Teaming with industrial cobots: A socio-technical perspective on safety analysis

A. Adriaensen[1,2] 🄳 | F. Costantino[1] | G. Di Gravio[1] | R. Patriarca[1] 🄳

[1]Department of Mechanical and Aerospace Engineering, Sapienza University of Rome, Rome, Italy

[2]Centre for Industrial Management/Traffic and Infrastructure, KU Leuven, Leuven, Belgium

Correspondence
A. Adriaensen, Centre for Industrial Management/Traffic and Infrastructure, KU Leuven, Celestijnenlaan 300—box 2422, 3001 Leuven, Belgium.
Email: arie.adriaensen@kuleuven.be

Abstract

Collaborative human–machine interaction will be progressively intensified in industrial applications. The aim of this article is to examine current approaches to cobot safety by showing that these approaches can additionally benefit from systems thinking methods. The first part of this article covers a narrative literature review on predominantly techno-centric robot safety approaches, with a strong focus on containing kinetic energy and ensuring separation with humans. The second part introduces systems thinking methods to analyze a socio-technical perspective on cobot safety, including joint cognitive systems and distributed cognition perspectives. This explorative research dimension is expected to overcome an overly narrow interpretation of safety issues, anticipating the challenges ahead in ever more complex cobot applications. This article embraces a socio-technical perspective to explore the potential of Joint Cognitive Systems to manage risk and safety in cobot applications. Three systemic safety analysis approaches are presented and tested with a demonstrator case study concerning their feasibility for cobot applications: System-Theoretic Accident Model and Processes (STAMP); Functional Resonance Analysis Method (FRAM); and Event Analysis of Systemic Teamwork (EAST). These methods each provide interesting extensions to complement the traditional understanding of risk as required by current and future industrial cobot implementations. The power of systemic methods for safer and more efficient cobot operations lies in revealing the distributed and emergent result from joint actions and overcoming the reductionist view from individual failures or single agent responsibilities. The safe operation of cobot applications can only be achieved through alignment of design, training, and operation of such applications.

KEYWORDS
collaborative robots, cobots, EAST, FRAM, functional allocation, levels of automation, socio-technical systems, STAMP

1 | INTRODUCTION

Collaborative robots perform tasks in collaboration with human workers within the scope of an industrial setting (Gualtieri et al., 2021). Different definitions of collaborative robots, also called cobots, have been proposed from which many adopt the following definition: any robot operating alongside humans without the presence of a fence is a collaborative robot (El Zaatari et al., 2019). Other definitions do not consider the absence of a fence but define cobots in terms of proximity or the intention to physically interact with humans in a shared workspace (El Zaatari et al., 2019; Hentout et al., 2019). Besides the element of increased proximity, there can also be an element of increased robot autonomy (Hentout et al., 2019), although the latter by itself does not define a collaborative robot.

It should additionally be noted that the collaborative robot as such does not exist and it is actually the application that makes the robot collaborative (Malik & Bilberg, 2019a). For the remainder of the article, we will simply use the term cobots, when in reality we mean "collaborative robot applications."

1.1 | Growing complexity in collaborative robot safety

There is an underrepresentation between cobot applications used in present-day industry versus a growing potential for cobot applications in academic research (El Zaatari et al., 2019; Saenz et al., 2018). In today's industry, collaborative robots are still used relatively independently of their human colleagues (Malik & Bilberg, 2019b) despite ambitions for an increased collaborative potential concerning this technology. Before cobots were introduced, traditional robots were regulated by several regulations in which separation between industrial robots and humans was rigidly prescribed. This conflicts with the very nature of collaborative workspaces. Unger et al. (2018) report that the uncertainty from safety certification reduces the economic attractiveness of collaborative solutions in comparison with traditional robots. Also, the lack of engineering tools for safety analysis of cobot applications causes a relatively slow uptake of this emerging technology (Saenz et al., 2018). Years after cobots were introduced, several normative standards have been updated in an attempt to fill the standardization void concerning this new technology. But several authors have reported that it is still unclear how to bridge the requirements to meet hazard and risk analysis, as the normative standards do not prescribe specific safety assessment methods (Chemweno et al., 2020; Delang et al., 2017; Guiochet et al., 2017). The challenge is twofold and lies in simultaneously assuring worker safety while adapting to the complexity of increasingly versatile applications.

1.2 | Degree of collaboration in current industrial applications

Collaborative robots still conservatively adhere to relatively fixed actions and motions and often remain restricted to pre-determined positions on the work floor (IFR, 2018). Reasons for using collaborative robots in industrial settings are saving floor space by giving up physical separation; allocating tasks to collaborative robots that are either ergonomically or psychologically inconvenient for humans; or for increasing accuracy, speed, and repeatability beyond human capability (El Zaatari et al., 2019; Galin & Meshcheryakov, 2019). In other words, currently, the ambition for versatile collaborations between robots and humans remains restricted to perform tasks where cobots replace humans, rather than engaging in genuinely supportive collaboration between them. Academic research is already concerned with developing more mutually supportive collaborative applications, highly suited for industrial tasks. Some examples (El Zaatari et al., 2019) are tasks such as (i) co-manipulation where a human guides an object path while the cobot supports the weight of the object; (ii) humans inserting bolts in a plate while a cobot tightens these bolts from the opposite side of the plate; or (iii) assembly actions that are dynamically distributed between humans and cobots according to workload and energy consumption. Such intensified mutual support of tasks will require further advanced perception, human awareness, or decision-making capabilities (El Zaatari et al., 2019). Safety is considered a main challenge in much of the literature regarding cobot systems (Chemweno et al., 2020; Lasota et al., 2017; Vicentini, 2020; Villani et al., 2018; Zacharaki et al., 2020). Intensified mutual support with increased task versatility applies to several EU projects, which display clear aspirations for higher degrees of human-machine collaboration for industrial applications in the near future (cf. Table 1).

Additionally, new forms of collaboration emerge, for example by the combination of mobile bases with collaborative manipulation robots (Hentout et al., 2019; Unger et al., 2018). These technologies introduce for more versatility, which confronts designers with understanding the joint behavior of both technologies.

1.3 | Aims of the study

We reviewed available literature on cobot applications, showing the limitedness of the degree of truly mutual cooperation between humans and robots. The latter are frequently relegated to sequential tasks or substitution of tasks previously performed by humans themselves. This also explains the limited scope of safety management nowadays, which is restricted to a techno-centric dimension, inherently focused on physical dimensions such as speed, kinetic energy, and physical separation.

It has been acknowledged that tasks involving both humans and technical artifacts cannot be studied independently from the agents involved (Trist & Bamforth, 1951). The notion of "socio-technical systems" indicates the symbiotic relationships between social and technical counterparts. This perspective requires a systemic point of view to ensure a joint understanding, exploration, and analysis (Patriarca, Bergström, et al., 2018). A research dimension relying on systems-thinking implies a focus on interconnections between components and causal links that are distant in space and time from

TABLE 1 EU projects with a concern for safety aspiration for higher degrees of human–machine collaboration

Project	Summary
SHERLOCK Project	"SHERLOCK project aims to introduce the latest safe robotic technologies including high payload collaborative arms, exoskeletons and mobile manipulators in diverse production environments, enhancing them with smart mechatronics and AI based cognition"
COROMA project – Cognitively enhanced robot for flexible manufacturing of metal and composite parts	"COROMA project proposes to develop a modular robotic system to perform multiple manufacturing operations, including safe human-robot collaboration, automatic manufacturing scene understanding, increased autonomy with self-learning and knowledge sharing capability"
COLLABORATE Project	"This project aims to equip robots with collaborative skills so that they can learn from the human and become valuable assistants for assembly operations, in an effective and safe manner"
ROSSINI—Robot Enhanced Sensing, Intelligence and Actuation to Improve Job Quality in Manufacturing	"The project aims to develop a disruptive, inherently safe hardware-software platform for the design and deployment of human-robot collaboration (HRC) applications in manufacturing"
THOMAS Project	"The project aims to create a dynamically reconfigurable shopfloor utilizing autonomous, mobile dual arm workers. These workers are able to perceive their environment and through reasoning, cooperate with each other and with other production resources including human operators"
SHAREWORK – Effective and safe Human-Robot Collaboration	"Europe-wide smart modular solution integrated by different software and hardware modules to allow robots to physically interact with humans within a collaborative production environment without the need for physical protection barriers"

Source: Adapted from 7 European Projects on Human Robot Collaboration You Must Know (n.d.).

actions under investigations. It is frequently sparked by research concerns in relation to context, interactions, emergence, and multiple perspectives (Engler Bridi et al., 2021; Wilson, 2014). Modern adaptive systems thus demand systemic methods to overcome the limitations imposed by linearity and reductionism inherent in traditional approaches to safety management (Hollnagel, 2018). Systems-thinking is currently dominant in many safety-critical domains such as space operations (C. W. Johnson & de Almeida, 2008), aviation (Adriaensen et al., 2019), road (Newnam et al., 2017), rail transport (Salmon & Read, 2019), and construction (Saurin, 2016).

