors in robot-human co-worker order-picking systems were trunk, neck and arms
Pasparakis, De Vries, and De Koster (2023)	Experimental approach	Order picking	Autonomy of dynamics in human–robot cooperation influences order picker satisfaction
Pesigan and Remijn (2024)	Survey	Order picking	(i) No significant difference in physical demand between manual and technology assisted systems (ii) Higher percentage of errors attributed to boredom and loss of attention

To address this gap, the first research question seeks to identify key variables that represent human factors within all areas of a warehouse, while the second explores how these variables interact over time to affect operational performance. These questions aim to bridge between the human elements and warehouse system optimisation. To establish a strong theoretical foundation, this study integrates socio-technical systems (STS), systems thinking, and human factors engineering. First, we drew on STS theory, which formed the basis of our framework. This theory suggests a system view of an organisation (in our case a warehouse) that concerns the integrated social elements (people/individuals, their relationships, organisation, performance management, and the way they operate) and the technical elements (technology, methods, knowledge, processes, and equipment that assist its operations) (Thomas, Sampson, and Zhao 2003; Trist 1981; Vlachos 2023). Meanwhile, systems thinking is utilised to assemble components connected based on degree of certainty of cause-and-effect variables and degree of agreement to the best course of situation in an organised way to produce a consistent outcome (Sterman 2000). Finally, human factor engineering aims to study the interactions that occur at the human–machine interface, which directly relate to observational system features such as physical, cognitive, perceptual and psychosocial experiences in the workplace (Grosse et al. 2023; Neumann and Village 2012).

Consequently, by bridging these theoretical perspectives, this study improves the understanding of human factors in warehouse management, providing theoretical and practical contributions to the discipline. The new framework presented in this paper maps the interaction between identified variables and their relationships over time, emphasising a holistic perspective to clarify complex interactions and facilitate discussions among stakeholders. This system-based approach promotes a more constructive method of mental model mapping and perception, which might be overlooked in quantitative methods.

3. Methodology and data collection

This study employs qualitative system dynamic (SD) modelling based on systems thinking. Systems thinking follows the living systems theory as the systems organically grow or dissipate over a period of time (Richmond 1994). SD modelling methods involve developing causal loop diagrams (CLDs) which offer a qualitative modelling technique used to analyse the causal relationships and identifying feedback loops between key variables. CLDs depict system structures by creating causal relationships among variables, illustrating hypotheses (Sterman 2001). It is essential to note that CLDs do not depict the ultimate simulation but can help in building detailed models at later stages. For instance, they assist in achieving a seamless transition to the final quantitative stock and flow diagram employed in simulations (Lane 2016). Figure 1 illustrates the research framework designed in this study, integrating Delphi techniques. The research framework also includes a key stage in which we have identified key human factor variables for which we used a systematic literature review technique. We then ran a Delphi-styled survey with experts in logistics industry/academia and iterated the development of CLD over three rounds of consultation. The details of the steps involved have been explained in the following sections.

3.1. Developing dynamic relationships through causal loop diagram

There are five steps designed for developing the qualitative system dynamics to investigate the topic under study as below:

3.1.1. Step 1: problem articulation

Problem articulation begins the modelling process by identifying research issues and relevant variables or concepts. This step aims to define and explain research problems and key variables or concepts, establishing the groundwork for analytical and modelling phases.

3.1.2. Step 2: developing conceptual framework through systematic literature review

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) principles are utilised in this step to identify the existing relationship of man-machine interactions and efficiency of warehouse operation, consisting of two major components of research question formulation and search strategy. A total of 1745 records were retrieved through a comprehensive search of databases and search engines, out of which 1065 were excluded based on abstract readings. Ultimately, 33 out of 69 articles were included for identifying variables and causal relationships (see Appendix A). The selected articles were then analysed and categorised based on four themes: *warehouse operations* (inbound and outbound), *machine input*, *human input*, and *human factors* based on how Staudt

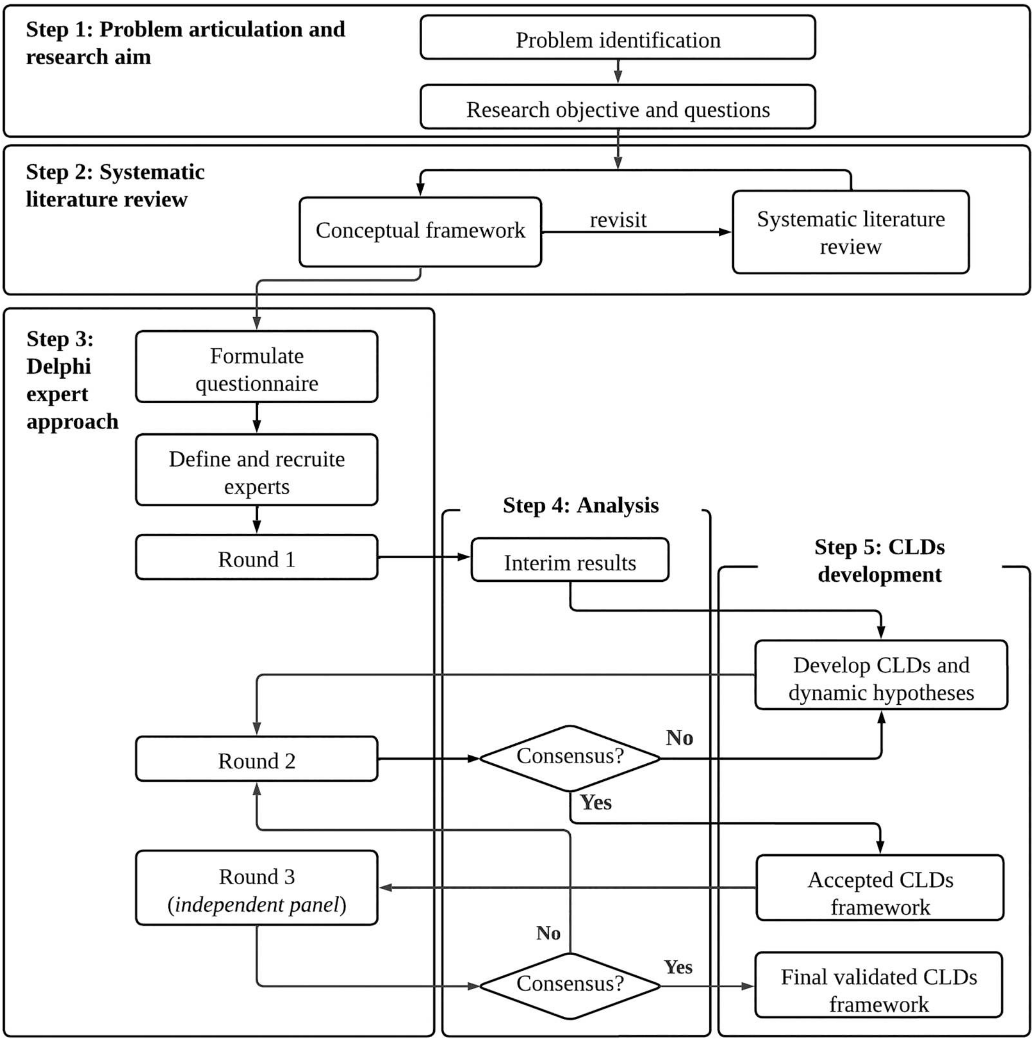


Figure 1. Research framework.

et al. (2015) had classified warehouse indicators into groups of activities and resources. Through content analysis, 47 variables were identified by utilising NVivo version 14 and categorised under relevant themes (see Appendix B).

