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Systems-theoretic interdependence analysis in robot-assisted warehouse management

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ABSTRACT

The safe and efficient application of collaborative robots requires an understanding of actual work practices transformation, emerging from the adoption of new technological instruments. Functional systems-thinking is largely absent in literature about collaborative robot applications. In this context, this study proposes a framework that combines two safety analysis methods, being the Functional Resonance Analysis Method and Interdependence Analysis. Both safety and efficiency are examined by selected case study highlights to gain an in-depth understanding of human operators' role as the central driver of human–machine (eco)systems in a warehouse distribution system, in which warehouse robot assistance is provided. Whereas the Functional Resonance Analysis Method first maps the work system interactions as a whole, Interdependence Analysis is subsequently applied to investigate individual inter-agent exchanges by the principles of Observability, Predictability, and Directability as a core principle for goal coordination between multiple agents, including warehouse robot agents. The case study examples reveal the combined effects of the working system environment and the robot application but also demonstrate possible operational solutions to deal with socio-technical complexity.

1. Introduction

Traditional robots have been deployed in fenced workspaces to substitute human operators performing repetitive and hazardous tasks with high accuracy. Collaborative robots (cobots) were introduced to additionally enable humans and robots to work in the same workspace or to mutually collaborate on the same task, without the need of being separated from humans (Hentout et al., 2019). Besides industrial manipulating robots, warehouse robots are also considered to fall under the broad definition of cobot technology (Lambrechts et al., 2021; Neumann et al., 2021), due to their characteristic of performing distributed tasks in a shared workspace with the possibility for unintentional contact; all of this while coordinating sequenced handover tasks.

In the literature on cobots and Industry 4.0 (I 4.0), there is a high focus on mechanical hazards and techno-centric solutions (Adriaensen et al., 2021; Margherita and Braccini, 2021; Nayernia et al., 2021), whereas several scholars describe the absence of functional systems-thinking and human factors (HF) perspectives in safety analyses (Brocal et al., 2019; Kadir et al., 2019; Neumann et al., 2021). Industry 5.0 (I5.0), as recently defined by the European Commission (Breque et al., 2021), puts human well-being at the centre to complement the technological potential from I4.0, characterised by high system interconnectivity (Badri et al., 2018). Thereby, I5.0 advocates an additional societal transformation by empowering humans as drivers of system resilience. In such systems human-automation symbiosis is not designed to replace human abilities, but to assist humans to produce more efficient and effective system performance (Romero et al., 2017).

Abbreviations: AMR, Autonomous Mobile Robots; CWA, Cognitive Work Analysis; FRAM, Functional Resonance Analysis Method; HF, Human Factors; HTA, Hierarchical Task Analysis; I4.0, Industry 4.0 (I4.0); I5.0, Industry 5.0 (I5.0); IA, Interdependency Analysis; JCS, Joint Cognitive Systems; OPD, Observability, Predictability, and Directability; RCS, Robot Control System; TAD, Task-as-Desired; WAD, Work-as-Done; WAI, Work-as-Imagined; WMS, Warehouse Management System.

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Several scholars have argued that system failure is the product of the product of poorly-aligned or poorly-integrated activities, rather as being the result from individual performance (Mosey, 2014; Trentesaux and Millot, 2016). Scholars also argue that the future gains in safety performance will need to consider systemic models (Komljenovic et al., 2017). This requires an understanding of the actual transformation of work practices which emerge from the adoption of new technological advances in different operating contexts (Adriaensen et al., 2019).

Accordingly, the research question of this paper is about understanding whether, and to which extent, a theoretical framework based on modern systems-theoretic methods can successfully capture operational nuances of robot-assisted production management solutions. We build our framework on previous research, which combines the Functional Resonance Analysis Method (FRAM) (Hollnagel, 2012) with Interdependence Analysis (IA) (Johnson et al., 2014) to integrate an approach for systems modelling with an analytic method for the design of human–machine co-agency.

The framework is applied to analyse a warehouse distribution system to gain an in-depth understanding of the role of human operators within larger human–machine (eco)systems. Both safety and efficiency will be examined by functioning mechanisms selected from the warehouse management system modelling, as obtained by the FRAM-IA framework.

The remainder of the paper is organized as follows. Section 2 will cover a literature review and research motivation; Section 3 explains materials and methods; Section 4 provides a case study description, and Section 5 summarises the results by several case study highlights presenting the real-life application potential of the proposed approach. The discussion and conclusion can lastly be found in Section 6.

2. Literature review

Poor understanding of workers' tasks can lead to underperformance of the work environment and phantom profits (Rose et al., 2013). To treat workers as a sustainable resource, it is necessary to understand how automation produces qualitative shifts in work systems, forcing people to adapt their previous practices in novel ways (Adriaensen et al., 2021; Dekker and Woods, 2002). How new tasks present new requirements, which in turn result in unanticipated possibilities or pose new constraints on human performance. The notion of 'substitution fallacy' (Dekker and Woods, 2002) describes an oversimplification of the substitution of worker's tasks when I4.0 technologies and collaborative robots introduce new hazards and dependabilities (Adriaensen et al., 2019; Guiochet et al., 2017). Much progress in safe human–machine interaction is the result of research efforts on agent-centred human-aware robots (El Zaatari et al., 2019; Gualtieri et al., 2021; Hentout et al., 2019; Lasota et al., 2017), or human-aware mobile cobots in particular (Hellström and Bensch, 2018). In addition to understanding cognition from humans and providing robots with similar cognitive mechanism, scholars have reported the need for a holistic understanding that considers socio-technical relations within the human-robot ecosystem (Honig and Oron-Gilad, 2021; Kim, 2019; Margherita and Braccini, 2021).

2.1. *Human-robot ecosystem as a socio-technical system*

Human operators, robot agents and robot control systems (RCS) form novel patterns of distributed cognition and distributed decision-making (Fiore et al., 2011), in which the system as a whole can be considered as a new unit of analysis, i.e. the adaptive cognitive system (Romero et al., 2017; Woods and Hollnagel, 2006). This consciousness requires new ways of performance analysis (Chacón et al., 2020; Jones et al., 2018), as suggested by research on Joint Cognitive Systems (JCS). JCS is concerned with "the analysis and design of factors, processes, and relationships that emerge at the intersections of people, technology and work" (Woods and Hollnagel, 2006). According to JCS thinking, the human–machine or human-system ensemble is considered together as the basic unit of analysis. JCS recognises that a symbiotic human–machine system can have cognitive properties that cannot be reduced to the cognitive properties of individual elements but are dependent on how functions and information are represented, combined and propagated in the cognitive system as a whole (Hutchins, 1995). Other domains have previously been studied such as joint human-technical performance, embedded in purposeful socio-technical systems (Le Coze, 2013; Leveson, 2011; Rasmussen, 1997; Waterson et al., 2015) concerning safety and mission success. Nonetheless, the JCS perspective has been applied only marginally to the domain of industrial cobots (Chacón et al., 2020; Jones et al., 2018) and I4.0 technologies (Philippe Rauffet et al., 2019).

2.2. *Ecological approach versus cognitivist approach*

To perform a task or work analysis, the analysis can be rooted in two foundational approaches. In a cognitivist approach, work constraints originate from workers' intrinsically subjective interpretations and mental models. The approach used in this study avoids the typical cognitive decision biases (Montibeller and von Winterfeldt, 2015) and emotion-prone risk decisions (Kahneman, 2011) described in the literature and instead focuses on the functional interaction potential. So far, human factors research predominantly emphasised cognitivist approaches (Vicente, 1999), for example widely applied in the design of human-robot or human-system interfaces, in which the correct interpretation of semantical information from an interface depends on the mental model the worker has about the system's functioning. Meanwhile, the ecological approach of task analysis modelling has received far less attention. In the ecological approach, the analysis focuses on the work constraints from the physical and external reality in which workers are situated and which exist independently from workers personal beliefs and competencies.

2.3. *Safety perspective*

Safety is increasingly defined as the positive capacity of creating mission success under a variety of circumstances (Leveson, 2011; Patriarca et al., 2018a; Woods, 2015). This matches the transition from marking safety as the mere absence of harm, towards the positive support of system resilience as expressed in the EU's definition of Industry 5.0. (Industry 5.0 | European Economic and Social Committee, 2018). From the human-centric perspective, both safety and efficient system performance cannot be treated as mutually separated issues. Suboptimal understanding of cognitive ergonomics and human factors create the potential for employee and system underperformance, inaccurate decision making and eventually psycho-social stress on employees (Martinetti et al., 2021; Sgarbossa et al., 2020). Hence, both efficiency and safety can benefit from generating a better functional understanding of emerging socio-technical interactions applied to new human-centric approaches (Kadir et al., 2019). Such a view complements the traditional safety perspectives of merely avoiding harm. This is achieved by escaping an overly narrow focus on techno-centric failures (Trentesaux and Millot, 2016) and by additionally considering that "interactions with technical parts of the ecosystem can be the source of unexpected failure, help detect unexpected failures, and facilitate resolutions" (Honig and Oron-Gilad, 2021).

2.4. *Scope of the work*

The need to manage mission success by taking human factors into account requires novel frameworks able to capture functional genesis and propagation in human–machine systems, assessing interaction failure potential and transformed work practices. We hypothesise that the performance of the system cannot be understood from the analysis of the individual physical and cognitive interactions alone but materialises from a systems-thinking perspective (Dekker et al., 2011), in line with

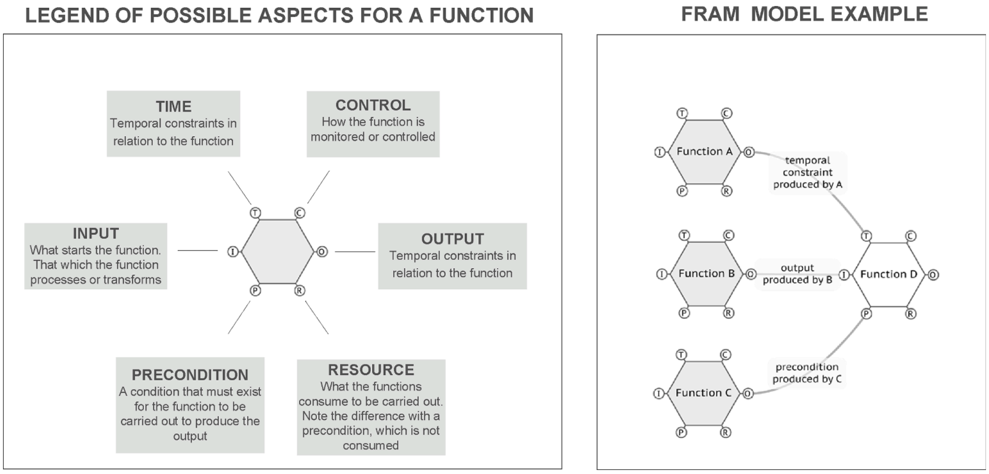


Fig. 1. Basic constituent elements of a FRAM function (left) and simple FRAM model with exemplary interconnections (in this case, from top to bottom, output-time, output-input, output-precondition).

the JCS perspective. Although the holistic socio-technical perspective has indeed been applied to cobots other scholars (Coelho et al., 2018; Guiochet et al., 2017; Honig and Oron-Gilad, 2021; Jones et al., 2018; Kim, 2019; Margherita and Braccini, 2021; Neumann et al., 2021; Sgarbossa et al., 2020), our framework firstly proposes co-agency from cobots to be functionally assessed in terms of task analysis by merging FRAM and IA. The FRAM-IA framework is theoretically described in Adriaensen et al. (2022), and applied to a case study in this publication.