The explorative research question of this article has a double motivation. First of all, by the inherent features of cobot operations recalling the fundamental aspects of socio-technical systems, but also by the successful contributions available in the literature from systems-thinking applied to safety management (Dekker, 2011), Despite the widespread range of applications of systems thinking, cobot safety is indeed still limitedly explored from a socio-technical systemic view (Jones et al., 2018). Nonetheless, systemic risk analysis would ensure that the whole system is studied within which risks occur, rather than focusing on work and task in separation, or on individual agents.

In line with modern safety management, we then provide an overview of the potential usage of systemic methods for cobot safety management to extend the technocentric view toward the inclusion of interactive socio-technical and organizational contexts from multiple perspectives. Based on evidence from the literature on safety management for socio-technical systems, we finally suggest three systemic approaches, that is, the Systems Theoretic Accident Model and Processes (STAMP) (Leveson, 2011b), the Functional Resonance Analysis Method (FRAM) (Hollnagel, 2012) Event Analysis of Systemic Teamwork (EAST) (Stanton et al., 2018), subsequently applied to a real cobot, used as a staging area for development. The aim of the article is two-fold. First, we examine the governing safety perspective encountered in literature on industrial cobot safety. Secondly, we introduce systems thinking methods to analyze a socio-technical perspective on cobot safety, including joint cognitive systems and distributed cognition perspectives. This explorative research dimension is expected to overcome an overly narrow interpretation of safety issues, anticipating the challenges ahead in ever more complex cobot applications. Here, we have used the notion of a joint cognitive system (Hollnagel & Woods, 2005) to indicate the focus shift from the interactions between humans and machines toward a proper human-machine symbiosis (Tzafestas, 2006). This shift in research focus is characterized by goal orientation, control, and co-agency. In this sense, cognition needs to be studied not just as a situated or embedded entity, but rather encompass how it is extended and distributed in the world (Blomberg, 2011).

The remainder of this article is organized as follows. Section 2 provides an explorative literature review about the substitution approaches of functional allocation (Section 2.1); the traditional technocentric paradigm for cobots (Section 2.2), and the socio-technical view on cobots (Section 2.3). Section 3 will introduce STAMP, FRAM, and EAST as three systemic safety analysis approaches that will

subsequently be applied to a demonstration case study in Section 4, including an overview of their potential for industrial cobots' safety. Finally, a discussion and conclusion will be presented in Sections 5 and 6.

2 | LITERATURE REVIEW

2.1 | The substitution approaches in functional allocation

Functional allocation is an area in human factors safety to decide whether a task in a work system will be apportioned to humans, to automation, or both. The literature mainly provides two traditional approaches to perform function allocation in automated systems. The oldest method is known as *the* "Men-are-better-at/Machines-are-better-at" (MABA–MABA) classification scheme (Fitts, 1951), introduced in 1951. It consists of allocating tasks to either humans or machine agents simply by studying their respective strengths and limitation, derived from a pre-defined inventory of capabilities (Table 2). Another traditional approach, which appeared much later in 1978, is the Levels of Automation (LoA) approach (Endsley, 1999; Parasuraman et al., 2000; Roth et al., 2019). It introduces an objective basis for making human-automation allocation choices by assigning recommended levels of automation to technologies.

Finally, it could be argued that there is a third approach, being a body of literature that dismisses the MABA-MABA and LoA approaches as oversimplifications of the problems space (de Winter & Dodou, 2014; Dekker & Woods, 2002; Jordan, 1963; Roth et al., 2019). The critics argue that in both approaches functional allocation is treated as a simple act of substitution, whereas what is needed is a transformation of the interdependencies between how humans and autonomous technologies interact, additionally embedded in changes of operational context. For industrial cobot applications, an agreed methodology for functional allocation is still unavailable (Delang et al., 2017), or is often produced by ad hoc

decisions, rather than by fully-informed, well-defined strategies (Lindström & Winroth, 2010).

2.1.1 | MABA-MABA classification scheme

Named after its inventor Paul Fitts, the MABA-MABA approach is also known as the Fitts list (Fitts, 1951). There is great merit in the Fitts list for being the first systematic attempt to map strengths and weaknesses from humans versus machine capabilities (Table 2), even if the critiques correctly observed that the comparison remained static (de Winter & Dodou, 2014; Jordan, 1963). Empirical data about human–machine interaction in aviation, robotics, and car driving has confirmed many of Fitts's predictions (de Winter & Dodou, 2014).

But, the "who does what question" does not necessarily provide a good answer to the challenges of "what needs to be done" (Roth et al., 2019). The MABA MABA approach has been critiqued for its risk of focusing on technologic capabilities and leaving the humans with the "leftover tasks" (Norman, 2015; Roth et al., 2019), and for preferring comparability of human and machine over a more goal-oriented human-machine complementarity (Jordan, 1963). The key principle in the MABA-MABA classification is the simple act of replacing one agent for another, while what is needed is an understanding of interaction in terms of mutual task support and distributed cognition. This is especially true for the next generation of genuinely collaborative tasks. Despite many critiques (de Winter & Dodou, 2014; Dekker & Woods, 2002; Jordan, 1963), the Fitts' list remains the dominant approach (de Winter & Dodou, 2014; T. B. Sheridan, 2000).

The MABA-MABA approach is often tacitly assumed, but can be recognized in the cobot literature: "sensitive tasks are carried out by the human, while strenuous tasks are executed automatically by a small payload robot" (Hägele et al., 2016). Other examples can be found in (Hentout et al., 2019) reporting that human skills include: "high availability," "handling of complex parts and processes," "high task flexibility," and so forth whereas machines are better at

TABLE 2 Fitts list or MABA-MABA classification scheme

Humans appear to surpass present-day machines in respect to the following:	Present-day machines appear to surpass humans in respect to the following:
1. Ability to detect small amount of visual or acoustic energy.	1. Ability to respond quickly to control signals, and to apply great force smoothly and precisely.
2. Ability to perceive patterns of light or sound.	2. Ability to perform repetitive, routine tasks.
3. Ability to improvise and use flexible procedures.	3. Ability to store information briefly and then to erase it completely.
4. Ability to store very large amounts of information for long periods and to recall relevant facts at the appropriate time.	4. Ability to reason deductively, including computational ability.
5. Ability to reason inductively.	5. Ability to handle highly complex operations, i.e., to do many different things at once.
6. Ability to exercise judgment.	

Source: Adopted from Fitts (1951).

"exact playback of paths," "reliable performance of repetitive tasks," and so forth.

Ranz et al. (2017) adapted the focus concerning functional allocation in industrial settings from mere task execution capability toward efficiency indicators such as cost minimization of allocation, suitability, availability, and operation time, and used algorithms that produce capability indicators for tasks that are unique for either humans or machines while leaving other tasks to be performed by either humans or robots.