3.1.3. Step 3: expert surveys

Expert surveys are a valuable tool for gathering perspectives and opinions on a complex issue from individuals with the necessary knowledge and expertise. This approach is an ideal method for obtaining insights for defining variables, constructing causal links, and verifying mental mapping (Senge 1990).

3.1.4. Step 4: descriptive and content analysis

The data obtained from expert surveys undergo a thorough examination utilising descriptive and content analysis techniques. This step aims to identify themes, pattern, and synthesising meaningful insights from expert perspectives to map the variable relationships and feedback loops.

3.1.5. Step 5: formulating dynamic hypotheses and visualising CLDs

Developing a dynamic hypothesis within CLDs is frequently referred to as 'conceptualisation' or 'system conceptualisation' (Randers 1980). During this phase, causal diagrams are constructed to depict the interaction and causal links between variables, visualising how variables influence each other. These frameworks provide a visual representation that facilitates understanding of the system's dynamic behaviour. Table 2 summarises the representations for drawing CLDs which will be useful for understanding the models discussed later in Section 4.

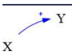
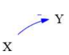
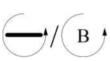
3.2. Three-stage survey method with expert panels

This section discusses the formation of an expert panel using three-stage Delphi-style approach including an independent panel for validating the model in the third and final stage. Delphi is a group facilitation technique that utilises a series of structured surveys to reach a consensus on the opinion of experts (equivalently, panellists, participants, or respondents). Delphi methodology is a unique way of eliciting and improving group judgement based on the premise that a collection of experts is preferable to one expert when precise information is lacking (Kaynak and Macaulay 1984). Studies using the Delphi method include the participation of knowledgeable people about the subject under study (Hasson, Keeney, and McKenna 2000). Experts must have experience, the appropriate qualifications, and an adequate understanding of the research subject (Efimenko et al. 2019). A professional expert must have at least *5* years of industry experience (Devaney and Henchion 2018), and an academic expert must have at least *10 international publications* to be considered (Rosa Pires da Cruz, Ferreira, and Garrido Azevedo 2013). This study employed the expert survey following the Delphi method to assess the understanding of variables pertaining to warehouse operations and the integration of humans and machine into the work system. The questionnaire and methodology for this study was approved by the Business, Environment and Social Sciences Ethics Committee University of Leeds under the reference AREA FREC 2022-0267-209.

3.2.1. Design of the first two rounds

The questionnaire and data collection were conducted using Version 2 Online Surveys. A conceptual framework of causal relationships between identified variables is first presented and described in detail. Following this, experts are asked to assess the importance of each variable in relation to the impact of human factors on warehouse operations. A causal tree diagram is used to visually demonstrate the relationships between variables involved in each sub-system as shown in Figure 2. The use

Table 2. Notations used for drawing the CLDs.

Graphical icons	Interpretation
	When X increases (decreases), it leads to a corresponding increase (decrease) in Y. A positive sign denotes that an increase in X results to an increase in Y.
	When X increases (decreases), it leads to a corresponding decrease (increase) in Y. A negative sign denotes that an increase in X results to a decrease in Y.
	Delay marks add inertia to systems, induce oscillations, and frequently dictate compromises between short-term and long-term consequences.
< X / Y >	Refers to shadow variables that are present elsewhere in the CLDs but are replicated near the effect variable of a relationship to improve the CLDs' visual clarity.
	Balancing loops, often called negative loops, induce opposite changes to counteract one direction. This loop type actively restores a system to equilibrium after a disruption.
	A positive or reinforcing loop is a self-reinforcing cycle where a variable change causes subsequent changes in the same direction. This loop amplifies the initial effect and can cause exponential growth or decline.

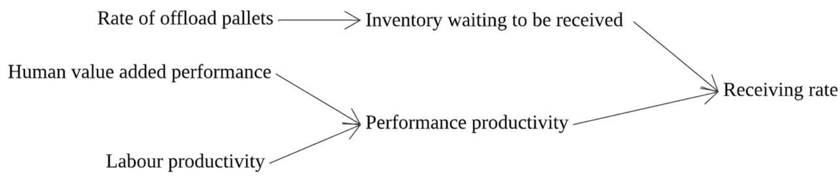


Figure 2. Example of tree diagram of inbound process sub-system generated on Vensim.

of such tree diagrams provides an easy-to-read, displaying information of complex system in a relatively small space.

In the first round of the survey, panel members were tasked to rate the identified variables using a 5-point Likert scale, ranging from 'not important' to 'very highly important', and provided with *open-text space* to explain their evaluation and make suggestions for potential revisions and additional content. Given that Likert scales are ordinal, the median or mode was employed as the measure of central tendency (Jamieson 2004). To evaluate each variable, the proportion of panel experts reaching a consensus on its practicality was calculated, with an 80% agreement threshold (Delbecq, Van de Ven and Guftafson 1974; Jorm 2015). In order to determine the consistency of opinions among all experts, this study utilises Cronbach's alpha of each variable, indicating score of 0.7 or above is satisfactory, and 0.8 or higher is often excellent (Van Griethuijsen et al. 2015).

$$\alpha = \frac{K}{K-1}\left(1 - \frac{\sum_{i=1}^{K}\sigma_{y_i}^2}{\sigma_y^2}\right); \quad y = \sum_{i=1}^{K} y_i \tag{1}$$

Based on results in round 1, the revisions were made to the initial CLDs, adding new connections and feedback mechanisms, and dropping poorly ranked variables. Quantitative data (ranking of important links) were statistically analysed, while qualitative data (free text answers) were coded thematically using NVivo software. From the ranking variables, the most important variables in each sub-system were identified based on consensus, which was determined by achieving a Cronbach's alpha score of more than 0.7, indicating high agreement among the experts. Variables that were ranked low and/or had no additional qualitative evidence to support their significance were dropped from the original CLDs. Conversely, additional variables introduced by experts were incorporated in the causal relationships with qualitative evidence, allowing for the reconstruction and refining of variables links in the system.

In the second round, the revised CLDs was handed to the participants, who were given a chance for making additional modifications or to accept it as a suitable depiction of human and machine interaction in the warehouse operations model. If the participant suggested additional changes to the CLDs, they were asked to outline any incorrect or missing variables or relationships using the drop-down options in the cause-and-effect relationship. On the Version 2 Online Surveys, the participant can identify and modify the relevant relationships by selecting the 'Cause' variable and 'Effect' variable columns that they wish to modify. Table 3 summarises the consensus-based criteria adopted in this study. Hence, the developed CLDs underwent further modification to evolve an agreed version at the end of round 2.