In line with Vicente (1999) and Rasmussen (1994), we defend to take the ecological approach as the starting point of the work analysis, because ultimately the cognitivist challenges of system interaction are nested in the ecological challenges that operators are faced with in socio-technical systems.

3. Materials and methods

We aim to study the propagation of functional interactions as they appear to the workers in the system as the basic structuring element of our analysis. The focus of our study is therefore not on the individual mental models from humans or computational models from robots and control systems. The scope is restricted to the warehouse operators and robot agents, as well as human agents involved in operational warehouse supervision.

3.1. The functional resonance analysis method (FRAM)

It has been applied to a variety of work domains like aviation, railroad transport, healthcare and other fields (Patriarca et al., 2020). The FRAM is a method capable of mapping non-hierarchical, non-linear relationships, ideally suited to meet a Work-as-Done (WAD) description. WAD is defined as how work is routinely performed in practice, often including implicit interactions. WAD differs from other varieties of human work, such as Work-as-Imagined (WAI), with the latter defined as the way somebody's work is considered to be done by a third person, including policy makers, researchers, or regulators. WAD also differs from procedural formalisation of specific work (Work-as-Prescribed – WAP) (Moppett and Shorrock, 2018). For this study, we added Taks-as-Desired (TAD) as FRAM functions that are identified as 'absent' in the observer WAD, but desired for system to overcome current operational issues. One of the main advantages of FRAM is that it is a *method-sine-model*, making it a non-reductionist method in which the work system shapes the resulting model, rather than the underlying method assumptions. However, FRAM has only been marginally applied to collaborative robot applications (Adriaensen et al., 2021; Chacón et al., 2020) or I 4.0 technology (Mofidi and Nadeau, 2021).

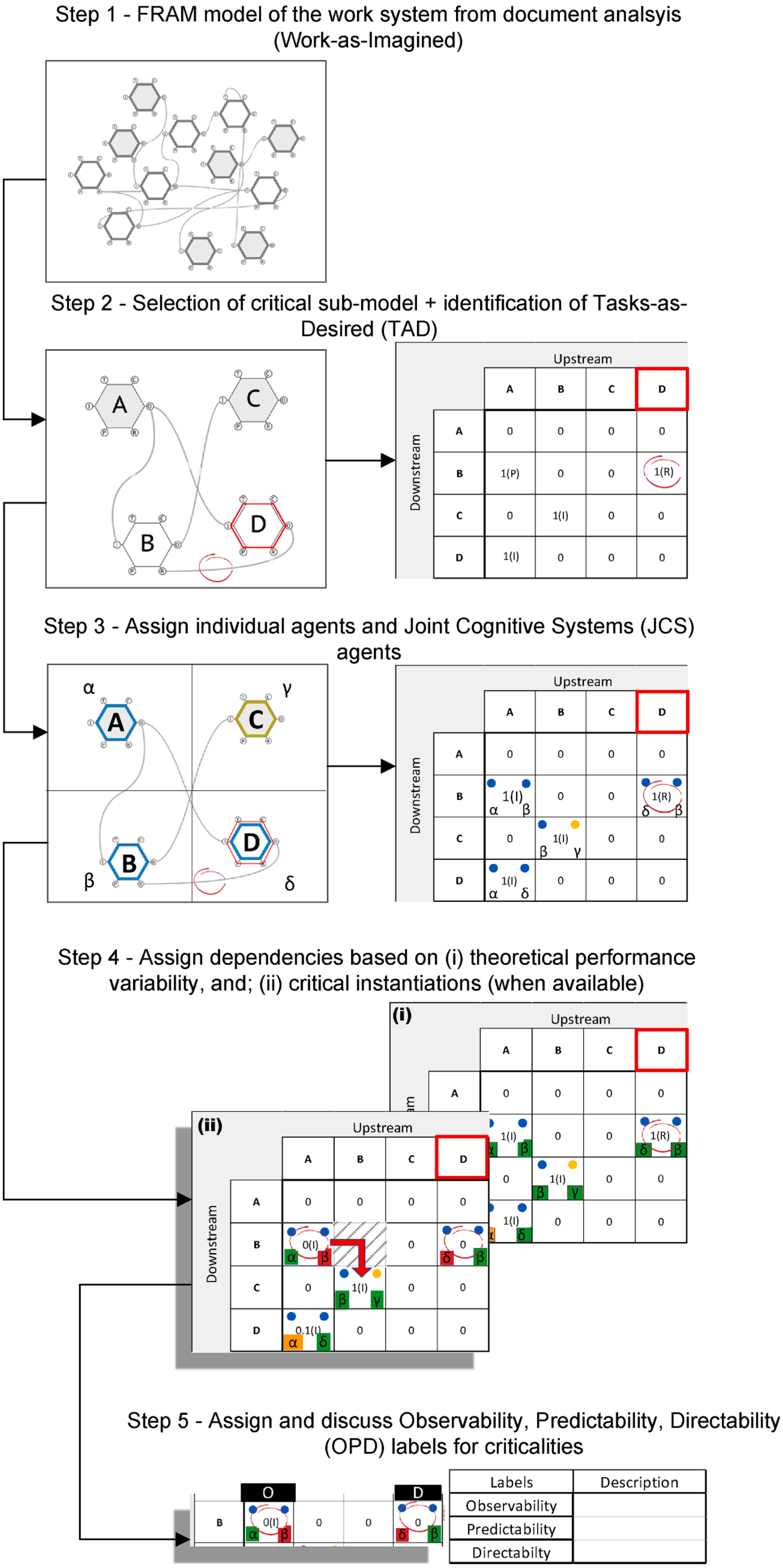
We refer to Hollnagel (2012) for the full theory explanation of the FRAM methodology, sketched in its main elements in Fig. 1.

A single function and its six potential aspects are illustrated on the left, while the right side illustrated a simple FRAM model connecting the outputs of functions A, B, and C connected to the input from function D.

3.2. Interdependence analysis (IA)

IA has originally been created to be applied to the analysis of human-robot co-agency (Johnson et al., 2011, 2014, 2018). In IA 'capacity' is considered to be "the total set of inherent things (e.g., knowledge, skills, abilities, and resources) that an entity requires to competently perform an activity individually". Consequently, "dependence exists when an entity lacks a required capacity to competently perform an activity in a given context" (Johnson et al., 2014, p. 47). Interdependence, as shaped by capacity, is the central organizing principle (Johnson et al., 2014) to support the joint activity of human-robot design in coactive design. It can be defined as "the set of relationships used to manage dependencies" (Johnson et al., 2014, p. 49). These dependencies are further broken down by the principles of Observability, Predictability and Directability (OPD) as the central functional organising principles for goal coordination. Note that second-order design principles for automated systems such as reliability and accountability (Balfe et al., 2012) are also important interaction principles resulting from repetitive behaviour, but ignored in this study as our research has a deliberate focus on real-time operational functionality. The OPD capacities in this study are not to be interpreted as the observable or predictable character of the system as a whole but are to be considered on a function-by-function basis (from which ultimately the aggregation enables a systemic analysis). Interdependence Analysis thereby looks at the very elements that shape system performance by individual interdependencies (in this study between two suqbsequent FRAM functions) in line with the previously explained ecological perspective in which the design instructs the agents' behaviour. OPD principles assigned at the level of individual functions are especially useful in systems in which human and machine work together simultaneously in shared control, allowing little time for real-time corrections. This operational focus then leads to better understanding of mechanisms of *meta*-cooperation (Flemisch et al., 2019) at the more operational and strategical levels when monitoring, managing and ultimately designing systems.

In its original form (Johnson et al., 2011, 2014), IA applies Hierarchical Task Analysis (HTA) to compare several human-robot sub-tasks as concurrent design alternatives. As our framework aims to apply IA theory to existing cobot prototype designs or even operational set-ups, HTA is replaced by a FRAM model to depict the network of possible



	A	B	C	D
A	0	0	0	0
B	1(P)	0	0	1(R)
C	0	1(I)	0	0
D	1(I)	0	0	0

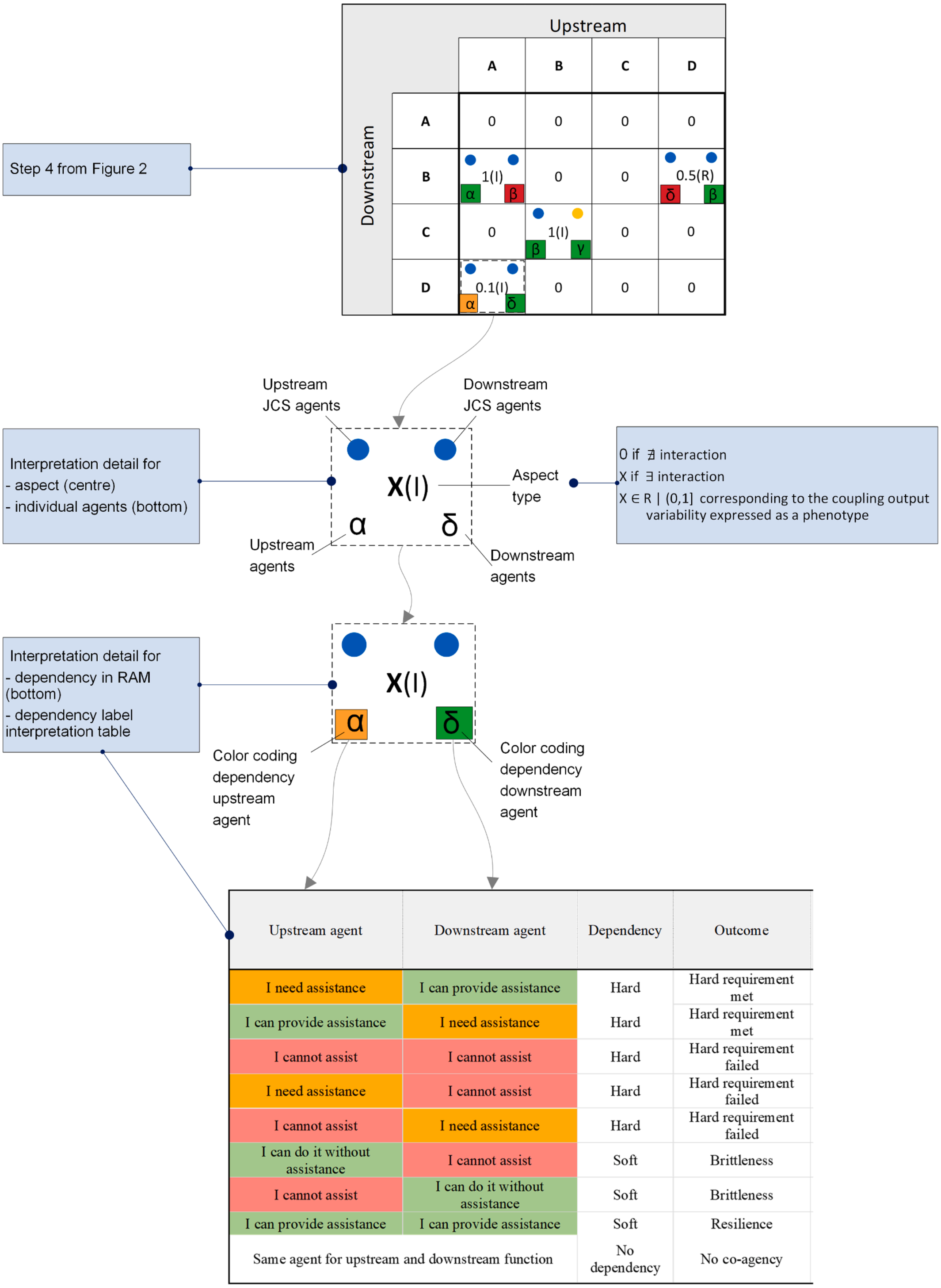
	A	B	C	D
A	0	0	0	0
B	1(I) α β	0	0	1(R) δ β
C	0	1(I) β γ	0	0
D	1(I) α δ	0	0	0

	A	B	C	D
A	0	0	0	0
B	0(I) α β		0	0 δ β
C	0	1(I) β γ	0	0
D	0.1(I) α δ	0	0	0

B	0(I) α β	0	0	0 δ β

Labels	Description
Observability	
Predictability	
Directabilty	

Fig. 2. Five-step methodology.