2.1.2 | Levels of automation

The earliest account of the LoA perspective can be found in a Naval Research Report about tele-controlled undersea operations for vessels with robotic manipulation arms from 1978, written by Sheridan and Verplank (1978). The LoA approach provides taxonomies to specify cognitive aspects involved in automation (Roth et al., 2019) on a continuum from nonautomated to fully automated systems (Table 3).

Parasuraman et al. (2000) further refined the idea that entire tasks can simply be substituted by breaking them down into four types of activity (acquisition, analysis, decision, and action selection) associated with the 10 levels of automation. The LoA approach has been adapted as the typical allocation perspective in the design of self-driving cars and unmanned aerial systems (Roth et al., 2019; SAE International, 2018), and has a significant impact on the design of robots (M. Johnson et al., 2011). An important critique to the LoA is that apart from labeling, it does not provide principles or guidelines for the designers of autonomous human-machine systems" (M. Johnson et al., 2011; Norman, 2015).

TABLE 3 Levels of automation of decision and action selection

Level	Automation
High	10. The computer decides everything, acts autonomously, ignoring the human
	9. Informs the human only, if it, the computer decides to
	8. Informs the human only if asked, or
	7. Executes automatically, then necessarily informs the human, and
	6. Allows the human a restricted time to veto before automatic execution, or
	5. Executes that suggestion of the human approves, or
	4. Suggests one alternative
	3. Narrows the selection down to a few, or
	2. The computer offers a complete set of decision/action alternatives, or
Low	1. The computer offers no assistance: humans must take all decisions and actions

Source: Adapted from Parasuraman et al. (2000).

Even though the original approach was designed for the cognitive control of computerized systems, the LoA approach has meanwhile been adapted to manufacturing (Frohm et al., 2008; Lindström & Winroth, 2010) by proposing a double LoA taxonomy for both computerized and mechanized tasks. The mechanization perspective ranges from no interference, over measuring, correcting, and finally anticipating mechanical outcomes (Frohm et al., 2008). LoA can also be reported as a minimum-maximum range of tasks to be automated (Lindström & Winroth, 2010), resulting in a flexible range of LoA that reflects a potential area of automation for the manufacturer.

Guerin et al. (2019) applied an LoA-inspired modeling tool for Industry 4.0-based assistance systems to the specific activity of order picking, based on functional and cognitive constraints modeling. Although applying some elements of an adapted LoA taxonomy, the authors have taken into account several advances in functional analysis such as abstraction hierarchy, the importance of contextualization, and task and organizational interaction as their unit of analysis.

Johnson et al. have proposed to replace an LoA analysis in human-machine design and robotics (M. Johnson et al., 2011, 2018) with an analysis of interdependencies to build a theory of joint activity. An interdependency analysis would logically be determined by a functional understanding of the work system. We indeed propose a potential way forward in this regard, through specific approaches (STAMP, FRAM, and EAST) described in Section 3 to analyze interdependencies between human, technical, and organizational functions and controllers.

2.1.3 | Coactive design

Coactive design wishes to advance beyond the limitations of LOA and expresses the view that the choice for automating system elements is anything but a binary choice (M. Johnson et al., 2011). It departs from the idea that complete manual or automated control does not apply to many systems. Coactive design is based on joint activity theory and considers the effects of coordination, as an essential trait of nearly all activities that involve more than one agent. It reconsiders the question of allocating functions by transforming it into the question of how to support agent interdependencies. Whereas in LoA the human is primarily considered with respect to the machine's actions, the fundamental principle of coactive design is that interdependence must shape automation.

Coactive design proposes observability, predictability, and directability as the three most fundamental interdependence relations, although others can be allowed into the analysis.

Observability is concerned with making system status visible, as well as knowledge about other agents, tasks, and environment. Predictability requires that actions should be predictable enough for others to rely on them concerning their own actions and directability is interpreted as the ability of agents, human and technical alike, to influence each other's behavior.

Coactive design departs from the idea that interdependence must shape automation, thereby proposing to invert the relationship

between automation and interaction (M. Johnson et al., 2018). A method used to achieve this is to make an interdependency analysis by modeling the human, the machine (by algorithms, and interface element), and the work (by dividing it into tasks and further in capacities) (M. Johnson et al., 2011). Each task capacity is then compared against the human tasks or the automated alternative elements, which are assessed for observability, predictability, and directability. Because the task has been decomposed in multiple capacities, manual and automated elements can be combined into a coordinated whole. The interdependency analysis informs the engineering design as an approach that resists the substitution fallacy.

2.1.4 | Transformed work and interaction-based considerations

Automation produces qualitative shifts in work systems, which will force people to adapt their previous practices in novel ways (Dekker & Woods, 2002). The safety literature describes these substantial effects of automation as "transformed work practice" (Bradshaw et al., 2013). In human-computer interaction Carroll and Long (1991) defined this as the task-artifact cycle. The latter captures the idea of a cyclical relationship between tasks and artifacts, where new tasks introduce new requirements for the design of artifacts. These in turn result in unanticipated possibilities or pose new constraints on the performance of the task. Both tasks and artifacts continuously co-evolve, rather than substitute previous tasks or artifacts. This motivates our choice to study the emergent properties from humans and machine agents as the unit of analysis, additionally embedded in changes of operational context (Sections 3 and 4).

2.2 | Traditional techno-centric approaches to cobot safety

We have consulted a number of surveys (Galin & Meshcheryakov, 2019; Guiochet et al., 2017; Lasota et al., 2017; Malik & Bilberg, 2019b; Villani et al., 2018; Zacharaki et al., 2020) and literature reviews (Hentout et al., 2019) about safety-related aspects of HRI to examine the focus of cobot related risks in the literature. Some reviews had restricted scopes such as emerging research fields in collaborative robotics (Gualtieri et al., 2021); cobot programming (El Zaatari et al., 2019); applied terminology in collaborative applications (Vicentini, 2020); risk and hazard assessment from the ISO/TS 15066:2016 perspective (Chemweno et al., 2020); or safety through compliant actuators (Grioli et al., 2015; Ham et al., 2009; Vanderborght et al., 2013; Wolf et al., 2016).

In the literature reviews, there is a strong focus on hardware-related safeguards and generic collision avoidance strategies to prevent unsafe human–robot interaction. Contrarily, hazards embedded in the broader work system or hazards generated by added decisional complexity receive little attention (Chemweno et al., 2020; Guiochet et al., 2017). Psychological and societal impact have deserved some attention (Galin & Meshcheryakov, 2019; Lasota et al., 2017; Zacharaki et al., 2020), but mainly look at postimplementation influences on work quality. The prediction and cognitive aspects of human or cobot are almost exclusively used to the benefit of predicting motion and avoiding collisions (Gualtieri et al., 2021; Hentout et al., 2019; Lasota et al., 2017; Vicentini, 2020), while there is a lack of attention in the literature on dependability, task design, context, and environment. Chemweno et al. (2020), and Guiochet et al. (2017) are notable exceptions. Most safety methods focus on the assessment of collision risks often assumed to be known a priori by manufacturers, integrators and users, (Chemweno et al., 2020). This critique is acknowledged by the review data from Gualtieri et al. (2021), which describes research coverage from emerging fields in safety and ergonomics of industrial collaborative robot literature between 2015 and 2018. The authors reveal a notable lack of contextual topics such as *Product and Process* Design and *Case Studies*, whereas the strategies for *Contact Avoidance* and *Contact Detection and Mitigation* are indeed confirmed to be the main categories of interest in the literature by coverage of 40,3% and 23,9% respectively (Gualtieri et al., 2021). Other reviews use different or merged labels with equal meaning, but the categories of *Contact Avoidance* and *Contact Detection and Mitigation* can be distilled as the greatest common denominator in tentative taxonomies from varying cobot reviews (El Zaatari et al., 2019; Gualtieri et al., 2021; Hentout et al., 2019; Villani et al., 2018; Zacharaki et al., 2020).