3.2.2. The third round: independent panel for validation

The third and final round of the survey involved recruiting an independent panel to validate the CLDs developed. In this part of the survey, experts were able to evaluate the factors and relationships in the model and propose new factors and relationships they deemed missing by using the same approach as in the Round 2 survey. At this stage, if experts recommend any changes, the

Table 3. Consensus-based criteria.

	Round 1		Round 2	
	Method	Consensus	Method	Consensus
Existing variables from literature	Rate on 5-point scale*	At least 80% of the experts chose option 4 and 5.	Chance to respond to factors opted for removal	More than one expert arguing for removal.
Existing relationships	Not applicable	–	Rate on 3-point scale**	At least 80% of the experts chose option 2 and 3.
New variables	Suggest new factor	Suggested by expert.	Not applicable	–
Cause–effect relationships	Not applicable	–	Cause and effect links	More than one expert arguing for removal or differentiation.
New relationship/ link	Not applicable	–	Rate on 3-point scale**	At least 80% of experts selecting option 2 and 3.

*1-Not important, 2-Very low importance, 3-Low importance, 4-High importance, 5-Very high importance.
**1-Not relevant, 2-Somewhat relevant, 3-Very relevant.

framework will be revised and informed to other participants in previous stages for consensus agreement before the framework is accepted.

3.3. Survey participation

The selection procedure for the panel was executed with diligence, considering each participant's years of experience in the sector and their record of publications in scholarly journals. The round 1 sample achieved 14% of response rate, accounting for about five of 38 experts, four experts participated in round 2 (80%), and four experts participated in the external panel session (26%), who had not participated in the previous rounds. The recruited academic experts hold a doctorate and have published ten or more scholarly articles in peer-reviewed international journals. They also provide a wealth of experience in optimising SD simulations across logistics and supply chain issues. The industry experts, on the other hand, have diverse educational backgrounds, occupying tactical and strategic decision-making positions and have more than ten years of practical industry experience. One of the industry-independent panel adds essential insights as a SD consultant in supply chain. Notably, despite the relatively small number of experts, their contributions were highly valued and rigorously evaluated when gathering data for this analysis. Expert opinions were carefully examined, median values are determined, and Cronbach's Alpha was used to determine consistency (Wu et al. 2022). When consistency was reached, the five experts' average consensus on incorporating human factors in warehouse 4.0 variables was established. The variables are removed from CLDs mapping if consistency is not achieved.

4. Main findings achieved

In the initial phase, participants were assigned to evaluate 49 factors (synonymously, variables) identified from the literature survey. From the ranking of variables, the most important ones in each theme were identified. Following the completion of evaluation, a consensus was reached to eliminate 10 factors in the first round of revision. These variables were assigned low rankings and qualitative evidence, indicating little importance in representing different subsystems. The panel of experts reached a unanimous agreement during the subsequent round to incorporate 17 new factors sourced from relevant research/industry experience. In addition, 47 variables achieved satisfactory consistency measure, with Cronbach's Alpha of more than 70%. Round 2 encompassed the elimination of an extra seven variables. These variables were considered extraneous within the CLDs links and relationships, which are unnecessary and can be removed without affecting the overall system. Once the final framework is validated and accepted, we observed dynamics within those CLDs based on each variables behaviours of multiple subsystems: warehouse operations and transport planning, human and machine resources and impact of human factors on warehouse system performance.

4.1. Optimising material flow within warehouse operations and transportation planning

The expert panel discussed the flow of materials in warehouse operations and transport planning. The results of the CLD analysis indicated that the core areas of this model (Figure 3) consisted of one balancing loop and two reinforcing loops. The primary activities of a warehouse were represented by inbound activities, such as receiving, putting away, and storing; while the outbound activities comprised order picking, packing, and shipping. A balancing loop negatively affects items that are continuously coming in by the inbound process, representing the capability of a warehouse to execute receiving and storing activities. The industry experts suggested that the inbound rate is highly influenced by exogenous variables:

> The accuracy of data received from pre-alert documents. [Expert 5]

> [The n]ature of loads [such as] stable[,] unstable[,] mass[, and] transport form? [Expert 1]

Any changes to the exogenous variables, such as the type of goods and the accuracy of incoming shipping note, significantly impact the unloading rate of a warehouse. The assignment of warehouse resources, such as humans, machines, entrance doors, and the number of arriving trucks define the inbound rate of a warehouse. In other words, if a warehouse with limited resources and low productivity has a high number of trucks arriving at its facility, it will lead to congestion and negatively affect its transportation planning. Hence, the balancing loop of B1 indicates that the efficient storage

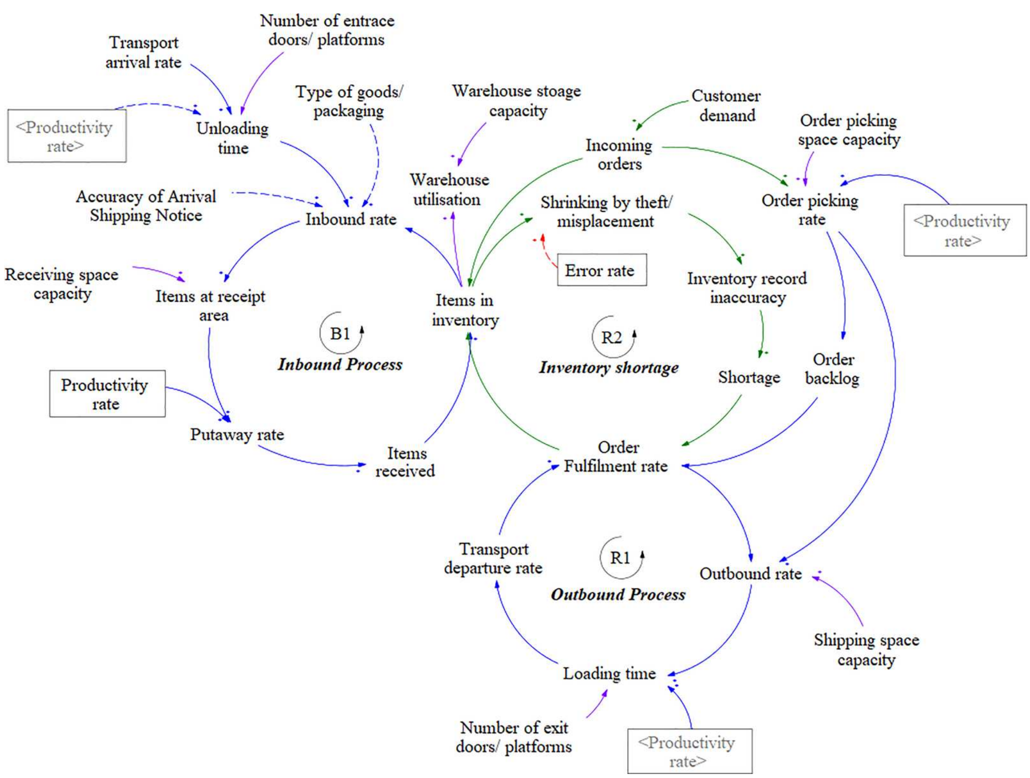


Figure 3. The physical flow of materials in warehouse facilities.

of the items in a warehouse depends on efficiently executing its receiving and arrangement activities.