	A	B	C	D
A	0	0	0	0
B	● ● 1(I) α β	0	0	● ● 0.5(R) δ β
C	0	● ● 1(I) β γ	0	0
D	● ● 0.1(I) α δ	0	0	0

Upstream agent	Downstream agent	Dependency	Outcome
I need assistance	I can provide assistance	Hard	Hard requirement met
I can provide assistance	I need assistance	Hard	Hard requirement met
I cannot assist	I cannot assist	Hard	Hard requirement failed
I need assistance	I cannot assist	Hard	Hard requirement failed
I cannot assist	I need assistance	Hard	Hard requirement failed
I can do it without assistance	I cannot assist	Soft	Brittleness
I cannot assist	I can do it without assistance	Soft	Brittleness
I can provide assistance	I can provide assistance	Soft	Resilience
Same agent for upstream and downstream function		No dependency	No co-agency

Fig. 3. Interpretation legend for steps 3 and 4 of preceding Fig. 2. (Guides interpretation of matrix cells).

functional inter-agents exchanges, as the expression of systemic co-agent interactions (Adriaensen et al., 2022). This modelling approach permits the inclusion of functions executed by individuals, as well as functions carried out by joint cognitive agents, all of which can be depicted across various levels of abstraction (Patriarca et al., 2017).

3.3. FRAM-IA framework

Whereas FRAM is used as a first step in the framework to model the tasks in the socio-technical as a whole or to produce sub-models of specific problem spaces, IA is applied to the individual exchanges between any two agents, in other words, the instances of co-agency. The first steps of the framework are therefore entirely devoted to the FRAM modelling. Initially, by building a FRAM model with the traditional hexagon-type representation, with subsequent transformation into a Resilience Analysis Matrix representation (RAM), as applied in previous studies (Lundberg and Woltjer, 2013; Patriarca et al., 2018b). The RAM matrix cells (see Fig. 2) represent the output couplings from the upstream function (row labels) connected to an aspect of a subsequent downstream function (column labels). The RAM allows to systematically assess dependencies based on the relative capacities (as defined in Section 3.2) of the upstream and downstream agent. Fig. 2 illustrates the different framework steps, as described below Fig. 2.

The methodology is developed according the following steps (see Adriaensen et al., 2022):

Step 1 – Initial Socio-Technical Modelling

Develop a FRAM model of the work system, resulting from a list of functions derived from document analysis in line with a Work-as-Imagined (WAI) perspective.

Step 2 - Selection of the Problem Space

Step 2a - Selection of sub-models is performed, based on informants' feedback and observations from a WAD perspective, describing how work is routinely performed in practice.

Step 2b - Tasks-as-Desired (TAD) are introduced as a new notion in this research (see Section 3.1) depicting desirable but absent system features resulting from the operational informants in this study. TADs are represented by red bordered hexagon functions in step 2 of Fig. 2. Both upstream and downstream couplings of TAD functions are encircled by red markings because the couplings are not present in the work-as-observed, because they are derived from desirable but absent functions. This step concludes the first requirement in the traditional FRAM methodology, being the description of the functions.

Step 2c – Transform the traditional FRAM model in a RAM presentation. In the RAM the TAD functions are now represented by the red-square-bordered functions in the top-row and their relative downstream couplings are marked by red circles just as in the traditional FRAM representation (due to the RAM logic, inherently displayed in the cells in the columns straight below their relative top row red-squared functions in the RAM).

Step 2d – Assign performance phenotypes in terms of timing and precision, which starts the second requirement of the FRAM methodology, being the identification of performance variability. For phenotypes that are not performed at all, the value 0 is assigned and red circles are used once more to indicate the absence of couplings.

Step 3 – Agent Assignment

Assign the individual agents and JCS agents performing the functions, based on the FRAM model of the work system as a whole from Step 1. See Fig. 3 for more details.

Step 4 – Interdependence Analysis - Dependency application

Step 4a – Assign dependencies to individual inter-agent exchanges, as the expression of co-agency, according to Fig. 3. Dependencies are based on theoretical performance variability and updated according to observed performance variability (WAD).

Step 4b Represent critical functional propagation (optional step) by connecting the propagation with arrows between couplings. The resulting impact of propagation on dependencies is subsequently re-assessed. This closes the third phase of the traditional FRAM methodology requirement, being the aggregation of performance variability.

Fig. 3 provides an extended legend enabling to perform steps 3 and 4 of the five-step methodology in Fig. 2.

Step 5 - Interdependence Analysis - OPD Label Application.

Assign and discuss OPD labels for all failed hard requirements (see the table insert at the bottom of Fig. 3, i.e. orange-red or red-red pairs and the text explanation below it) identified in step 4. (also, see Adriaensen et al., 2022 for theoretical development):

Only inter-agent exchanges are assessed. Intra-changes, which essentially do not represent co-agency, can be ignored for this part of the FRAM analysis. They are not excluded from the analysis, but their effect is considered through propagation instead. In the traditional FRAM methodology, this finally supports the management of functional resonance or the identification of its consequences (Hollnagel, 2012). The result is now a systematic analysis of which inter-agent capacities need further attention.

The Greek letters α, β, γ, and δ represent the different agents (e.g. robot agent, human operator, etc.) adjacent to a specific function in the traditional FRAM model and are repeated at the bottom of the matrix cells in Fig. 3. The cell represents the coupling, whereby the left Greek letter represents the upstream agent, and the right Greek letter represents the downstream agent.

Table 1
Interpretation of OPD Principles (Johnson et al., 2014).

OPD principles	Description	Can take the following forms
Observability O	GENERAL: real-time observability of the outputs from socio-technical agents (human/robot/ warehouse mgmt system elements): transmitting and receiving current information, signals, status, knowledge of the system, team, task, and environment (e.g. robot indication, agent positions, product identifier)	reveal status reveal intention interpretation of signals observable transformation of information across media observable transmission of physical states and forces monitoring actions
Predictability P	the degree to which socio-technical agents (human or autonomous robot agents) can rely on outcomes when considering their own actions, including the degree to which a system predicts future states or reveals future system status / or reveals the boundaries of failure or critical system performance before these boundaries are actually reached by the outputs of the agents or the parameters they produce (announcement of available orders, closest robot announcement)	a priori agreements the use of models synchronization of actions use of time-projected information cues that support the prediction of boundary conditions for users (guidance, suggestions, warnings)*
Directability D	the ability to direct behaviour and to have one's behaviour directed from (socio-technical agents) human, autonomous robot agents, or warehouse system elements, including the ability to direct physical control (obstacle stops navigation), processes (e.g. reduce flow), agents (physically redirect robot), or system states (e.g. emergency stop)	task allocation role assignment cues that support redirection of actions (guidance, suggestions, warnings)* control transfer corrective actions (incl. outputs of monitoring actions)

* appears twice depending on the fact if it provides information or redirects agents.

The term JCS agent from Fig. 3 is used to indicate a functional cluster in which different agents work together to perform a specific functional purpose in co-agent relationships. JCS agents therefore represent a socio-technical purpose. Imagine for example the three blue functions of JCS(I) to be a cluster of functions where three individual agents α, β, and δ jointly facilitate the navigation in the robot ecosystem. The left-side coloured dot represents the downstream and the right-side coloured dot represents the upstream JCS agent in relation to the coupling from the displayed matrix cell. When left and right coloured dots have identical colours, down- and upstream functions belong to the same JCS agent or the same functional cluster. Note that other JCS agent clustering of related functions can be selected, based on the scope and problem space of the analysis.

At the centre of each matrix element, the output variability is expressed as a number representing FRAM phenotype attributes: 0 if $\nexists$ interaction; X if $\exists$ interaction, with, $X \in \mathbb{R} \mid (0,1]$, with 1 being the optimal output gradually decreasing to 0 as the absence of the output and suboptimal performance anywhere in between. Next to the attribute, the first letter of the FRAM aspect type that connects two functions (e.g. 'I' for Input and 'R' for Resource) is displayed in brackets in the RAM representation.

The next step, depicted by step 4 in Fig. 2 will assign the dependencies from IA with the help of the colour-dependency table at the bottom of Fig. 3. An orange-coloured field means an agent requires

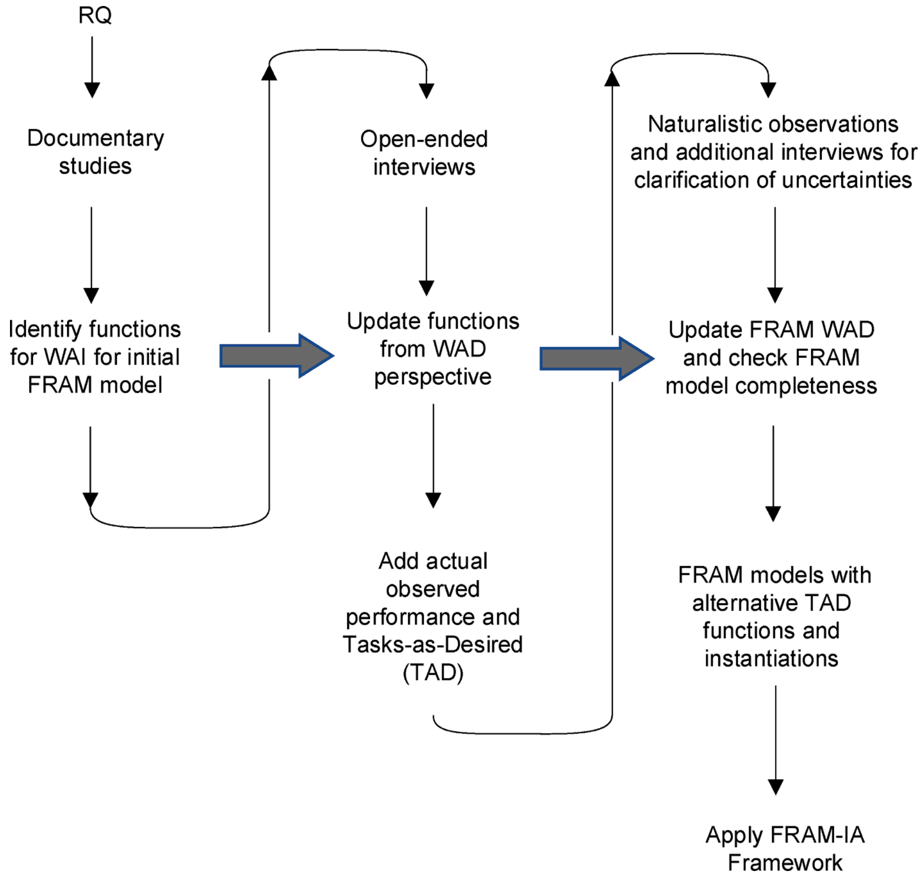


Fig. 4. Data management process followed in the research.

assistance, whereas a green-coloured field means that an agent can provide assistance. Dependencies involving red colours imply that at least one agent cannot provide assistance. Combinations with red-coloured fields are critical if the requiring agent lacks the capacity to perform the function without the assistance of a supporting agent, resulting in three possible ways by which a hard requirement can fail (see the table insert at the bottom of Fig. 3). Failed hard requirements are defined by the fact that either a requiring agent is not assisted, or both agents are unable to perform a function, and will therefore receive a further qualitative evaluation by examining which OPD principles are involved. Guidance for the OPD interpretation can be found in Table 1.