Lasota et al. (2017) use different labels for *Contact Avoidance*, *Detection* and *Mitigation* strategies, structured by gradually increased anticipation to assure human–robot separation, that is (i) *Control*, (ii) *Motion Planning*, (iii) *Prediction*, with *Control* further divided into *Pre-* and *Post-collision* avoidance methods. Hentout et al. (2019) discuss HRI in industrial collaborative robotics by applying both intrinsically safe design and active strategies. We consequently propose Figure 1 to structure the current research focus in the collaborative safety

FIGURE 1 Collaborative robot application safety methods in order of progressively more complex safety behaviors, ordered from reactive to pro-active approaches

literature, starting with reactive approaches to the far left gradually increasing to increased system anticipation with progressively more complex safety behaviors to the far right. More complex and anticipative safety behaviors come at the cost of increasingly complex implementation (Lasota et al., 2017). Figure 1 is based on the granularity used by Lasota et al. (2017) and the comprehensiveness available in Hentout et al. (2019).

Intrinsically safe design can be achieved by reducing the kinetic energy of the moving parts, increasing energy-absorbing properties of protective layers, installing airbags and soft rounded covers around potential contact surfaces, or limit the robot's velocity or maximum system energy (ISO, 2016; Hentout et al., 2019). Some reviews exclusively focus on inherently safe design through compliant actuators. Such actuators provide varying stiffness, gear ratios, and damping properties, reviewed in Ham et al. (2009) and Wolf et al. (2016). Compliant actuators can also be actively controlled by software, additionally reviewed by Grioli et al. (2015), Vanderborght et al. (2013).

Control methods (Lasota et al., 2017) (Figure 1) are reactive in nature by providing either separation or energy reduction. *Pre-collision* (Lasota et al., 2017) works by quantitatively limiting speed or energy, by monitoring robot-operator separation distances, or by guiding the robot away from the human as a result of increased speed or reduced separation. A collision cannot always be avoided and *Post-Collision* methods have additionally been introduced (Galin & Meshcheryakov, 2019; Hentout et al., 2019; Lasota et al., 2017; Zacharaki et al., 2020).

Motion planning and *Prediction* (Lasota et al., 2017) (Figure 1) add additional degrees of anticipation, changing from reactive to proactive strategies. Whereas *Motion Planning* is based on constant updates of current world states that put static constraints on robots' movements, *Prediction* is about forecasting more dynamic situations by integrating future tasks and motions of human agents. *Prediction*, therefore, requires a mental image of the reciprocal agent's actions, whereby most research has been devoted to human behavior prediction (Hentout et al., 2019) and more efforts need to be devoted to the effective communication of the robot's intent (Lasota et al., 2017). In contrast to academic research projects, industrial applications are mainly restricted to hardware features of intrinsically safe design or the reactive control approaches at the left of Figure 1. This difference in range between academic research and industrial reality can be understood by the fact that currently most industrial cobot applications consist of independent or sequential tasks (IFR, 2018; Malik & Bilberg, 2019b) and rarely perform tasks where human and machine simultaneously engage in true collaboration on a single task.

For safety in industrial cobot applications, the nature of such collaboration intent is usually taken as the a priori point of departure (Vicentini, 2020) linked to safety requirements in normative standards. Several literature reviews (El Zaatari et al., 2019; Galin & Meshcheryakov, 2019; Hentout et al., 2019; Villani et al., 2018) point to taxonomies for the level of shared interaction that is automatically linked to specific operation modes as described in ISO/TS 15066:2016, adapted from (Hentout et al., 2019):

- Coexistence in which humans and robots share the dynamic workspace while operating on dissimilar tasks. This is generally linked to collision avoidance strategies (Hentout et al., 2019), at the left side of Figure 1. The majority of industrial tasks are to be found in this category (IFR, 2018; Malik & Bilberg, 2019b).
- Cooperation in which humans and robots work on the same purpose in the same workspace simultaneously. Cooperative tasks require force-feedback sensing and advanced collision *Detection and Avoidance* sensing (Hentout et al., 2019).
- Collaboration in which humans and robots perform complex tasks with intentional contact and physical collaboration. This requires the measuring of forces and torques and the prediction of human motion intentions, the latter inherently linked to *Prediction* at the far right of Figure 1.

Industrial tasks are consequently linked to the safety requirements described as one of four possible operation modes described in ISO 10218:2011 (2011) and ISO/TS 15066:2016 (2016):

- *Speed and Separation Monitoring (SSM)*: Robot system and operator can move simultaneously in the same collaborative workspace, as long as safe distances relative to the robot systems are assured, in line with *Contact Avoidance* strategies (*Pre-Collision*, *Motion Planning*, *Prediction*), which are linked to the execution of coexistent tasks.
- *Power and Force limiting (PFL)*: In this mode concurrent use of the workspace and even contact between operator and robot are allowed and safety is provided by limiting power and force. In the literature reviews, this is labeled as *Contact Detection and Mitigation* and is typically used in performing cooperative and collaborative tasks. PFL can be achieved by *Intrinsically Safe Design* and by active *Control (Post-Collison)*.
- *Hand Guiding:* The robot is allowed to work in a noncollaborative mode without the presence of an operator. After the robot has achieved a safety-rated monitored stop, the operator is allowed to enter the workspace and control the robot through a hand-guiding device to lead the robot to a specific point of application. This is linked to a limited set of cooperative and collaborative tasks suited for hand guiding.
- *Safety-rated Monitored Stop*: This feature is used to discontinue robot motion in the collaborative workspace and the robot may only operate if there is no operator in the workspace. This operational mode is somewhat misleadingly listed as a collaborative mode as it is a stopping & transition function between collaborative and noncollaborative operation (Vicentini, 2020).

Vicentini (2020) end Aaltonen et al. (2018) have described that the problem of providing taxonomies for a priori assumed collaboration as the basis for ISO-related operational modes is twofold as the labels used vary, are subject to overlap, and are differently defined in the literature. See Vicentini (2020) for a comprehensive review of mixed-use of terminology in the cobot literature up to 2018. Secondly, Vicentini raises that it should be methodologically avoided

to base normative safety requirements on a nonnormative taxonomy. What currently is missing in the academic literature are safety analysis methods that extend to answer such questions from a socio-technical perspective. In Sections 3 and 4 we propose three systemic methods that provide nonreductionistic, nontaxonomic, and nonnormative analysis perspectives. To objectively assess and challenge design choices of intentional or unintentional contact, methods should also take into account unexpected behavior from degraded systems and reverberations from cobot integration into the context of a working system.

2.3 | Socio-technical view on cobots

This section proposes to additionally understand the challenges of collaborative robots through functional exchanges in work systems at meso- and macro-level. It brings the socio-technical perspective in line with the research perspective of Joint Cognitive Systems (JCS), which takes coagency as the basic unit of analysis, in which human and machine need to be considered together (Woods & Hollnagel, 2006), as opposed to the classical perspective of understanding humans and technology in isolation, connected through interfaces. The nature of collaborative work where both human and machine engage in joint behavior through a shared mental image motivates this study to take an agent-neutral perspective in terms of pure functional exchanges of task-relevant information, made possible with the methods from Section 3.

The JCS paradigm belongs to the discipline of Cognitive System Engineering (CSE), which is concerned with "the analysis and design of factors, processes, and relationships that emerge at the intersections of people, technology and work" (Woods & Hollnagel, 2006). CSE recognizes that mental models are not the only basis to understand cognition (Cognition in the Mind) and thus, the understanding of safe designs is not restricted to controlled experimental conditions. CSE indeed studies actual features of a work domain more closely to the test operating conditions in the field, embedded in actual fields of practice (Hollnagel & Woods, 2005), also known as Cognition in the Wild (Hutchins, 1995). In this view, the central role of the human operator as the problem holder receives a different emphasis, being that human–machine interaction deficiencies cannot be understood as deficiencies in an absolute sense but are dependent on the system characteristics "because of the way that they shape practitioner cognition and collaboration in their field of activity" (Woods et al., 2017, p. 152). Therefore, cognition is said to be "situated." When applied to the example of collaborative robots, risk cannot only be understood from the techno-centric perspective of mere energy containment in terms of managing speed, force, and separation.