Likewise, the outbound process represents a positive reinforcement loop in fulfilling orders within the supply chain. Higher customer demand increases the number of orders that a warehouse receives and its picking rate which, in turn, increases the demand for humans and machines to pick and pack the orders received. The picked items are then repacked or loaded onto a designated truck at the exit door for distribution or transportation to the destination. Hence, a higher transportation departure rate indicates a higher order fulfilment rate, indicating efficient warehouse operations and transport service planning. As inventory management is essential to the efficient functioning of a warehouse, item theft or misplacement can lead to inventory shortages, representing a reinforcing loop. Hence, inventory shortages or order backlogs may negatively impact the order fulfilment rate of a warehouse. Productivity influences the unloading time, putaway rate, order-picking rate, and loading time.

> Perhaps I would have also evaluated the components of the 'productivity performance' [variable as it] is where aspects relat[ing] to interactions with technology [might reside. For example, when it is] time to check orders on the [Warehouse Management System] (WMS) [and] usability. [Expert 3]

An independent panel suggested a significant modification to the initial causal relationships. Originally, it was assumed a positive relationship between productivity and inbound rate. However, this link was revised to reflect an indirect relationship, where productivity influences the unloading rate, which then determines the inbound rate. This adjustment shows that inbound rate not only influenced by unloading rate as a mediating factor between productivity and inbound rate, but also other exogenous variables (type of goods and accuracy of arrival notice).

4.2. Improving the utilisation of human and machine resources

Human resources comprise workers devoted to executing inbound or outbound operations (Figure 4). At the beginning of every simulation, all the workers were part of the stock of available pool, while the other stocks were empty. The workers were required to perform outbound or inbound activities. If the total number of operational workers increased, it meant that more workers had been assigned to an inbound or outbound activity and, therefore, the total number of available workers had decreased. Consequently, the total number of operational workers decreased, closing the feedback loop. B2 and B3. This illustrates how changes in worker allocation in inbound or outbound activities can affect the distribution of workers in a system, potentially achieving a balance

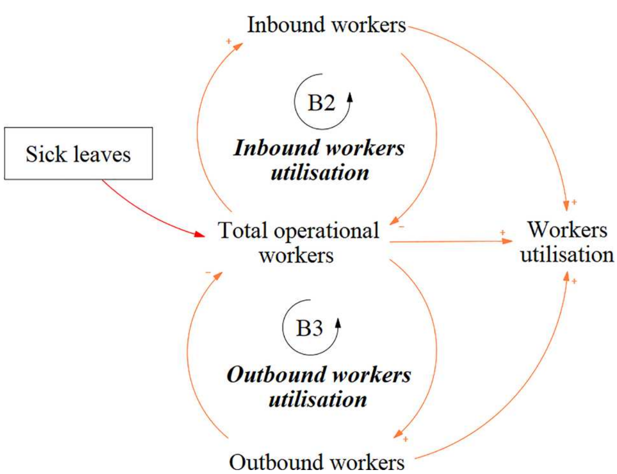


Figure 4. The accumulation of operational workers.

between worker distribution and operational requirements. In addition, an expert commented that fatigue and sick leave recovery time may impact the number of workers, thereby, affecting productivity and disrupting resource allocation planning.

> Fatigue and known error rates and error recovery time … . [Expert 1]

The number of absences and the need for replacement workers increases when many workers are fatigued. Fatigue can cause significant absenteeism in many industries; including logistics and production; thereby, decreasing productivity and increasing healthcare costs.

Meanwhile, the machines in a warehouse are often associated with various factors, such as maintenance, usage, downtime, and output. This model visually represented and explained the balancing loop of machine output (Figure 5). Industry experts across the stages have a significant consensus on this loop and did not suggest any changes or have any comments. High machine availability enables the greater utilisation of machine capacity, improving overall machine performance. The integration of digital technology for information workflows substantially improves the operational efficacy of warehouse logistics in the retail industry. Nevertheless, machine maintenance as well as wear and tear, which increases when machines are utilised at higher capacities, may decrease overall machine availability. B4 illustrates how the correlation between machine availability, utilisation capacity, and performance affects the overall efficiency and dependability of a warehouse system, with adjustments that may, potentially, balance machine capacity and availability.

4.3. The impact of human factors on system performance

The impacts of human factor variables, such as physical, cognitive, perceptual, and psychosocial factors were assessed in detail to determine how they affect warehouse performance as well as the overall efficiency of logistics operations.

4.3.1. Ergonomic design and well-being

The physical aspect of a human–machine sub-system primarily affects productivity and output in jobs that are physically demanding (Figure 6). Furthermore, the physical demands of a workplace may result in significant overloads that risk the health and safety of workers as well as a decrease in output. An industry expert suggested including workload in the system loop:

> Biomechanics workload, physiological workload … . [Expert 1]

The automation and distribution of tasks allow humans and machines to work together and decrease the physical workload for humans. Although it is desirable to reduce physical workload,

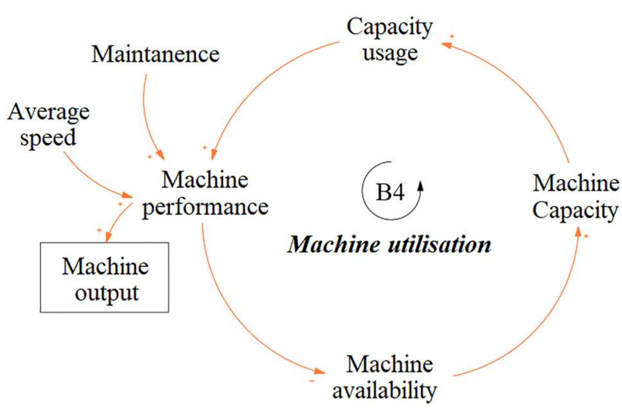


Figure 5. The utilisation of machines.

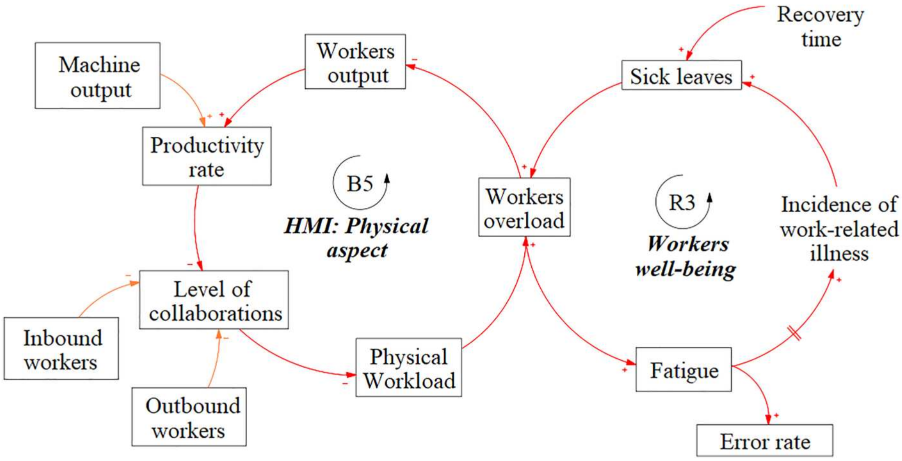


Figure 6. The physical impact in human–machine interactions.

increased reliance on machine inputs could overwhelm workers as they will be required to coordinate and operate more machines, leading to overloads. Worker productivity and efficiency may also suffer. When productivity declines, the degree of human–machine collaboration may be re-evaluated and reveal new collaboration parameters. The iterative B5 loop seeks to balance collaboration and maximise productivity without physically overloading the workers.