A coupling is always the aspect which is produced as the output from the upstream function and the OPD label is assigned from the perspective of the receiving < downstream function >. The following guiding phrase can be used when determining the OPD label: "*What type of label (O, P, or D) is produced at the level of the |coupling| when its state or performance is received by its subsequent < downstream function>?*".

By applying the colour coding from Fig. 3 to the RAM representation, the analyst can see in a glance which inter-agent exchanges have critical dependencies. Note that intra-agent exchanges (two agents with the same Greek letter) have no dependency assigned to them, simply because co-agency is not present. Note that nevertheless their performance still plays a role in the propagation of the FRAM model.

The framework foresees to display critical propagation on the RAM representation (optionally), to assess the consequent impact on downstream dependencies.

The only missing step is to provide values for performance and timing phenotypes typically a three-step scale. The value 1 is used for optimal phenotypes, whereas values lower than 1 (excluding 0) can be assigned to forms of suboptimal performance and timing. The value 0 has the additional meaning that the output in relation to the downstream function is absent in a certain instantiation. The (traditional) FRAM allows to either use the phenotypes as simple throughputs into the subsequent downstream function, or use the most optimal phenotype for activating the next downstream function (e.g. in case the function represents a selective decision or negotiation).

3.4. Data management process and knowledge elicitation

The case study data was used to build a FRAM model about the work system. Internal software architecture from monitoring systems or cobot interfaces has been considered out of scope (and thus modelled as black box information), keeping the focus on the functional interactions from operators, robots, system outputs and supervisors.

The research method applied an iterative data gathering process to proceed from a FRAM model, initially based on a normative WAI understanding of the system, as conceived from a theoretical design perspective, towards a descriptive WAD. Taks-as-Desired (TAD) were added as FRAM functions that are identified as 'absent' in the observer WAD, but functionally required to overcome current operational issues. The data management process of the research is displayed in Fig. 4.

Document studies have been carried out to gain an initial understanding of the robot system under analysis. Examined documents included user manuals, system integration documents, and operator training material. At this stage, main actors were assigned and HTA reasoning was applied to the functions derived from consulted desktop data. After the desktop phase, one researcher was given an introduction training to learn the operational circumstances of both traditional and robot-assisted warehouse distribution (duration 90 mins) concerning the induction, order picking and packing processes. Due to the Covid-19 pandemic restrictions in workplaces, physical presence in the warehouse was partially replaced by webcam-supported training, whereby a company trainer showed the different operational steps and interface inputs on the warehouse floor. After the subsequent initial modelling of

Table 2
Performance phenotype assignment applied to step 2 from Fig. 2.

Phenotype value	Description
0	coupling is absent because upstream function is absent upstream function is present, but the individual coupling is structurally/functionally absentcoupling is not performed at all in a specific instantiation
0.5	the aspect from the coupling may or may not be executed, or is suboptimal with an undesirable impact on performance and/or timing
1	optimal performance and timing of the aspect (either theoretical or derived from actual observations)

functions and agents, open-ended interviews were conducted online with operators (n = 6), and supervisors/managers (n = 5) to elicit possible operational issues (total of 7 h). This was followed by naturalistic observations in the robot-assisted warehouse processes (total of 6 h) and observations of the traditional warehouse processes (total of 2 h). The observations included the possibility of asking questions to operators and supervisors at work. After the observations and the iterative approach of updating FRAM models in line with WAD observations, two additional interviews were planned with managers (n = 2, total of 2 h) to check uncertainties and verify assumptions, to be able to close the FRAM models and include instantiations and TAD functions. Finally, several case study task scenarios, based on reported criticalities by informants, were selected and further processed by the FRAM-IA framework for the case study examples presented (Section 5) in this paper.

The five-step methodology as presented in Fig. 2 from Section 3.3 was specialized with minor adjustments. Although in theory, the framework foresees to assign phenotypes in terms of both performance and timing variability, the field of application has been restricted to only two values (in addition to 0, where relevant), as presented in Table 2, and only concerning performance levels.

The value 1 is assigned to optimal performance which meets the theoretical design perspective, whereas the value 0.5 is assigned to functions that are known with certainty to be suboptimal or from which the performance may or may not be optimal, derived from observations and interviews.

4. Case study description

The warehouse distribution process is typically divided into an induction, picking and packing phase. In addition to a WMS also found in non-robot assisted systems, the robot ecosystem here comprises an additional RCS, which will be responsible for task distribution and robot route optimisation. The human operators have the freedom to cover the shortest distance to the nearest robot available (see Fig. 5). This increases system efficiency as operators can perform tasks more efficiently without losing time covering long routes when navigating between picking locations (Lambrechts et al., 2021).

Induction, picking and packing cycles are not idealised closed systems. In reality, supervisors monitor and manage process conflicts, time progress and dynamic resource availabilities. This is depicted by the control-feedback loops with accompanying text-boxed arrows from supervisors (see Fig. 5) to the operational process and back. The supervisors' monitoring stations are physically co-located in the same warehouse floor as the operations.

In the FRAM representation of the socio-technical system, we will adhere to the colour coding presented in Fig. 6 with green, yellow and red for the respective JCS agents (functional clusters) of Induction, Picking, and Packing, while blue is used for Supervision and grey for Navigation JCS agents, and finally purple for emergent conditions and

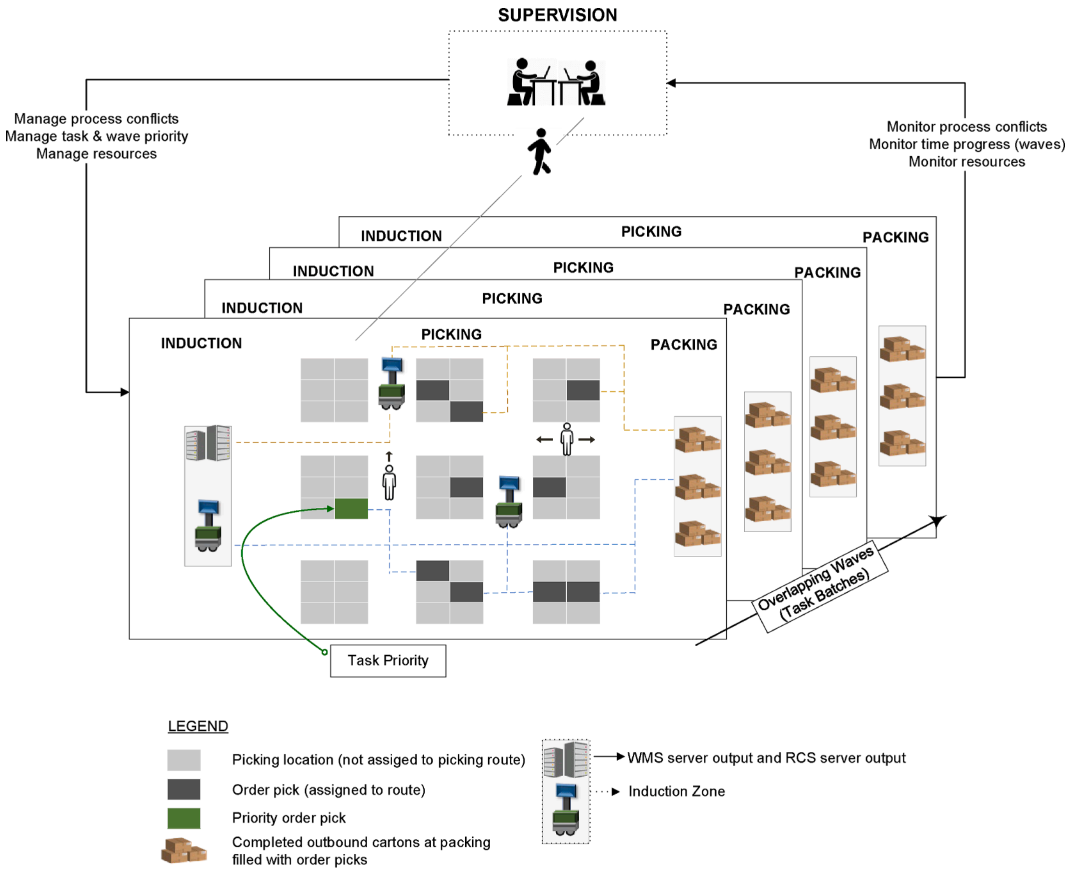


Fig. 5. Schematic layout of warehouse picking process performed by human operators and autonomous warehouse robots (with supervisor intervention).