A JCS perspective further extends that situated interaction with the world, which inevitably involves interactions with other agents and dynamic contexts, and it forces the analysis to include a new system where joint activity is distributed. Although cobots as an applied technology only started to come out in 2008 (Hentout

et al., 2019), scholars from other domains have previously studied human-technical joint performance, embedded in purposeful socio-technical systems (Le Coze, 2013; Leveson, 2011b; Rasmussen, 1997; Waterson et al., 2015). Much of JCS research has been concerned with the identification of recurring patterns (Woods & Hollnagel, 2006; Woods, 2002) in automation-induced problems, often in contrast with the putative benefits that designers proposed before design implementation.

The literature draws from experience that machines not always act as a team player (Bradshaw et al., 2013; Hollnagel & Woods, 2005; Klein et al., 2004; Norros & Salo, 2009; Sarter & Woods, 1997) by doing things that humans do not anticipate or understand. Automation surprises occur when the actual system behavior is not in line with the user's expectations (Hoffman & Militello, 2008; Sarter & Woods, 1997; Sarter et al., 1997). Such surprises generally emerge because of a divergence of mental models and low system observability or feedback failures, especially when managing dynamic and nonroutine operations (Hoffman & Militello, 2008; Sarter & Woods, 1997). It has been demonstrated that although high levels of automation enhance routine performance, system failure performance is negatively affected by higher automation levels (Onnasch et al., 2014). Managing systems under nonroutine operations or demanding circumstances is a field of inquiry that has so far received little attention in the cobot literature, requiring more research efforts (Guiochet et al., 2017).

Mutual prediction of both human and robot behavior will play an increasingly important role in safe collaboration tasks and is a frequently researched topic in academic research (Gualtieri et al., 2021; Hentout et al., 2019; Lasota et al., 2017). Whereas prediction of motion paths and imminent collision has received considerable attention in the literature (see Section 2.2), such prediction additionally depends on the operator's *Mode error and mode awareness* (Sarter & Woods, 1997), which occurs when the operator misinterprets the different meanings from automation functions resulting from multiple device mode settings. *Mode awareness* has received little coverage in cobot applications but was recently applied to cobot case studies by Gopinath and Johansen (2019).

To the best of our knowledge, Chacón et al. (2020) and Jones et al. (2018) have been the only authors so far to propose a JCS perspective to design socio-technical systems for collaborative agents and CPS. Chacón et al. (2020) describe a human-centered architecture for cognitive advisor agents in the framework of a human cyber-physical production system (H-CCPS). The proposed H-CPPS includes a human dimension (operators including their situations based on their objectives and context), connected to a physical dimension (resources connected to the production system through sensors and actuators), and connected to a cybernetic dimension (computing, network, and cloud infrastructures) (Chacón et al., 2020). As the final decision always remains with the human operator, which we previously defined as the problem holder principle, the design of the system is aimed at adaptive control and supervision of automated production system, including response to unexpected or novel situations. Chacón et al. (2020) additionally suggested the use of

FRAM (as previously mentioned in Sections 3 and 4) to examine the functioning of their H-CPPS, which is one of the approaches discussed in Sections 3 and 4.

Essentially, demands for the management of automation create the fundamental question for the socio-technical safety analysis: "What does it mean to be in control in a Joint Cognitive System?" and "How is control distributed across such systems." In light of the previous JCS principles derived from the literature, this generates sub-questions that should take into account how control is embedded in the situated cognition of the work system as a whole and how control is affected by disruptions and nonroutine situations. In the next section, we present three socio-technical safety analysis approaches that provide different ways to answer these research questions.

3 | ABOUT SYSTEMIC SAFETY ANALYSIS

Literature about contemporary systems thinking inspired accident causation approaches have described STAMP, FRAM and Accimap as the most recurring analysis approaches, chosen by (Underwood & Waterson, 2012) from a total of 13 systemic models. The result was further confirmed in a review (Hulme et al., 2019) of 73 articles between 1990 and 2018 about the application of systems thinking accident analysis methods to the field of occupational safety. Hulme et al. (2019) also mentioned the Human Factor Analysis and Classification System (HFACS), which was not used in this study as it is not considered to align with systems theory (Salmon et al., 2020). We have disqualified Accimap, as it is a retrospective method only and to a great extent its principles, based on the ideas of a hierarchical control-based model from its originator Rasmussen, have been further encompassed by STAMP (Leveson, 2011a).

From the retained methods STAMP and FRAM we added EAST for the analysis of our demonstration case study on cobots, for its particular focus on distributed cognition, an important challenge in human-robot interaction. STAMP, FRAM, and EAST have been previously identified as well-equipped approaches for socio-technical safety analysis (Bjerga et al., 2016; Hovden et al., 2010; Hulme et al., 2019; Salmon et al., 2017). The generic languages of the different approaches additionally permit to extend the techno-centric risk dimension toward socio-technical considerations such as operational tasks, resources, tools, and processes. This enables a JCS perspective of distributed cognition and situated cognition as advocated in Section 2.3.

STAMP, FRAM, and EAST are all systems thinking approaches, which mark a change in perspective from decomposition by analytical reduction to the analysis of the whole. They all describe safety as an emergent property from the interaction of system components with each other and their environment. FRAM elicits functional exchanges in work systems, STAMP uses control action-feedback loops, and EAST uses several aggregated networks based on information exchanges.

The systemic approaches have previously demonstrated their usefulness in several other socio-technical systems (e.g., evidence available from recent literature on FRAM (Patriarca et al., 2020; Salehi et al., 2021), or from several recent cases in various safety and ergonomics domains applying STAMP and its associated techniques (Li et al., 2019; Patriarca et al., 2019; Stanton et al., 2019), or EAST (Stanton et al., 2018). FRAM and STAMP are in essence qualitative safety analysis approaches, although in the case of FRAM some quantitative extensions (Patriarca et al., 2017; Patriarca, Falegnami, et al., 2018), including the application of Fuzzy Logic (Hirose & Sawaragi, 2020; Slim & Nadeau, 2020), have been described. STAMP has been extended with system dynamics (Bugalia et al., 2020; Kontogiannis & Malakis, 2012) and model checking tools (Han et al., 2019; Yang et al., 2019). EAST already has a quantitative element built-in to its framework in the form of network metrics.

STAMP (based on Leveson & Thomas, 2018; Leveson, 2011b) is an accident causality model, in which a system is regarded as a dynamic process made up of interrelated components, kept in states of safe equilibrium by control loops. Whereas in many traditional causation models the most basic element is an event, STAMP uses constraints applied to different levels of control in a process model as the basis for analysis (Leveson, 2011b).

A socio-technical system is graphically depicted as a hierarchical control structure (HCS) with controllers that cascade from highest to lower levels of authority (Section 4.1). Controllers can be human or technical and can be further divided into sub-controllers. A team of people can be divided into individual human agents whereas a technical agent can be decomposed into subsystems such as processing units, mobile platforms, robotic arms, end-effectors, etc. Each controller enforces controller constraints, by applying control actions on the next lower level, whereas this lower level sends a feedback in return, essentially informing the higher level if the controller constraint is satisfied. Control actions and feedback are assessed against the context of the controllers' internal process models and safety control problems can occur because of mismatches between the internal models of humans and technical controllers. These can lead to the automation surprises described in Section 2.3.

An HCS exists out of a virtual unlimited series of control action-feedback loops, depending on the scope of the analysis, divided into levels of authority control. These authority levels can extend further than the operational level to include organizational, legislative, and societal levels of control on safety. Examples of control that exceed the engineering level can come in the form of regulations, procedures, and safety requirements, whereas audits, reporting, and parliamentary hearings can act as higher-order feedback mechanisms.