Fatigue may impair the physical abilities of workers, thereby, increasing the likelihood of incidents and sick leave. These variables significantly correlate with worker availability in terms of sick leave and recovery time. Fatigue occurs when workers face excessive physical workloads or extended working hours. Prolonged fatigue significantly increases the likelihood of work-related diseases among workers. When illnesses become commonplace, the number of sick days that workers require to recover increases. When the number of workers on sick leave increases, the workload of their co-workers increases, completing the feedback cycle.

R3 depicts how fatigue can cause illnesses and absenteeism, which affects the workload and well-being of the workers. Therefore, it is essential to manage the risks of more accidents and declining worker well-being to ensure a safe and productive workplace (Figure 6). An industry expert highlighted the need to include recovery time for sick leave taken due to biomechanical workloads, fatigue, or work-related illnesses:

> … recovery time allocations. [Expert 1]

Injury risk factors, such as high physical loads, can negatively impact the health of workers and the quality of a warehouse system's performance. When workers experience physical fatigue, their reaction time, accuracy and attention to detail will decrease, leading to errors, accidents and lower productivity.

4.3.2. Task complexity and training development

Cognitive factors are one the most critical aspects that warrant attention when humans interact with machines, devices, or systems that involve decision-making, problem-solving, and information processing. Experts agreed that the perceptual factors should be considered within the cognitive context, which is supported by Borges et al. (2021). They recognised cognition refers to the mental processes involved in perception, learning, memory, reasoning, problem-solving, decision-making, and other aspects of human thinking. When developing the cognitive system modelling, the industry experts recommended new variables with which to better understand the impact of human–machine interactions in warehouses:

Task complexity, decision support and feedback strategies .... [Expert 1]

The level of autonomy given to the workers affects the cognitive demand and knowledge that they are required to have to interact, use, assess, and operate machines (Figure 7). The industry experts concurred that a mental workload increases task complexity the most, resulting in negative worker output and productivity (R5). Tasks that are highly complex increase the mental workload of workers as they must manage multiple processes and use reasoning to perform them with significant precision, which takes a toll on the cognitive resources of the workers. Therefore, feedback strategies and task knowledge may positively or negatively influence task complexity.

Various feedback strategies can be used to influence mental workload and performance. However, some feedback strategies, such as overloading, delayed, negative, and inadequate feedback can decrease mental processing capabilities and performance. In the early stages of implementing a new technology, technical skills are required to use it correctly.

... the ability to concentrate, open-mindedness, flexibility, and willingness to learn new skills in a short time are characteristics that make it easier for [a] workforce to accept a new technology[, however,] always on the premise that the workforce is correctly informed about the objectives of the implementation of new technologies and correctly trained. [Expert 3]

If [proper] training is given, then it would [have a positive effect]. Otherwise, it [may] result [in] disaster [as T]echnological changes, especially if the rationale for their adoption is not adequately explained to [the] employees and if [the] employees are not properly trained, can negatively impact human factors, especially cognitive ones. [Expert 4]

As such, the present study developed a balancing loop (B8) on technological training that will provide a better understanding of training rate and the knowledge gaps of the workers. Users must possess the necessary knowledge and skills to effectively use the proposed model to achieve the desired outcomes. Their mental workload will increase if there is a gap in the knowledge between what the user knows and what is required to use the model effectively.

Warehouse workers are reluctant to [adopt] changes [that] they [do not] understand. This includes a work environment that is new to them and advanced technologies, automation[s], and change[s] in thinking patterns. [Expert 2]

As a result, a delay mark was introduced between the training rate and workers' knowledge gap. A worker's experience and education influence the knowledge that they possess and, consequently, the training that they require to address these gaps. The learning rate positively relates to decision-making performance, indicating that workers who learn quickly can make better decisions and perform their jobs more effectively. Lastly, as machines provide humans with the information required to make analytical decisions, the system modelled a balancing loop of the decision support system (B7).

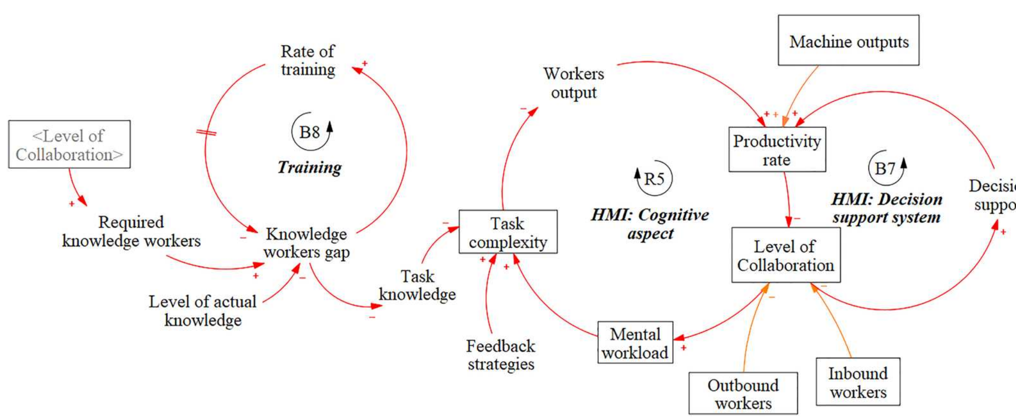


Figure 7. The cognitive impact in human–machine interactions.

4.3.3. Fostering psychological safety

The psychosocial aspect aims to foster psychological safety under two aspects: physical (B9) and mental (R6). Successful collaboration between humans and machines could, potentially, augment the physical and mental workloads that humans experience due to better job allocation (see Figure 8). The industry experts suggested that stress may be a critical human factor that should be considered in a loop model where humans and machines work together:

> I'd also include 'stress' in the mental or psychosocial aspects. [Expert 1]

> … [I]ndustry 4.0 firms' impact employee[s] psychologically. [Expert 5]

Stress occurs due to mental or physical workloads. B9 represents the impact of physical workloads on the psychosocial aspects of the workers, whereas R6 represents the impact of mental workloads. Expert suggested that support from co-workers and supervisors should be considered within the psychosocial context:

> Support from co-workers and supervisors … . [Expert 1]

The present study considered support from co-workers and supervisors as an exogenous variable as it may not directly impact the psychosocial aspects of the model. The stress levels of workers rise in response to greater physical and mental workloads, which may negatively affect their motivation. When workers are less inspired to work, it may decrease output and productivity. Furthermore, when experiencing high levels of mental and physical workload, workers are more likely to make errors. Therefore, the risk of human errors may be decreased by optimising workloads, such as by providing workers with decision support tools or reducing the need to multitask. It is crucial to understand the psychosocial dynamics inherent in this loop to enhance human–machine interactions and guarantee the job satisfaction of the workers.