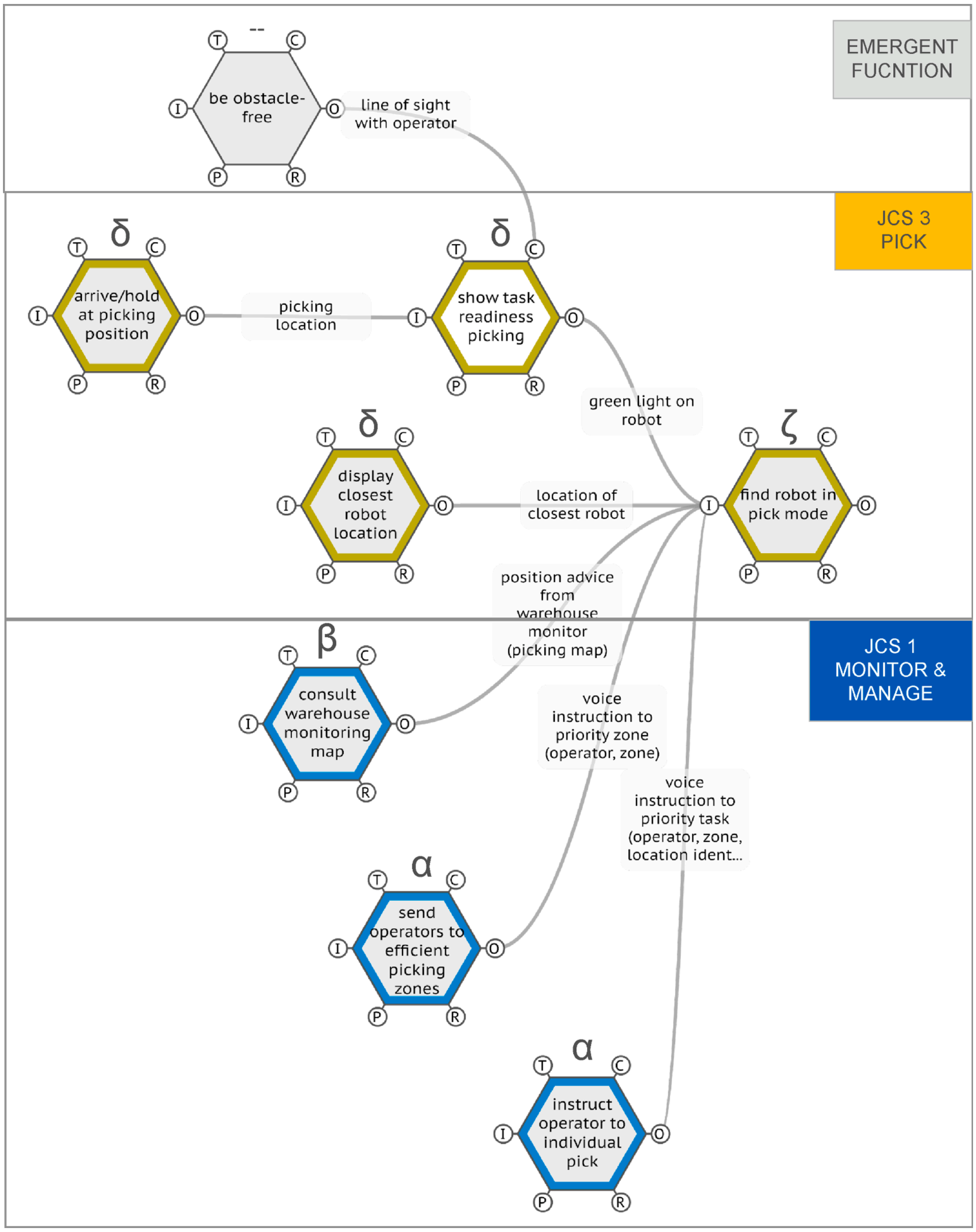


Fig. 6. Legend of JCS agents (functional clusters) and individual agents.

organisational tasks. The JCS agents represent a logical means-end hierarchy (Vicente, 1999) and correspond to the operational subdivision of the warehouse distribution process. Contrarily, the Greek letters correspond to the individual agents. Note that the induction, picking, and packing, all performed by human operators are represented by different Greek letter identifiers (γ, ζ, ε), as these specific tasks are performed by distinct groups of operators, whereas the same robots (δ) covering all these tasks in sequence are involved in any of three different JCS agents (green, yellow, red).

We will adhere to the following notation system, in which < functions > are placed between two opposed direction signs (< >) and | coupling| items are placed between two vertical lines (| |).

5. Results

The results section will cover different case study highlights, each with a different focus. The first fragment (Section 5.1) highlights an example of the resonance potential of the robot ecosystem design with the working environment. The second fragment (Section 5.2) discusses the interaction potential from an undesirable functional resonance leading to an unsafe outcome.

5.1. Case study highlight #1: Find a robot in pick mode

There are several ways to find a robot in pick mode, from which some options involve more agents than just the robot and the operator. This case study will study the possibilities to find a robot in pick mode from a multi-agent socio-technical perspective by the FRAM analysis below (Fig. 7). Note that the lack of an agent identifier, noted as (–), above the function < be obstacle free > simply means this is an agentless function in terms of an agent with a purpose, but instead emerges from the dynamic conditions shaped by the working environment.

The primary means for the picking operator (ζ) to find a robot (δ) is by the green indication light (Fig. 8) on the robot and in the FRAM model represented by < show task readiness picking >. This indication is shown by the robot when it is waiting to be assisted to complete an

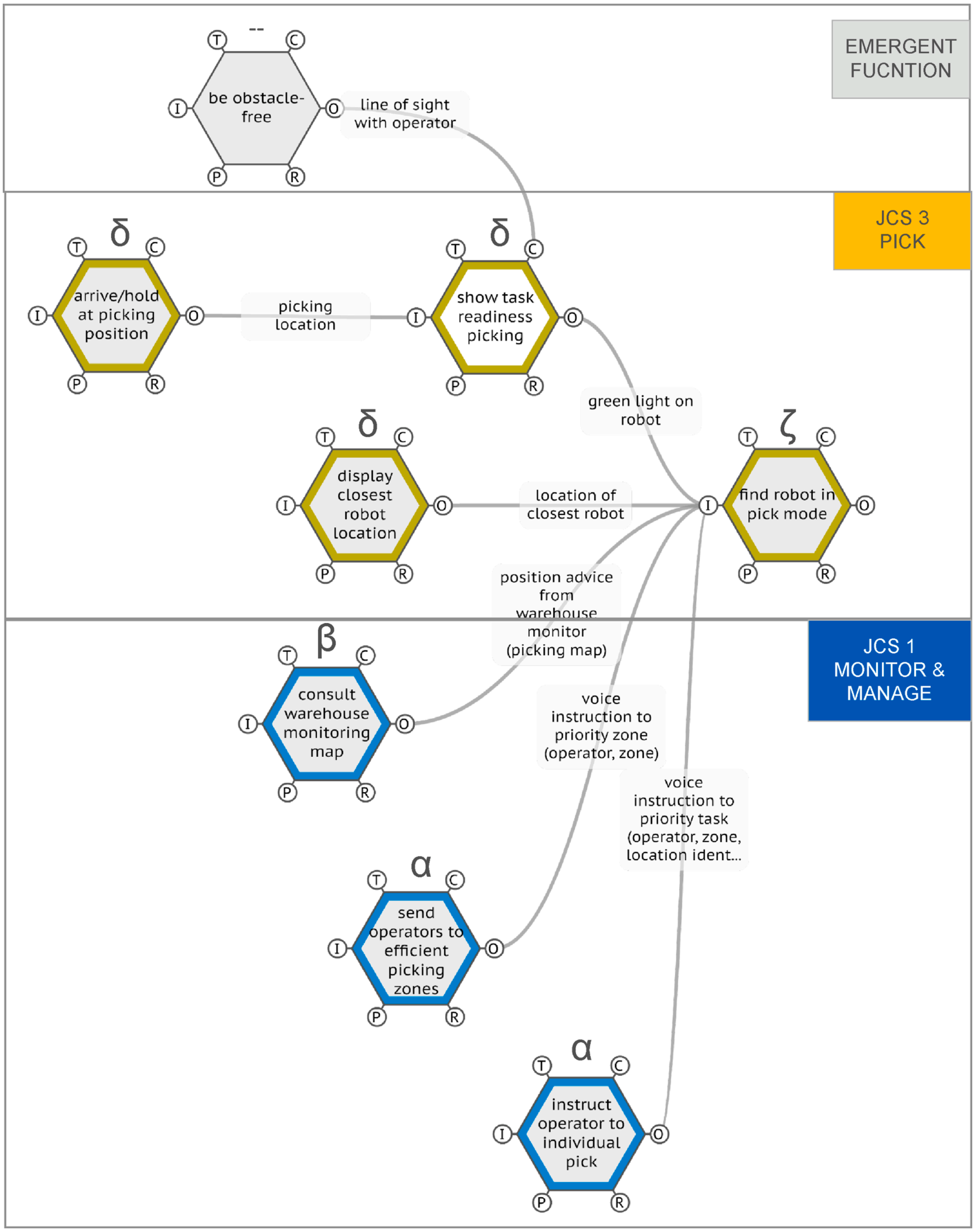


Fig. 7. FRAM model and RAM representation of the different upstream functions of the function < find a robot in pick mode> (For interpretation of codes and matrix elements, check Fig. 3).

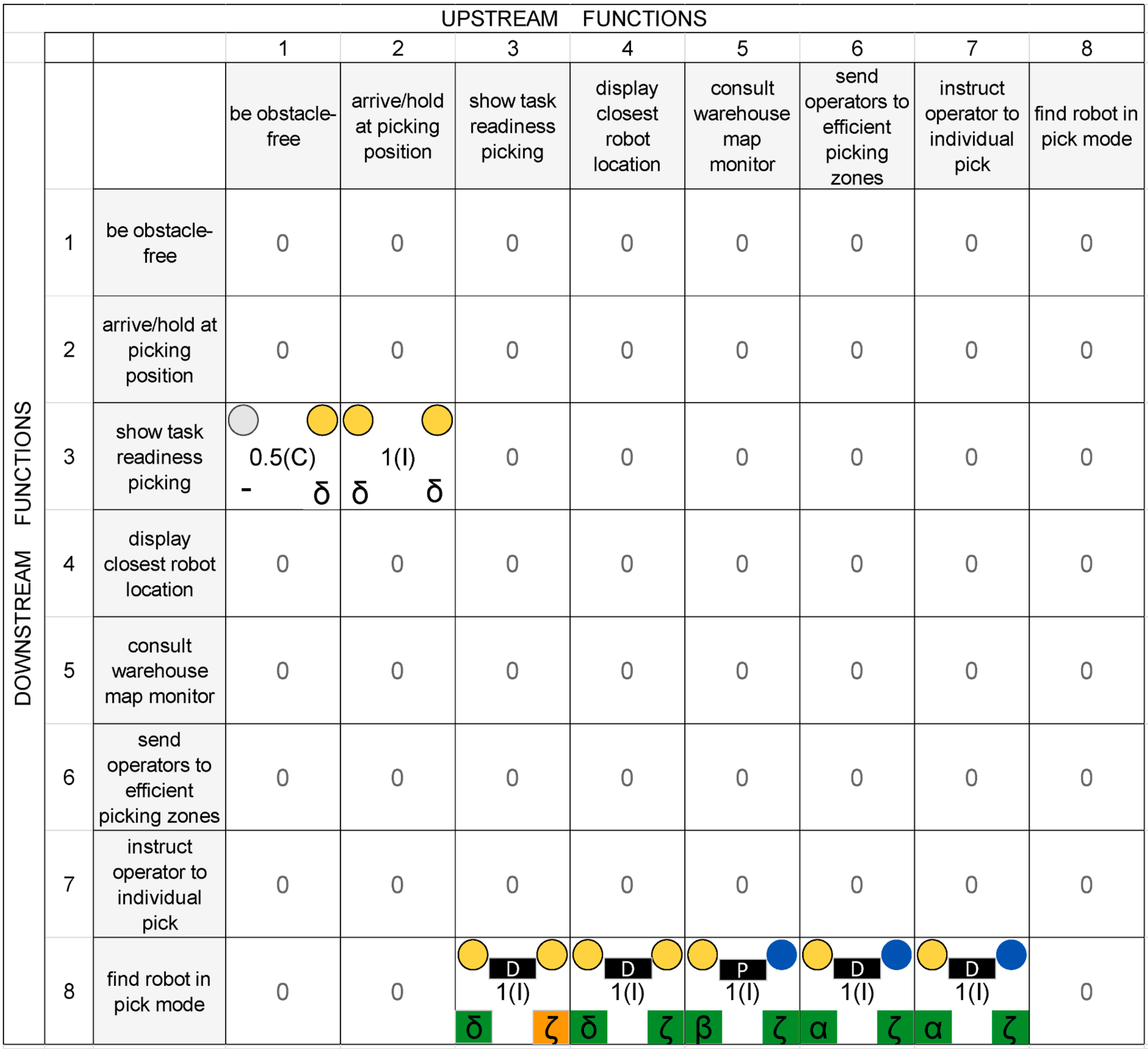
order pick.