The hierarchical levels of authority and the systematic control-feedback loops present a way to answer the question of what it means to be in control. The deconstruction into different controllers and sub-controllers interconnected by control loops makes it possible to systematically plot the dependencies in answer to the question of how control and cognition are distributed.

The HCS produced by the STAMP causation model serves as the basis for both a retrospective accident analysis technique CAST

(Causal Analysis based on Systems Theory) and a prospective hazard analysis technique STPA (Systems-Theoretic Process Analysis). While the main goal of the STAMP causation model is to identify inadequate control scenarios, STPA aims to subsequently develop systematic safety constraints to control unsafe scenarios in future designs. The application of STPA is out of scope for the demonstration purposes of this article, but an is covered in relation to cobots in another publication (Adriaensen et al., 2021).

3.1 | FRAM

The FRAM (based on Hollnagel, 2012) provides a nonhierarchical and descriptive model of a socio-technical system. The model is constructed around functions. These represent any acts or activities, simple or complex, that are performed to achieve a goal and are depicted by a hexagon (Hollnagel, 2012) (Section 4.2). Each corner of the hexagon represents one of the six fundamental aspect types (i.e., Input, Output, Requirements, Resources, Control, and Time). They shall only be described when it seems necessary and there is enough information to describe them (Hollnagel, 2012): (i) Input is what activates a function; (ii) Output is its result; (iii) Precondition describes the system condition that must be fulfilled before a function can be carried out; (iv) Time describes functional aspects; (iv) Control supervises or regulates the function, and; (vi) The resources aspect is what is needed or consumed.

These aspects represent the links between functions and produce a systematic network representation of functional dependencies (Figure 3, Section 4.2), which in FRAM are called couplings. Whereas the aspect types are defined by the connection to the next hexagon, they can also be attributed to various phenotypes such as adequate and inadequate timing, precision, speed, and force.

The potential for variability in the system is assessed by both endogenous and exogenous couplings and their upstream or downstream reverberations relative to a specific function. This potential is called performance variability. Unlike many traditional safety methods, performance variability is not per se regarded as negative but is a necessary system property to achieve work in light of trade-offs, finite resources, and time constraints. The performance variability of the model and its emergent behavior, as a result of upstream-downstream couplings, is called functional resonance. To manage variability, positive resonance should be amplified, while negative resonance should be dampened. This is for example achieved by inserting barriers, closing feedback loops, rearranging the order of functions, assigning roles to other agents, creating redundancies, or reorganizing the work system.

The methodological steps that are required in a FRAM analysis are as follows: (i) identification of functions; (ii) identification of variability; (iii) aggregation of variability; and (iv) assessing the consequences of the analysis or the management of the system's performance variability.

It is important to understand that the resulting FRAM model depicts the potential couplings in a representation of work as normally performed and is not possible to determine whether a function will always be performed in relation to other functions. Instead, an instantiation of a FRAM model represents the actual couplings or dependencies that have occurred or might occur under favorable or unfavorable conditions in a particular scenario. The focus of the FRAM is on the interplay of the dependencies. Therefore, the question of what it means to be in control will depend in the first place on how that control is distributed over the system.

3.2 | EAST

A comprehensive and recent overview of the different domain applications of EAST, with several methodological variations, can be found in (Stanton et al., 2018). EAST considers the overall system as the unit of analysis, by studying the interactions between humans and between humans and artifacts within the system itself. EAST is best described as a framework, as it combines several tools and methods that are specific to EAST but derives its data from techniques that exist independently of EAST.

At the core of the overall approach, EAST describes, analyses, and integrates activity by a multiple network representation: task, social, and information networks are first developed individually and are subsequently evaluated in an integrated network of networks.

The original EAST framework (Stanton et al., 2018) adheres to a preformatted methodological structure with (i) data collection methods (Activity sampling/observation, Critical Decision Method; (ii) data analysis methods (Hierarchical Task Analysis, Social Network Analysis [SNA]), and; (iii) representational methods (Network diagrams, Comms Usage Diagram, Coordination Demands Analysis, and Operation sequence diagram). A shortened form of EAST has been proposed to derive task, social, and information networks directly from the raw data (Stanton et al., 2018).

EAST outputs can be analyzed either qualitatively or quantitatively. The latter is achieved by applying network analysis metrics, whereas the qualitative data can be derived from network representations and additional supporting representational diagrams as described in step (iii) above. By assessing a distributed inter-agent representation of information and tasks, a JCS analysis is developed. The outcome of the analysis typically consists of a graphical presentation of distinct information, task, and social networks. This is followed by an integrated network combination of the individual networks, and finally, an interpretation of the metrics analysis that emerges from these networks. We refer to Table 4 for an overview of network metrics that have previously been applied in EAST, and which are based on SNA. Although the selection of metrics varies between individual domain applications and cases, they typically include several metrics that express the centrality and connectedness of nodes, and their relative distances to the other nodes in the network (Stanton et al., 2018).

TABLE 4 Description of Social Network Analysis metrics often used in EAST

Social Network Analysis metrics	Description
Emission degree	The number of ties emanating from each agent in the network
Reception degree	The number of ties going to each agent in the network
Eccentricity	The largest number of hops an agent has to make to get from one side of the network to another
Sociometric status	Refers to the number of communications received and emitted by each agent, relative to the number of nodes in the network
Agent centrality	Calculated to determine the central or key agent(s) within the network. There are a number of different centrality calculations that can be made. For example, agent centrality can be calculated using Bavelas–Leavitt's index
Closeness	The inverse of the sum of the shortest distances between each individual and every other person in the network. It reflects the ability to access information through the "grapevine" of network members
Farness	The index of centrality for each node in the network, computed as the sum of each node to all other nodes in the network by the shortest path
Betweenness	The presence of an agent between two other agents, which may be able to exert power through its role as an information broker
Eigenvector	Identifies those nodes connected to important nodes, which may provide a discreet intervention target

Source: Taken from Stanton et al. (2018).

Some scholars proposed an alternative approach to use EAST without the application of metrics, by applying the so-called "broken link approach" (Holman et al., 2020; Hulme et al., 2021; Lane et al., 2019; Stanton & Harvey, 2017; Stanton et al., 2019) The first part of this approach still involves the modeling of task, social, and information networks, but subsequently enables EAST networks to be used for predictive risk assessment by examining the effects of "alternative circuits," "short circuits," "long circuits," and "no circuits" (Stanton et al., 2018).

4 | EXEMPLAR CASE STUDY

We have based our demonstration case study on a real cobot application consisting of an already existing manipulating arm and gripper for heavy loads (David et al., 2014), newly mounted on an AGV-type mobile base. We created virtual data in an imaginary scenario for the joint behavior of manipulation and mobility, based on generic capabilities derived from a press release and an accompanying sample video. The case describes an existing demonstrator model (BA Group Robotic Systems, 2017) with proven technologic feasibility. With no access to performance results, functional data, or work environment, we developed a scenario to provide a set of credible but limited operating conditions in relation to technology that aims at next-generation industrial collaborative capabilities. The focus was not on generating actual engineering recommendations, but on the generic suitability of the proposed systems thinking methods to extend the current techno-centric safety perspective with a socio-technical safety analysis. The boundaries of the case study have been chosen to ensure a pragmatical yet representative research dimension relying on openly accessible resources available

online (demonstration videos and technical documents) for the demonstrative case study. Keep in mind that applying any of the systemic methods proposed in this article to a real-world case study would need to include subject matter experts with different roles such as designers, operators, and supervisors. In this limited demonstrative case study, the researchers' engineering background and previous research experience with industrial applications sufficed to provide plausible engineering solutions and socio-technical outcomes.