Workers that have more positive experiences when using technology to perform tasks are more likely to feel satisfied with their jobs. This was included as a psychosocial factor in the model, as it can enhance productivity, reduce workload and enable workers to perform tasks that might otherwise be unachievable. Conversely, negative experiences with technology can lead to frustration, decreased productivity and increased workload, ultimately leading to job dissatisfaction.

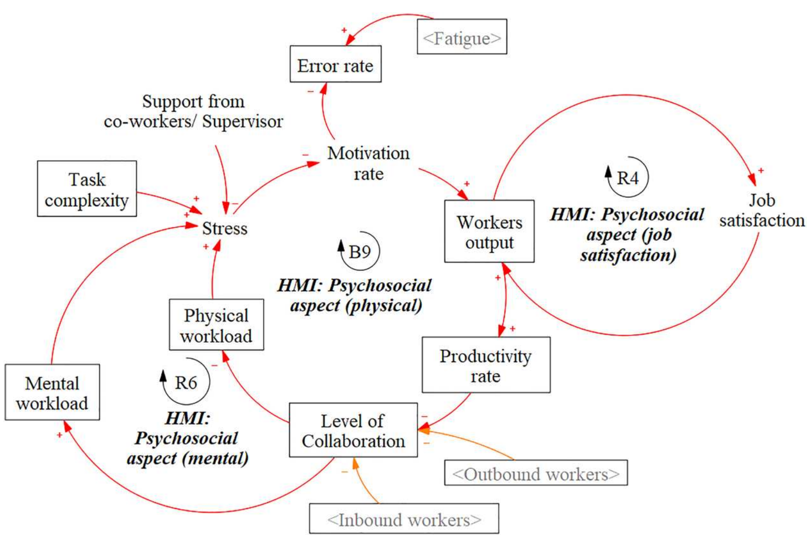


Figure 8. The psychosocial impact in human–machine interactions.

5. Discussion of findings

The use of systems thinking demonstrated that various themes within the subject area are interconnected, as illustrated in the combined CLDs as shown in Figure 9. These themes include warehouse activities, ranging from inbound to outbound processes (blue arrows), inventory management (green arrows), labour and equipment (orange arrows). The warehouse operational model is then linked to the human factors subsystems (red arrows), namely physical, mental, perceptual, and psychosocial. The adjustments made after the consultations with the experts were indicated by dashed lines. This aspect represents transversal indicators defined by different units and measurements to elucidate their complex interactions through feedback loops either a reinforcing or balancing effect on one another. The factors and relationships which have been identified support Sgarbossa et al. (2020)'s conceptualisation of the human factors within the production and logistics system. In addition, reinforcing and balancing loops illustrated in CLDs represent a useful framework for analysing how complex systems behave and can be controlled. In our system, we identified eight balancing loops that help maintain stability by counteracting changes, such as inbound process and workers' output. Simultaneously, we found six reinforcing loops that drive growth and amplify key trends, such as order fulfilment through outbound process, and worker well-being. Together, these loops interact to create a dynamic yet controlled environment, where reinforcing loops advance the system, while balancing loops ensure we do not exceed critical thresholds.

Understanding how human factors impact warehouse operations highlights the advantages of systems thinking, which can be synthesised into a dynamic causal relationship based on qualitative evidence. We observed dynamic hypotheses from our CLDs into level of autonomy, knowledge management, productivity performance, and workers' well-being. These formulated dynamic

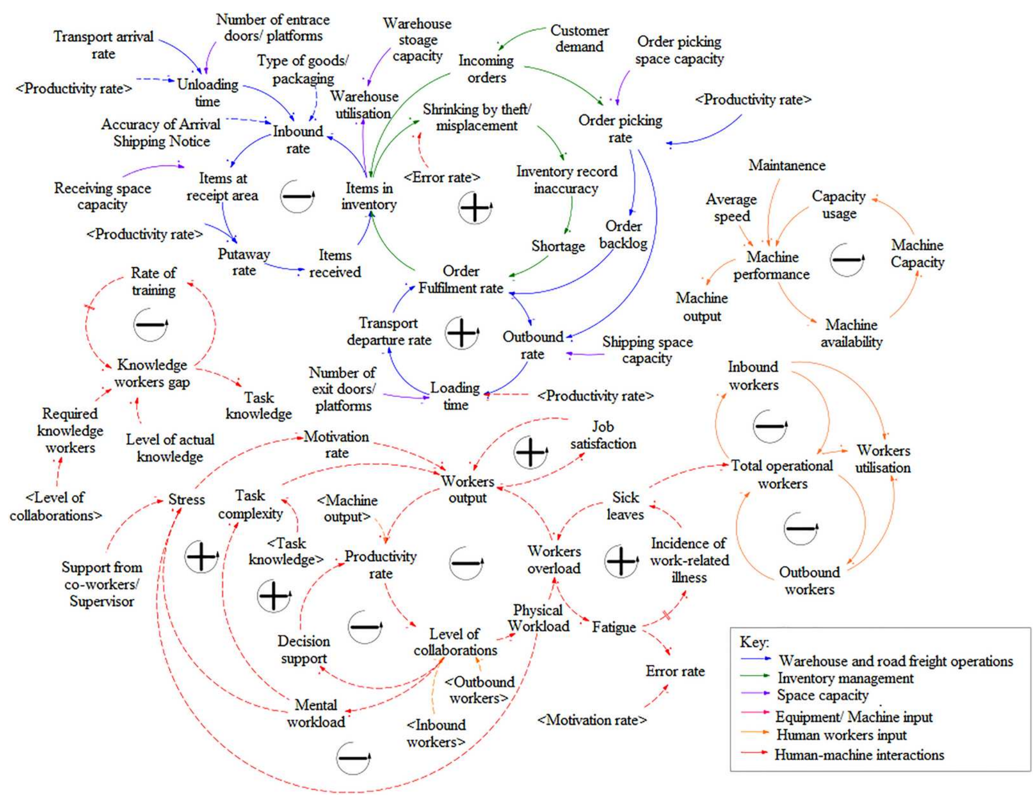


Figure 9. The human factors incorporated into warehouse operations.

hypotheses act as a guiding framework to build a more detailed quantitative model that can test and refine how the system behaves over time.

5.1. Recognising level of collaboration

The findings highlight the significance of incorporating a broader range of collaboration levels that would impact human factor elements in understanding dynamic planning during the implementation phase. This finding supports Pasparakis, De Vries, and De Koster (2023) who had highlighted that incorporating different level of worker autonomy leads positively to affect job satisfaction in warehouse operations. Additionally, by recognising and analysing the level of collaboration within the CLD framework, stakeholders can better understand how to optimise warehouse operations taking into account the holistic impact on workers' physical, mental, and psychosocial aspects. This approach can aid organisations in managing change more effectively, reducing employee resistance, and facilitating a smoother transition to an automated system. Based on the level of collaboration, managers may better deploy resources, therefore lowering overstaffing and downtime.