In addition to the green indication < show task readiness picking>, there are several other socio-technical possibilities for the operator to find a robot in pick mode, represented by the FRAM model from Fig. 7.

One additional option is < display closest location>, which refers to the robot's functionality by which at the finish of every preceding picking task, the warehouse robot's interface (ζ) will indicate the next closest available waiting robot that requires operator to assist. < Consult warehouse monitoring map> (β) on the other hand refers to the opportunity for the operator to consult a warehouse picking map with pick-ready robot locations (green dots on the monitor in Fig. 8). Together with the green robot indication (Fig. 8), the examples above present two more options in which the operator can verify the availability of a pick-ready robot. The operator perspective is represented in Fig. 8.

The remaining two options in the FRAM model from Fig. 7 that provide an input to the function < find a robot in pick mode > show possibilities in which the supervisor (α) redirects the operators to efficient picking zones (e.g. when few or no operators are available in zones with high robot activity), or < instruct operators to an individual pick>, which is a way for supervisors to prioritise individual pick orders.

The accompanying RAM representation displays the coupling between < show task readiness picking > and the < find robot in pick mode>, which produces the coupling in matrix cell |3-8|, |green light on robot|. The green-orange colour coding shows the dependency pair in which the operator needs a visual status signal from the robot to indicating that the robot is ready to pick, and the robot provides the signal to



			UPSTREAM FUNCTIONS							
			1	2	3	4	5	6	7	8
			be obstacle-free	arrive/hold at picking position	show task readiness picking	display closest robot location	consult warehouse map monitor	send operators to efficient picking zones	instruct operator to individual pick	find robot in pick mode
DOWNSTREAM FUNCTIONS	1	be obstacle-free	0	0	0	0	0	0	0	0
	2	arrive/hold at picking position	0	0	0	0	0	0	0	0
	3	show task readiness picking	⚪ 🟡 0.5(C) - δ	🟡 🟡 1(I) δ δ	0	0	0	0	0	0
	4	display closest robot location	0	0	0	0	0	0	0	0
	5	consult warehouse map monitor	0	0	0	0	0	0	0	0
	6	send operators to efficient picking zones	0	0	0	0	0	0	0	0
	7	instruct operator to individual pick	0	0	0	0	0	0	0	0
	8	find robot in pick mode	0	0	🟡 D 🟡 1(I) δ ζ	🟡 D 🟡 1(I) δ ζ	🟡 P 🔵 1(I) β ζ	🟡 D 🔵 1(I) α ζ	🟡 D 🔵 1(I) α ζ	0

Fig. 7. (*continued*).

enable the task of finding a robot pick mode. The RAM shows the four additional alternative functions right of matrix cell |3-8| for the operator to recognise or find a task-ready robot (Fig. 7) with the help of other system agents (α, β, δ). These green-green pairs inter-agent pairs indicate that these couplings provide redundant dependency options in addition to |3-8|, which can therefore be labelled as soft dependencies. Even in those cases where such additional position retrieval resources are used, the robot's task status by a visual signal remains to be perceived by the picking operator as a final confirmation (green-orange hard requirement).

After Steps 1–4 from the five-step methodology have now been performed by the previous stages of the analysis, the last step consists of describing the OPD labels, but only for those functions performed by different individual agents upstream and downstream of the coupling (i.e. co-agency). The OPD labels for inter-agent functions can be found in the RAM of Fig. 7 and are described in Table 3 below. Since there are no criticalities (e.g. failed hard dependencies) identified, the table in this example mainly displays requirements that provide resilient (positive) properties to the system.

The mix of Directability and Predictability principles and the way these principles are deployed at different points in the operational demands increase the system efficiency. On the simplest level operators can react to the instructions (Directability) immediately found on the robots (indication, position advice about next task on interface); augment Predictability by looking at monitors to retrieve robots outside their line of sight, and; and when required ultimately be overruled by the voice instructions (Directability) of supervisors which have more overview of the operational demands and emerging challenges, presenting and combining different levels of control.

5.2. *Case study highlight #2: Safety separation*

The safety separation highlight from this second example can be analysed with a FRAM model, to which the observed performance variability from a particular instantiation of the model will be added. The instantiation is based on an incident that occurred in the warehouse but did not involve any human operators.

The robot safety separation can be considered to have two lines of defence: (i) the first one is based on the fact that the warehouse robots have an internalised map with permanent obstacles to be avoided by the robots during navigation. For dynamic obstacles, including human operators, (ii) the second line of defence consists of a robot-installed LIDAR sensor which will make the robot alter its direction or ultimately stop its navigation in reaction to all static or moving obstacles within a certain scanning range. None of the interviewed participants could report a human-robot or obstacle-robot collision, and all informants showed a

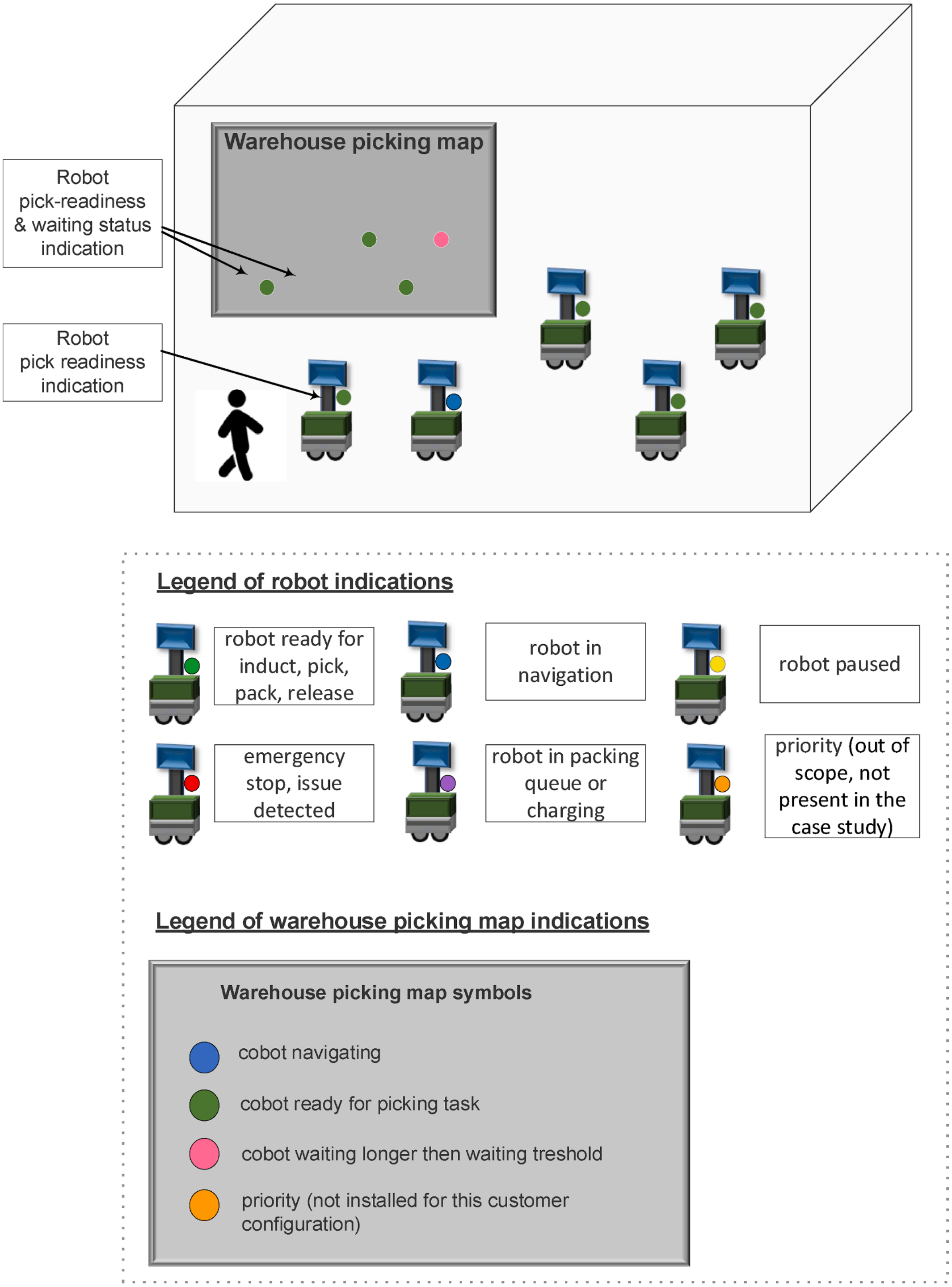


Fig. 8. Warehouse floor view of robot task-readiness on robot and warehouse picking map.

high trust in its demonstrated safety separation capabilities, even in response to swift movements of human operators. This indicates proper robot safety separation performance under operational conditions. Note that the two lines of defence, with a standard avoidance strategy for known obstacles, also create more performant and fluent navigation, compared to just having a single line of defence to only avoiding obstacles based on a LIDAR sensor.

When warehouse robots experience momentarily navigation loss or network connection issues, bots will stop navigating for safety reasons, and produce a visual signal to indicate that the robot needs assistance from a human operator to perform a reset procedure. Calibrating or re-calibrating the robot's position relative to the warehouse map consists of de-activating the robot and facing a QR-reader installed on the robot to specific QR-coded navigation reset points on the warehouse racks. A similar technique is described in (Zhang et al., 2015). Fig. 9 shows the FRAM model representation of the respective functions involved.

The previously assigned JCS agent 5 for navigation (grey) is further divided in this particular example in (i) sub-JCS agent 5a related to the LIDAR sensor defence, including its autonomous safety separation (light grey); (ii) sub-JCS agent 5b for navigation functions performed during the operational induct-pick-pack cycle (mid-grey); and, (iii) sub-JCS agent 5c for functions that relate to the internalised warehouse map

Table 3
OPD labels and description applied to the inter-agent functions of Fig. 7.

|coupling position| (phenotype)	Upstream agent function and capacity colour	Downstream agent function and capacity colour	Dependency/ Outcome	OPD label	Description
|green light on robot| |3-8| (1)	🟩 <show task readiness picking>	🟧 <find robot in pick mode>	hard/met	directabilty	Downstream agent requires assistance to know which robot is ready to perform a task. Upstream agent does more than providing Observability (revealing status by green indication as a task readiness signal) because it will additionally direct the behaviour of any available operator. Although intuitively, an indication just seems to reveal status, in this case it rather provides an instruction
|location of closest robot| |4-8| (1)	🟩 <display closest robot location>	🟩 <find robot in pick mode>	soft/resilient	directabilty	Resilient dependency (additional support to |3-8| not strictly required except to increase efficiency) supports directability options because it provides guidance about other robots' task readiness status. The robot from a previous task advises a human operator where the next task-ready robot can be found. Even more than predictability, this indication provides directability, because our warehouse observations confirmed that this guidance will redirect the operators navigation towards the closest robot
|position advice from warehouse monitor| |5-8| (1)	🟩 <consult warehouse map monitor>	🟩 <find robot in pick mode>	soft/resilient	predictability	Resilient dependency (additional support to |3-8| not strictly required except to increase efficiency) supports predictability by providing a warehouse picking map with task indications of available robots and their locations. It provides more than just revealing status because the operator is able to predict zones with more activity than others
|voice instruction to priority zone| |6-8| (1)	🟩 <send operators to efficient picking zones>	🟩 <find robot in pick mode>	soft/resilient	directability	Two supervisor options exist to redirect operator towards robots in targeted zones. (Subsequent observation of visual task-ready robot of green indication light by operator when in robot proximity is the logical consequence of this redirection)
|voice instruction to priority zone| |7-8| (1)	🟩 <instruct operator to individual pick>	🟩 <find robot in pick mode>	soft/resilient	directability	

navigation (dark grey).