The selected case study involves a mobile platform, which can move fully autonomously between tasks without operator interference (Figure 2, mode A). In collaboration with an operator, the swing arm from the manipulator can be used as a hand guiding device to grab and relocate heavy objects or workpiece extensions (Figure 2, mode B), for example, a drill workpiece extension. The swingarm is operated by a pair of handles, which simultaneously act as an enabling device when positive two-hand contact is established. The mobile platform can be used to transport objects or workpieces between locations. In the specific case of drilling, the mobile platform follows the lateral movements of the operator to execute precision drilling at repeated distances in a massive structure made out of concrete (Figure 2, mode C).

Figure 3 sketches the logic of the cobot operation, while an accompanying showcase video can be consulted (BA Group Robotic Systems, 2017).

We isolated a single scenario related to the cobot's drilling function, taking into account that this function requires a coordination challenge between the operator, the cobot's manipulating arm, and the mobile platform. Analyses of such systems applied to real-world examples would inevitably need to be extended to take into account the effects of multiple cobots and operators in a single
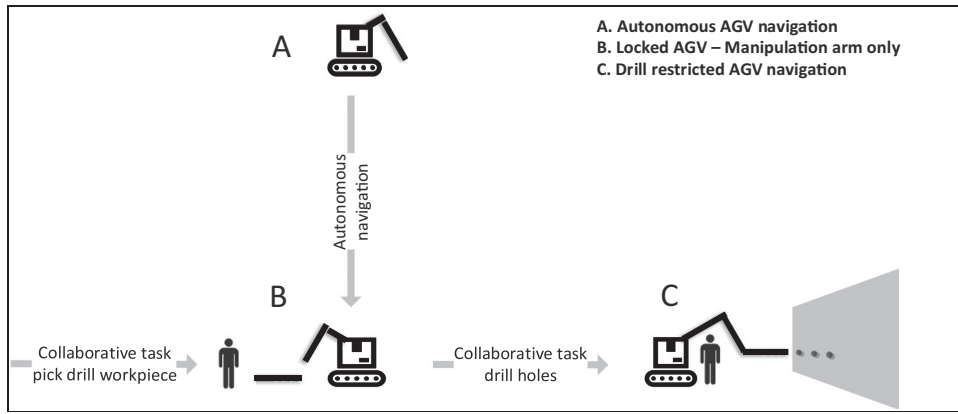
FIGURE 2 Sketch of the case study, with task-dependent mobile platform behavior
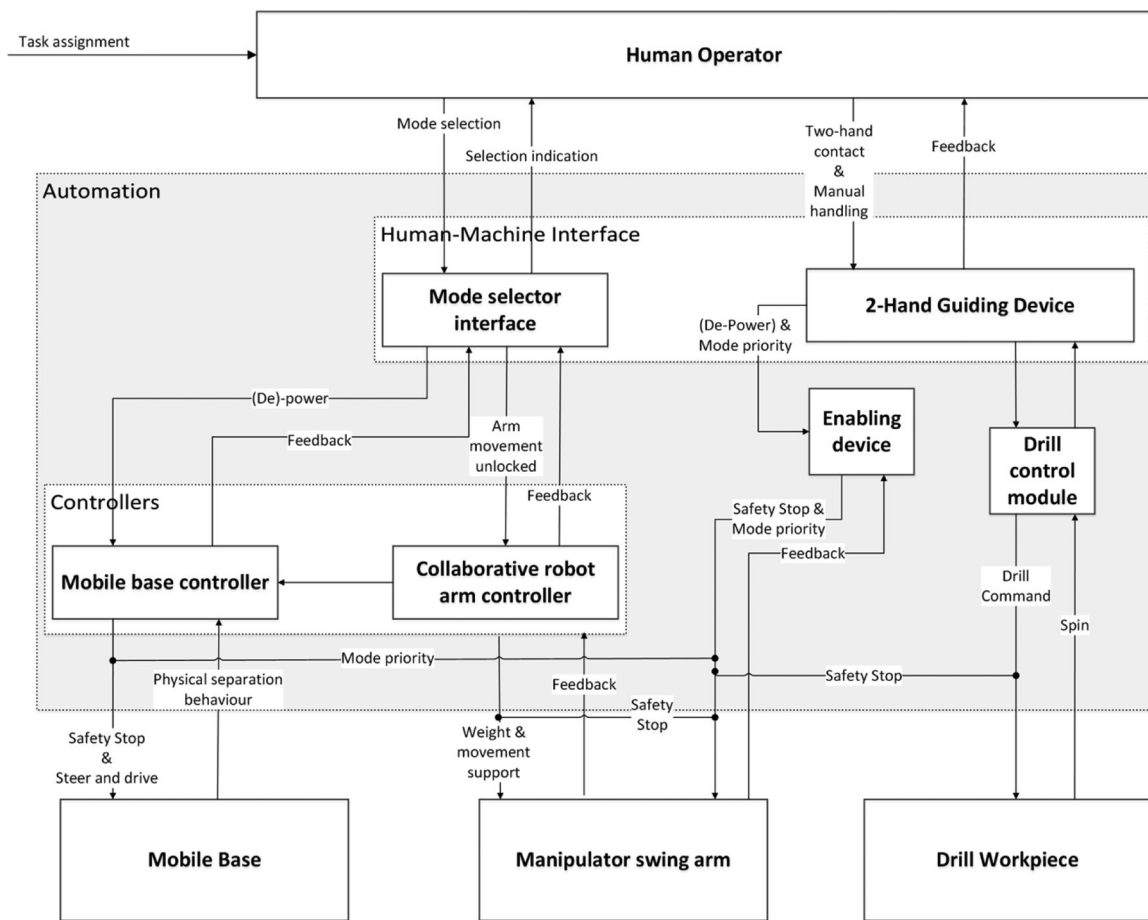

FIGURE 3 STAMP control structure of Human–machine interface (hypothetical). STAMP, System-Theoretic Accident Model and Processes

industrial setting, as well as the typical interconnectedness encountered in today's smart factories.

The mobile platform has three different mode behaviors, depending on the task: (i) the mobile platform moves fully autonomous between tasks without operator interference; (ii) the manipulating arm is used to pick or release objects or workpiece extensions, whereby the mobile platform is locked and does not move; and (iii)

the mobile platform follows the operator in the case of drilling holes. In the latter case, the cobot drives parallel to a structure or object from one hole to the next hole but does not drive or steer toward the object. Otherwise, this would balance out the direction and forces of the drill action, and additionally the cobot-operator separation could be violated. This is a serious hazard as the operator is positioned with his/her back to the cobot holding the drill hanging on the swingarm,

TABLE 5 Hypothesized Mode Conditions (MC) to create different mobile platform behaviors

Mode condition	Autonomous AGV navigation	Locked AGV navigation	Drill restricted AGV navigation
Collaboration mode (MC1)	Off	On	On
Two-hand contact enabling device signal (MC2)	Absent	Present	Present
Drill extension armed/active (MC3)	Off	Off	On
Safety controller (MC4)	Stop authority (priority over other conditions)	–	Stop authority (priority over other conditions)

reaching over the operator's head. In Table 5, we hypothesize the following credible mode priority requirements that result in three possible behaviors for the mobile platform.

4.1 | STAMP application

We first applied STAMP as an example to answer the questions of how control is distributed and maintained in the demonstrated cobot JCS system. We have generated two hierarchical control structures (Figures 3 and 4) with the controllers and their control action-feedback loops at different granularities.

Figure 3 shows a high-level diagram of the interface control structure and Figure 4 zooms further in on the mobile platform systems engineering. Hierarchical control structures contain different elements. The boxes depict the controllers which are the systems or subsystems that control the lower-order controllers. This is performed by control actions depicted by the arrows pointing downwards, whereas the loop is closed by the feedback information to the controller by the arrow pointing upwards. Controllers at the same level can communicate with each other outside of the control-feedback relationship, or even with controllers outside the HCS. Examples are <task assignment> or <workpiece input (drill)> (Figure 4) and are represented by horizontal arrows. The HCS can be used to analyze how for example mode management is used from a Joint Cognitive perspective, to verify how subsystems interact and how they are initiated by control actions from the human controller, which in the STAMP representation has the highest authority.