5.2. Optimising warehouse productivity performance

Warehouse optimisation is a strategic process of improving operations to achieve maximum efficiency and effectiveness. The CLDs in this study offer an investigation of human factors elements that contribute to resource optimisation, refining workflows, leveraging technology, and enhancing the warehouse productivity performance. This research has advanced warehouse productivity performance measurement by incorporating human factors, in addition to the conventional measures of output and labour hours (Corinna Cagliano et al. 2011; Ramirez-Malule, Jaén-Posada, and Villegas 2021). The CLDs can emphasise creating balancing feedback loop cycles that increase productivity by improving factors such as increased knowledge, reduced physical demand and task complexity, and increased decision support and motivation level. For instance, enhanced ergonomics reduce fatigue, improve cognitive focus, and facilitate better collaboration, resulting in increased productivity. In contrast, disregarding these human factors can result in balancing loops that impede productivity, such as increased absenteeism or errors. This finding is supported by a SD model utilised in understanding human errors (Barratt, Kull, and Sodero 2018; Neumann et al. 2018). The CLDs assist in developing interventions that sustainably enhance warehouse performance by strategically targeting these dynamics.

5.3. Improving knowledge

The potential dependency on technology demands a balanced approach and continues to be a significant challenge. Human resource and knowledge management in logistics highlight the significance of warehouse personnel training to adapt to technological advancements and improve their capabilities in the warehouse industry (Lambrechts et al. 2021). Higher technology adoption in warehouses requires more knowledge and training. This dynamic creates balancing loops, where the gap in workers' knowledge influences the rate of training, and training then reduces the knowledge gap. By enhancing knowledge, employees can better handle the work complexity through cognitive performance and physical demands, leading to more effective adaption and problem-solving in the face of challenges.

5.4. Promoting workers' well-being

Human factors, which comprise physical, cognitive and emotional states, substantially influence the concept of worker well-being. Comprehending how these elements interrelate and contribute to well-being is essential for improving employee performance and the overall workplace environment. Similarly, Neumann et al. (2018) simulated the dynamics of worker well-being in automotive disassembly operations, emphasising how human factors are essential to maintaining productivity and minimising health risk. Higher levels of automation are not always associated with higher levels of productivity, safety, or operator well-being when considering the entire system (Lagu and Landry 2011). By focusing on well-being, the CLDs demonstrate how creating a better workplace not only benefits employees but also contributes to long-term operational success.

6. Concluding remarks

The present study investigated complex causal relationships between human–machine interactions in warehouse operations using system dynamic modelling approach. Following the PRISMA procedure, a conceptual framework was developed based on 47 identified variables and their interdependencies from 33 selected articles. Through a three-stage expert panel Delphi-style approach, human factor variables were verified, and causal relationships between indicators were refined. The present study has thoroughly examined the theoretical basis considering the fundamental hypotheses involved in system conceptualisation and proposed a comprehensive qualitative model that illustrates how human factors can influence the optimisation of warehouse operations. Niu, Schulte, and Negenborn (2021) asserted that the lack of generalisation of human factors has limited the understanding of impact on warehouse operations. Thus, the CLDs developed in this study offer a general perspective of the wider warehouse system highlighting the human–machine interactions and their impact in warehouse settings, particularly on productivity and worker well-being.

6.1. Implications for theory

In this paper, STS theory served to enhance the importance of people within the technological systems in a warehouse setting, highlighting scope for deficit in productivity. The STS approach is particularly valuable for developing potential strategies to aid the understanding of the dynamic interaction between human and machine in warehouse operations. The application of systems thinking in integrating human factors in warehouse operations is still at an early stage. To the best of our knowledge, our study is the first to apply qualitative SD procedures through systems thinking to investigate the integration of human factors in warehouse operations. Our model contributes to the theoretical understanding of human factors in warehouse operations by utilising systems thinking, illustrating how human factors and warehouse operational processes are interdependent and evolve over time. This study extends existing theories of human factors engineering in warehouse management, offering a dynamic framework for designing a good balance between humans and machines to maximise joint productivity performance. This approach can be applied in different contexts related to operations management, such as non-operational warehousing activities, automated freight transportation, carbon footprint, and other logistics and supply chain applications. We resolved the issue of the study by using a systematic framework through literature, validating it with a novel expert Delphi approach to develop model building of CLDs, as illustrated in this paper. Although Harrison, Grant-Muller, and Hodgson (2022) previously utilised a Delphi approach in building their CLDs, our study designed two rounds of expert Delphi approach together with an independent expert panel. These participants were recognised as experts through defined criteria before deciding to include their data in the analysis. With that, we obtained constructive perspectives from people with extensive experience and knowledge in the subject matter from both industry and academia. In addition, an online survey tool was utilised to validate identified variables through Likert scales, drop box options for deriving cause-and-effect relationships between variables and open-ended questions to propose new variables. Unlike the standard approach in validating CLDs through focus groups, stakeholder interviews and workshops, we gained valuable insights to present the model building to experts online, which could save cost and time for researchers and participants.

6.2. Implications for management practice

This study contributes two-fold to practitioners, addressing joint productivity of labour and machine collaborations and redesigning work in collaboration with robots. Managers can better understand how human factors affect productivity, human errors, employee satisfaction and well-being, providing CLDs as a strategic tool for making data-driven decisions that balance operational goals and well-being. Our model highlights the importance of motivating, retaining and stimulating people to carry out their jobs alongside machines, which would hugely impact their output and the overall productivity of warehouse performance. The model has successfully integrated operational aspects of a warehouse with its effects on humans in a collaborative automated setting, providing measures that may interact with human factors to help stimulate performance. Thus, our model helps managers control and monitor how individuals behave in warehouses in collaboration with robots that leads to effective and targeted improvement measures.

6.3. Limitations and outlook

There are a number of limitations to this research. Our reliance on expert interviews conducted with different types of stakeholders, including academia, industry and consulting may result in a lack of generalisability of the model as these stakeholders could be considering different types of warehouses when responding to the questionnaire. However, we believe that this limitation is minor as the model presented in this study can be applied to any type of warehouse which involves fundamental activities such as inbound, outbound and inventory management. Future studies could also expand the scope to consider value added services in warehousing such as cross-docking, reverse logistics and sustainability to create a wider qualitative SD framework. In the context of human factors, further exploration of perceptual aspects, such as visual discomfort and vision-related issues, could be valuable as these are influenced by the type of technology used in the warehouse environment. Above all, system thinking allows for a broader comprehension of how a system's variables interact over time, offering qualitative insights of the whole system or problem. Future research should consider developing a quantitative system dynamics model to validate the identified relationships, test scenarios, and evaluate the dynamic behaviour of the system over time.