An instantiation of the FRAM model from which the sequence of events is displayed in Fig. 11 shows that at one particular moment (t1) the warehouse rack layout was restructured, but the required change of QR codes on the warehouse racks were not changed accordingly. Consequently, (t2) the robot was not correctly calibrated during a QR-reset procedure. Thereafter, the robot, (t3) based on incorrect calibration, (t4) navigated to an open staircase door, which was not recognised, simply because an open door does not create an obstacle, and remains a non-signal; and, (t5) finally the stair was not recognised because obstacles or holes in the ground are not noticed by the LIDAR sensor, (t6) simply because it is not designed for scanning below the robot, once again producing a non-issue. The robot consequently drove off some stairs with no humans in the vicinity. At the time of the instantiation, the Covid-19 pandemic triggered an operational process to increase ventilation by opening work floor doors. What was decided to actually be a safety measure, did in this instantiation not create a safe obstacle for the LIDAR sensor to trigger its second line of safety separation. This created a suitable example to examine the incident scenario with a FRAM analysis, as the scenario as a whole emerges from system resonance and propagation of undesirable performance variability, and not from problems of individual human reliability or inadequate robot design.

The propagation potential in the FRAM model can be interpreted accordingly. The phenotypes values produced in the RAM representation are based on the observed performance phenotypes with 0.5, meaning in this case that the functions were not always performed as

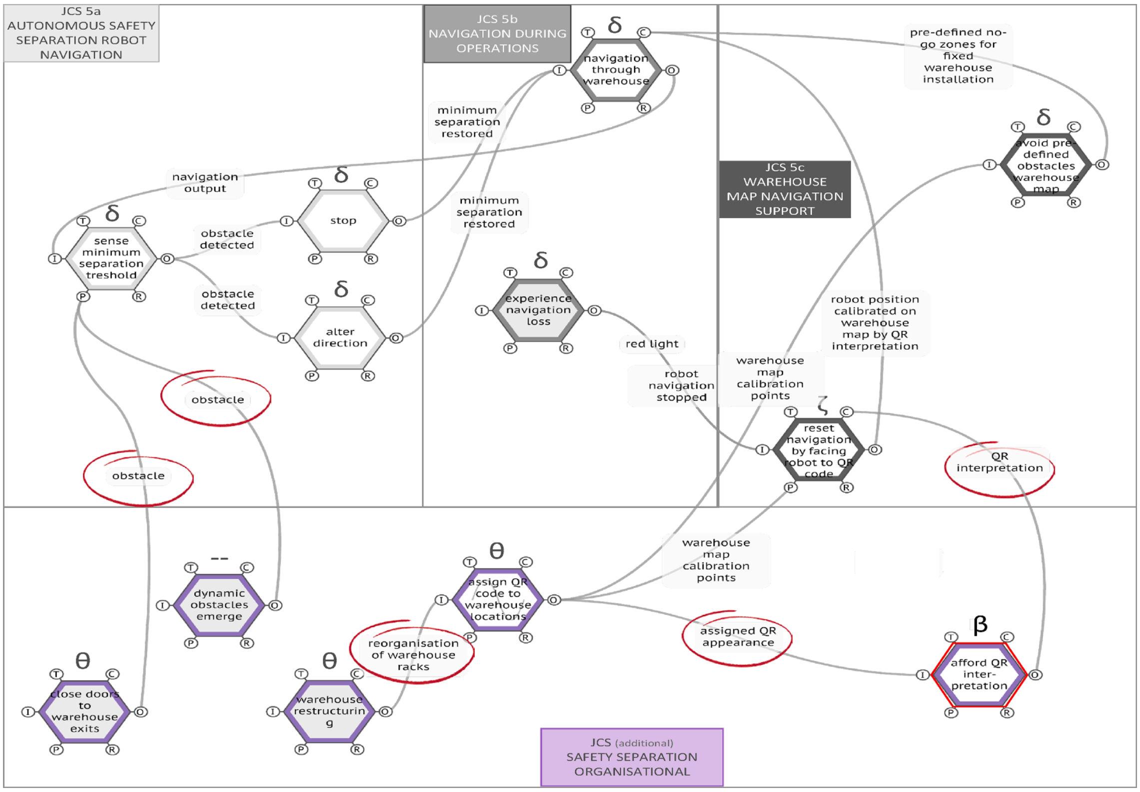


Fig. 9. FRAM model for functions involved in safety separation with two lines of defence.

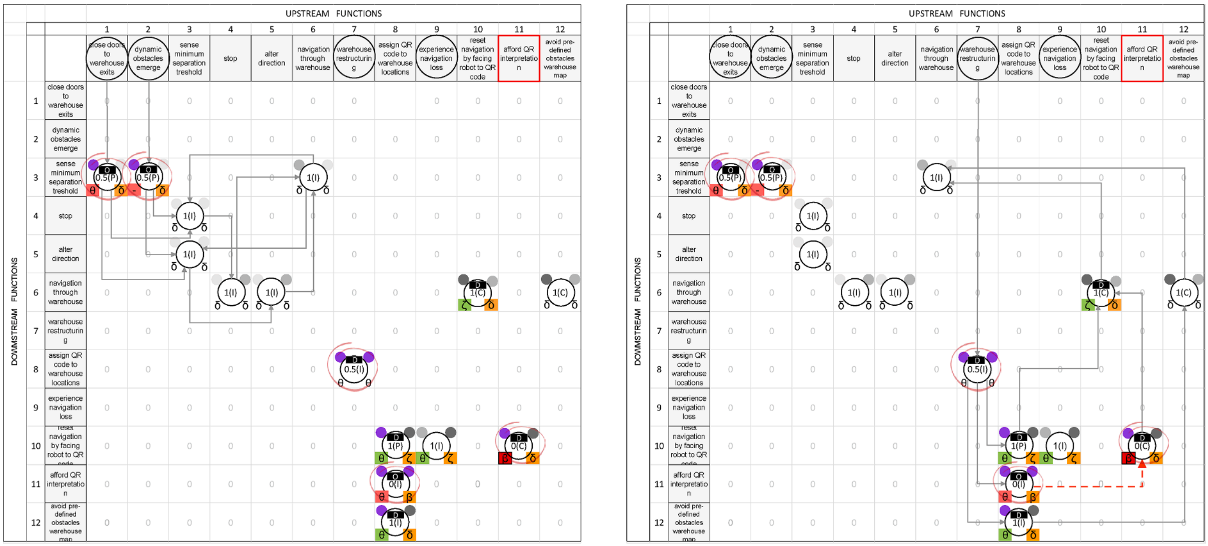


Fig. 10. RAM representation of Fig. 9, with two propagation starting from boundary functions 1 and 2 (left), and 7 (right).

expected. The grey arrows represent the propagation potential. The propagation downstream from a function in a RAM table can be read as follows (for a full explanantion of the propagation algorithm, see Patriarca et al., 2018b, pp. 8–9):

(i) first select the function at which the investigation the propagation of the analysis will start (e.g. because of an observed critical phenotype, or to start at a boundary function) and circle the corresponding function in the header row of the RAM representation;

(ii) connect the circled starting function from the top row to its downstream coupling in the column below this circled function by a straight arrow until that row of the downstream function, marking the first coupling. Circle the position of the coupling in the RAM;

(iii) copy the row number of this coupling, use the row number, and use the row number as the next column number (same function name) and again follow the column downwards until the row position of the next downstream function (single or multiple downstream functions). Mark the position of this subsequent coupling and connect an arrow from the coupling in (ii) to the

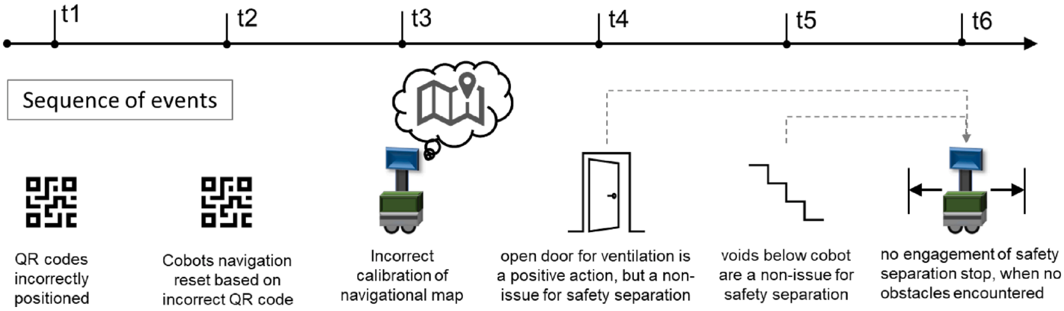


Fig. 11. Sequence of events illustration.

coupling from this step. Alternatively connect multiple arrows if multiple downstream coupling are identified after step (ii);

(iv) re-iterate the process from step (ii and iii) by connecting couplings accordingly, until;

(v) a stop condition can be derived, which either is a function for which no output coupling exists or if a closed-loop is encountered.

Note that assessing the propagation is not a novel addition for the FRAM-IA framework presented in this paper. It is already a part of traditional FRAM and belongs to FRAM's methodological step of aggregating the functional resonance (Hollnagel, 2012). In the example as presented in Fig. 10, the propagation can be started at each of the four *black*-circled starting functions (table header) with no upstream connections, as these present the boundary functions and typically serve as an entry point for the analysis. Fig. 10 presents two propagation potentials that ultimately converge in the same coupling |navigation output| (|6-3|). The principle of functional resonance provides the analyst with the possibility to discriminate between positive functional resonance, which according to the FRAM should be amplified, and negative performance propagation, which should be dampened. Negative functional resonance originates from two mechanisms, (i) the downstream propagation of negative resonance and (ii) the potential for multiple negative or even positive propagations to create a conflict when received by a single function. Positive functional resonance happens when either the system is functionally designed to fulfil its goals (i.e. functions and couplings are present and fulfil the functional requirements), and when the presence of negative resonance can be neutralized (e.g. due to the presence of a control).

Fig. 10 shows several entry point options for negative performance to propagate downwards to the central function < navigation through warehouse>, representing the action of safe and obstacle-free navigation through the warehouse. The critical couplings propagations (absent or not observed) are additionally marked with a red circle and are based on worst case observations (aligned with Fig. 3).

(i) Negative propagation #1 and #2 (see Fig. 10, left): |obstacle| emerging from < dynamic obstacles emerge > and < close doors to warehouse exits>: as the robot's sensor is not able to detect a void such as a downward staircase below its scanning height, two negative variabilities, both in this case obstacles (in specific voids which are not sensed as present) remain non-issues for the robot (indicated with phenotype 0.5 and marked with a red circle as a criticality). This will negatively propagate to ultimately reach the coupling |navigation output| (|6-3|).