In conclusion, growing opportunities for advanced technology in warehouse settings are becoming more relevant, providing theoretically challenging investigations in the field of human factors. Our work contributes to improving the synergy of humans and robots in warehousing systems with due consideration to human factors and behaviour.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Appendices

Appendix A. Systematic literature review of system dynamic research on warehouses

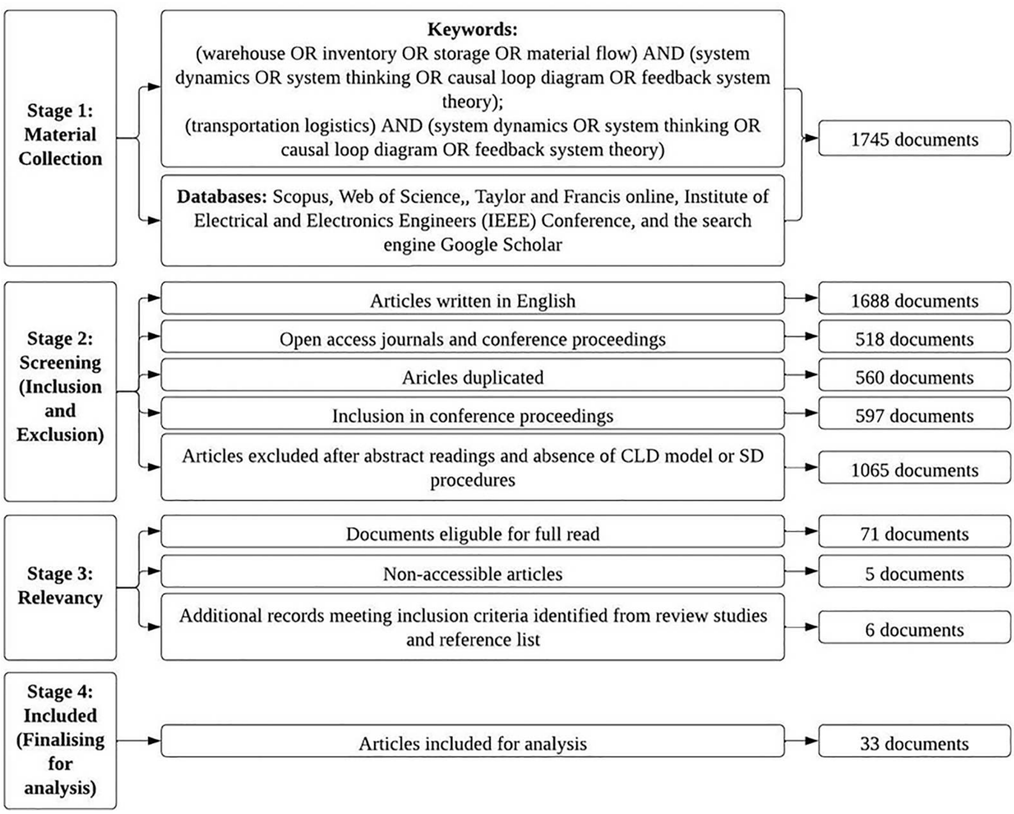

Figure A1. Flowchart describing the systematic review of articles for identifying key human factor variables (Initial literature review conducted May 2022, repeated in February 2023).

Appendix B. Key variables identified for developing causal loop diagrams

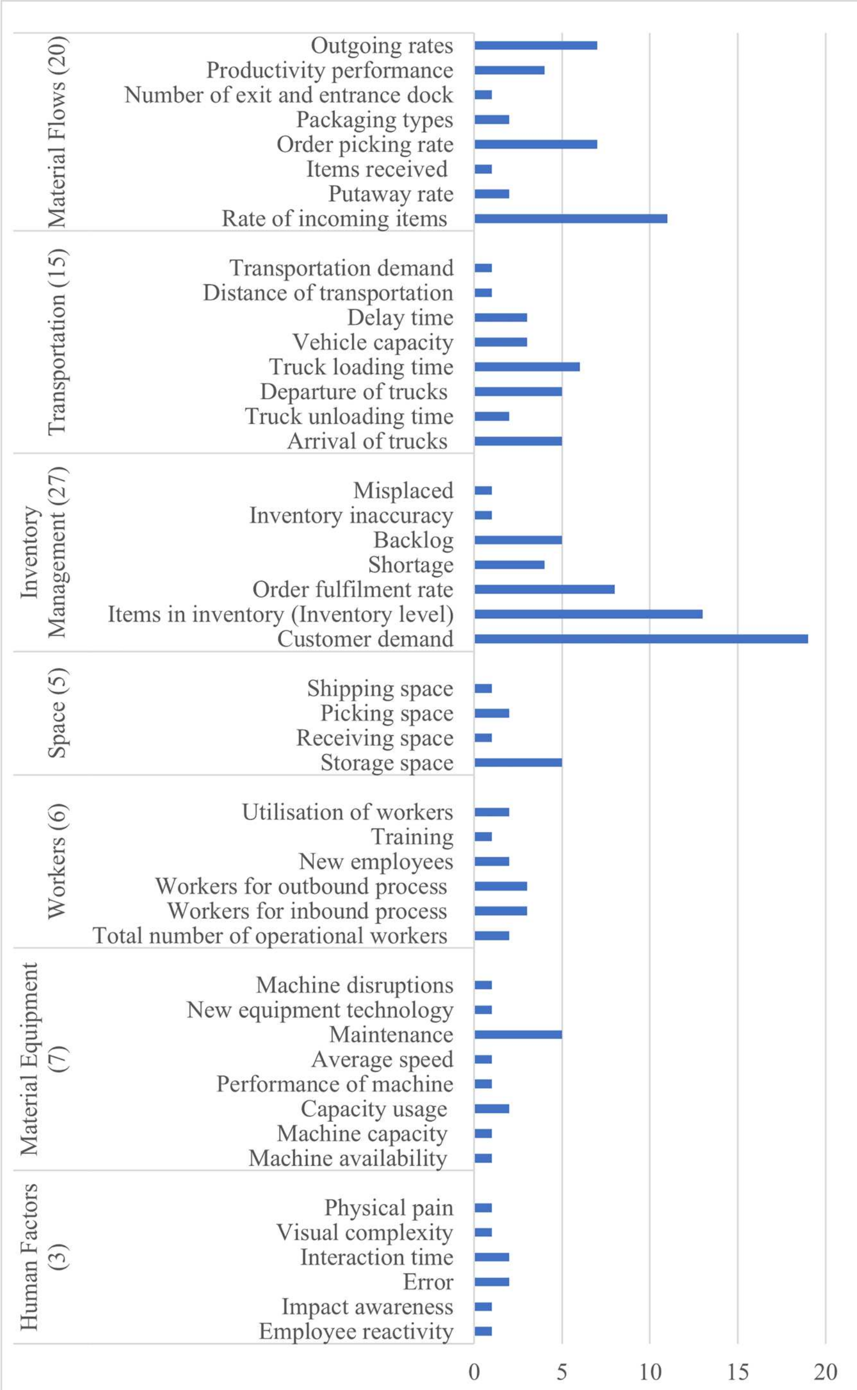

Figure A2. Summary of identified variables by seven categories.