(ii) Negative propagation #3 (see Fig. 10, right): worst case outcome from < warehouse restructuring > Although the manufacturer will obviously foresee that QR codes need to be re-assigned when the warehouse layout is changed, it is equally understandable that at one point in time, this action is overlooked due to several possible reasons (e.g. forgetfulness, organisational fragmentation of processes, miscommunication, etc). The phenotype 0.5 indicates that on rare occasions QR position codes are not correct following a warehouse restructuring, although they will be followed on many other occasions. This negative potential for variability will propagate through several functions to ultimately reach the coupling |navigation output| (|6-3|), the output from the central function < navigate through warehouse>

(iii) Absence of positive propagation: The TAD function < afford QR interpretation> (red squared), and the consequent opportunity to detect correct |QR code interpretation| during recalibration, is a desired functional resonance that is missing by design (dotted red arrow). The missing function indicates the fact that a human operator is simply not able to interpret a QR code. If the QR code or an alternative method would be meaningful to the operator, it would act as a control for < reset navigation by facing robot to QR > and the operator would not reset the navigation. The Observability principle of the QR interpretation, or the absence thereof, creates the pivotal function that could neutralise the remaining negative propagation potentials and prevent the undesirable outcome. Unlike many negative propagations from which the conditions are sometimes hard to foresee, the absence of this specific TAD is a design issue that could be mitigated.

The qualitative analysis of the OPD labels is provided in Table 4 below. The start if negative functional resonance is marked with a single asterisk (*) and the absence of dampening negative functional resonance is marked with a double asterisk (**). The red cells producing failed requirements are based on worst case observations.

From the analysis in Fig. 9, the JCS agents give insights in the systemic exchange of individual and JCS agents. At first sight only functions from JCS agent 5 'navigation' seem involved, including two different safety separation defences, i.e. autonomous safety separation by LIDAR sensor observation (JCS agent 5a) and warehouse map navigation support (JCS agent 5c). It is however the interaction from emergent organisational and contextual factors (JCS agent 6) that have surprisingly introduced negative functional resonance in this system. The system vulnerability can be considered to be already dormant by the design with an essential vulnerability for the QR code to be non-interpretable for humans, whereby this vulnerability only resonates when certain additional contextual factors are introduced. The remaining downstream functions will work as designed (phenotype value 1), and will react in a correct way to an incorrect Input, Control, or Precondition. None of sources of negative variability in isolation would have produced the undesirable event. Introducing a control mechanism of Observability in the socio—technical design (QR code interpretation) as being able for the human operator to interpret the QR code, would have dampened the total of negative resonance produced in this case study highlight. Such unforeseen design dependencies can emerge from types of symbiosis where emerging dependencies are only uncovered by a very specific configuration of events. This stresses that even in symbiotic human–machine interaction with shared human-robot control of certain functions, human operators need to be aware of hidden dependencies to reduce automation surprises (Pacaux-Lemoine and Trentesaux, 2019).

Table 4
OPD labels and description applied to the critical functions of Figure 10.

Dependency	Upstream agent function and capacity colour	Downstream agent function and capacity colour	Dependency/ Outcome	OPD label	Description
dependency |1-3| |obstacle| *	🟥 <close doors to warehouse exits>	🟧 <sense minimum separation treshold>	hard/failed	observability	The requiring agent is the sensor depending on the obstacle to be present in an observable state. In some rare cases no |obstacle| is created by <close doors to warehouse exits> as an open door cannot be observed by the sensor design (non-issue. This is reflected in propagating into the absence of an |obstacle detected| in the subsequent |3-4|, |3-5| opportunity and even further downstream ultimately affecting |navigation output|. Although the requirement is usually met for most obstacles we applied the worst-case conditions for the safety requirement to be labelled as failed
dependency |2-3| |obstacle| *	🟥 <dynamic obstacles emerge>	🟧 <sense minimum separation treshold>	hard/failed	observability	The requiring agent is the sensor depending on the osbtacle to be present in an observable state. In some rare cases no |obstacle| was created by <dynamic obstacles emerge> as a void from a downward staircase cannot be observed by the sensor design (non-issue. This is reflected in propagating into the absence of an |obstacle detected| in the subsequent |3-4|, |3-5| opportunityand even further downstream ultimately affecting |navigation output|. Although the requirement is usually met for most obstacles we applied the worst-case conditions for the safety requirement to be labelled as failed
dependency |7-8| |reorganistion of warehouse racks| *	<warehouse restructuring>	<assign QR code to warehouse locations>	no co-agency	-- (directability)	Strictly speaking this coupling does not produce co-agency, but we included this intra-agent coupling because of the effect of negative functional resonance on subsequent inter-agent interactions. Even when only a single individual agent is involved, an OPD label is nevertheless provided because in reality the two functions are likely to be performed by two different individuals.The singele individual agent is therefore only true from a taxonomic perspective. Although in the majority of cases QR codes will be correctly applied during warehouse restructuring, it has inadvertently not been performed in the observed case study. The requirement label was therefore assigned under worst-case conditions. This coupling would normally provide the |pre-defined no-go zones on the warehouse map| further downstream and lead to correct navigation output.
dependency |8-11 | |assinged QR appearance| **	🟥 <assign QR code to warehouse locations>	🟧 <afford QR interpretation>	hard/failed	observability	The requiring agent is the downstream human operator, dependent on the appearance of the QR code assigned by another colleague. Although an appearance is something that is always produced, regardless of its correct result. an OPD label is always to be interpreted by what the coupling produces for the receiving downstream function. Since the QR appearance is meaningless to the human receiver, the requirement has failed.
dependency |11-10| |QR interpretation| **	🟥 <afford QR interpretation>	🟧 <reset navigation by facing robot to QR code>	hard/failed	directability	The requiring agent is the downstream human operator, dependent on the systems-side QR artefact. In the imagined/desired case this coupling emerges from a TAD, where it is imagined that the human operator is able to interpret the result from the function <afford QR interpretation>, In case the QR appearance could be interpreted as a control for the human operator, the downstream negative functional resonance could be stopped and corrected.

6. Discussion and conclusion

The FRAM has been widely recognised as a method to model a variety of socio-technical systems, while simultaneously IA has provided new ways of examining how interdependence should inform automation. The proposed FRAM-IA framework is applied to warehouse robots where interdependence is an essential part of the system's performance, providing a useful extension to the traditional FRAM method. The use of TAD functions is provided as a support for managing the functional resonance, the last step in the traditional FRAM. There is no fixed set of rules in the FRAM to ultimately manage functional resonance, because the theory states that this process will depend heavily on the nature of the system under observation and not on a one-solution-fits-all approach. For this reason, adding TAD during the data aggregation from function that were already observed to be desirable, can be a useful approach to already map design issues that are strictly design requirement mitigations, but have been confirmed to be potential mechanisms to stop observed negative functional resonance.

The safety separation case provided an example of how safety as the absence of immediate harm to people and objects can be better understood from the functional resonance perspective which is central to the socio-technical FRAM philosophy. We should keep in mind that FRAM provides a functional approach, but this does not necessarily reflect the technical challenges from a system-integration perspective.

We have per definition looked at scenarios with the possibility to critically assess safe and efficient performance, and from which we have subsequently looked at critical or resilient dependencies. What has not been emphasised in our analysis has been the majority of inter-agent exchanges from which the emerging dependencies are successfully and tirelessly complemented by the supporting agent. When producing models for the whole warehouse distribution system, the majority of dependencies would produce a long list of such successful assisting-requiring (green-orange) dependency pairs. This was also supported by our own observations in the warehouse distribution process. This brings us to a possible limitation of the applied FRAM method and by extension our FRAM-IA framework. Producing FRAM-IA analyses of every single function in a warehouse distribution process requires extensive research or safety analysis resources from multiple analysts in cross-disciplinary teams, particularly at the chosen level of granularity. Especially when considering that several agents like planners, IT, maintenance, managers, analysts, etc. should additionally be considered for a full-fledged analysis.

An agreed methodology for functional allocation in automation issues is still unavailable (Delang et al., 2017), and there is a need for fully-informed, well-defined strategies (Lindström and Winroth, 2010). We consider our FRAM-IA framework as a contribution to support this goal, as it can produce a deeper understanding of the systemic effects from the transformed work practices brought by collaborative robots. Although the models produced by the FRAM-IA framework look much like a traditional FRAM result, the phenotypes and requirements are based on agent interdependence which shifts the focus from observed performance outcomes to the interaction potential. The additions of introducing met and failed interaction requirements support this analysis and lead to straight forward recommendation that nevertheless are integrated in systems thinking. The introduction of criticalities on the other hand, supports to prioritize the safety analysis which can help to reduce the resource intensive requirements of a FRAM analysis.

The first-time application of this FRAM-IA framework still involved much manual work by the FRAM analysts, even though we were able to use two existing FRAM tools: the FMV PRO for FRAM modelling and formal checking (Hill and Hollnagel, 2016), and myFRAM for RAM representation (Patriarca et al., 2018c). Future studies could involve the possibility to incorporate FRAM tools for standardising inter-agent dependencies. We advocate to include such interdependency analysis in more formal verification rules (Lališ et al., 2019). The recently introduced FMI tool as part of the FMV PRO (Hill and Hollnagel, 2016) could provide a useful way of automating if-then rules to better support generating results with the FRAM-IA framework. Although the FRAM-IA provides a useful deconstruction of the interdependence potential and informs socio-technical design, future research could research if there are reoccurring patterns in OPD patterns that either support or deteriorate goal coordination between agents. It can be hypothesised that certain OPD configuration patterns are beneficial for specific system-unique goal coordination challenges. The FRAM-IA framework could then be used in future work research to find recurring patterns of robust, reliable, recognisable, and predictable multi-agent goal coordination configurations (Flemisch et al., 2022) by the systematic deconstruction of its OPD interdependencies. The contribution of this paper is restricted to a case description, whereby case-specificity is reported to be both a strength and a limitation of the FRAM. To conclude, the case study successfully applied the FRAM-IA framework in practice, which was previously developed as a theoretical framework (Adriaensen et al., 2022), and thereby adds an incremental step for managing functional resonance and goal coordination.

Assigning timing variability as an additional phenotype would have required extensive logging of warehouse functions and duration and would have exceeded the research scope. Future studies could therefore benefit from collecting data from sensors or wearables to feed real-time or near real-time models, obviously providing greater capabilities of efficiency analysis.

As both, the principles of capacity and dependency are inherent to all collaborative systems, and additionally, the interaction principles of Observability, Predictability and Directability remain true for every purposeful multi-agent structure, the FRAM-IA framework appears to be generically applicable to any other human–machine collaborative application.

As for managerial implications previously demonstrated methods of technological cobot capabilities and logistics efficiency can now be complemented by functional task and work system analysis. The proposed framework has the benefit of taking into account the socio-technical context of the particular workplace on human-robot interaction, providing new tools for safety and interaction analysis.

CRediT authorship contribution statement

Arie Adriaensen: Conceptualization, Methodology, Formal analysis, Data Curation, Writing, Writing - Review & Editing - Original Draft. **Liliane Pintelon:** Conceptualization, Methodology, Writing - Review & Editing, Project administration, Supervision. **Francesco Costantino:** Project administration, Conceptualization. **Giulio Di Gravio:** Project administration, Review & Editing. **Riccardo Patriarca:** Conceptualization, Methodology, Validation, Formal analysis, Writing - Review & Editing, Visualization, Supervision, Review & Editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Health and Safety.

All Health and Safety rules have been adhered to by the researchers during company visits. For most of the research project duration, access was not permitted to the warehouse or offices due to COVID restrictions for non-business critical activities such as scientific research. Therefore, most observations were replaced by online warehouse walkarounds with webcam support and personal interviews were replaced with online interviews.

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