Following STAMP theory, inadequate control may result from missing constraints, inadequate safety controls, missing lower-level commands, or inadequate feedback to enforce constraints (Leveson, 2011b). Although a systematic and comprehensive examination of control requires to subsequently perform the steps provided by STPA as a complement to a STAMP analysis, the HCS developed here summarizes the system's architecture, which provides the basis for the examination of the control's dependencies.

The mode controller accepts multiple inputs (MC1, MC2, MC3) (Table 5 and Figure 4) and one overriding safety controller (MC4). By decreasing the granularity and looking at Figure 3, it can be learned that the hand guiding device, which inherently triggers the enabling device by positive contact from two hands simultaneously, is further connected to other subsystems such as the swing arm and drill

workpiece, apart from being interconnected to the control module that serves the mobile base via the enabling device (Figure 4). An inadequate control where the operator tries to manipulate the cobot with only one hand will not activate the enabling device (Figures 3 and 4) and create a fail-safe condition. This fail-safe state shall subsequently not interfere with any other safe control constraint states. This coordination is essentially what drives and supports a systems-thinking analysis by checking compatibility requirements for all subsystems under all scenarios. The dependency between operator input and mode management is but one example of how control is distributed over the system and an answer to what it means to be in control.

In this particular case, mode priority is initiated by a socio-technical context, because the drilling is one specific task in the organization of the work system. The mobile base navigation behavior subsequently results from a particular combination of mode selector, enabling device, and drill extension activity. It is essential that the operator is aware of why the system behaves as it does, earlier described as mode awareness.

See Adriaensen et al. (2021) for an STPA application of the scenario presented in this article. Even without performing STPA the HCS provides a means to verify several inadequate control and inadequate feedbacks. Similar systems thinking requirements and interactions can be identified by extending the scope and adding supplementary inquiries. <Task assignment> is, therefore, an example of a contextual factor which is related to the situated cognition of a work-specific system, whereby drilling for example creates dust which can affect the safety sensor(s), a condition which is not encountered in the cobot task modes A and B in Figure 3. Inadequate sensor feedback will be overridden by the stop authority from the safety controller. The inadequate feedback scenarios, whereby the sensor becomes covered with drilling dust, will trigger the overriding safety controller. With this example, we have provided a STAMP view on one inadequate control and one inadequate feedback, out of many other examples that can be investigated in a full-fledged analysis.

4.2 | FRAM application

The FRAM model was made with myFRAM (Patriarca et al., 2018), an open add-on for Microsoft Excel, from which the results were
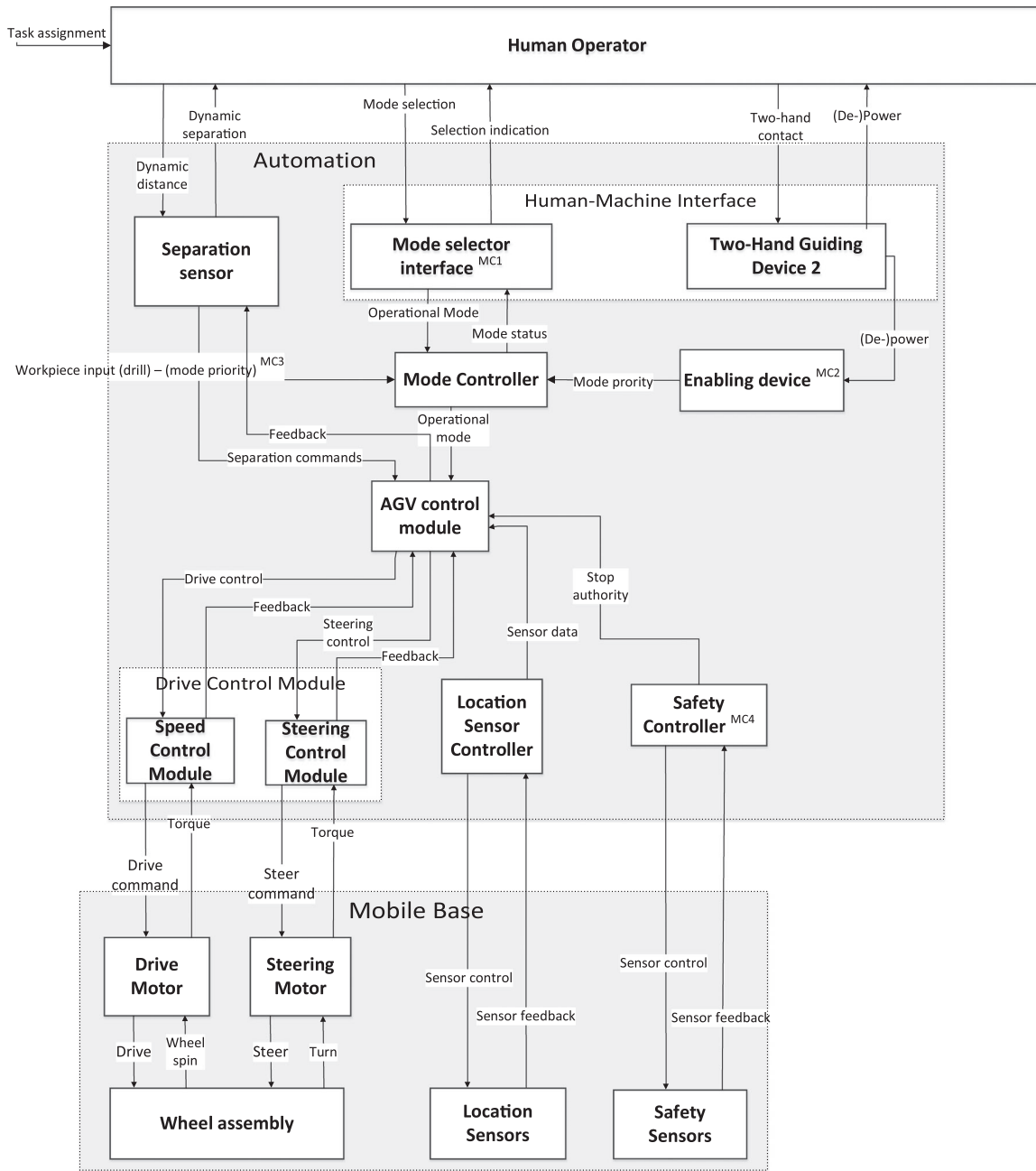
FIGURE 4 STAMP control structure of Mobile platform (hypothetical). STAMP, System-Theoretic Accident Model and Processes

subsequently exported in the traditional hexagon-based representation offered by the Functional Model Visualizer (FMV) (Hill & Hollnagel, 2016).

As for STAMP, for the FRAM application, we have chosen the same drilling function, because of its relevance for coordination challenges between agents. The FRAM model displays an interdependency analysis of functions, which can be read as functional exchanges between agents, human and technical alike. The colors assigned to the hexagons represent the different agents (see legend in Figure 4). For this functional analysis, we used a JCS perspective where the socio-technical system is displayed as a number of functional exchanges and whereby the traditional boundary between

medium and agent is abandoned in favor of accepting technical systems as agents of their own (Adriaensen et al., 2019). A functional analysis in this JCS sense accepts both physical changes and system state configuration changes from subsystems and components as functional tokens in a FRAM analysis. Agents and functional clusters were assigned to each of the functions individually from a bottom-up perspective.

In the FRAM language functions are described by a verb, depicted in the hexagons, for example <Pick drill workpiece>, which produce outputs, for example |Drill extension attached|, and can subsequently be linked as aspects of one or more downstream functions. The overwhelming number of aspect labels have not been

displayed for readability of the model, even if the limited scope produced a moderate 23 functions, already providing evidence on the need for a systemic analysis to gather the complexity of joint socio-technical operations. For this case study, we have grouped the functions in colored clusters (see legend Figure 4). These clusters offer a functional representation that makes evident how the unit of analysis cannot be disconnected between human and technical agents, rather aiming at a perspective of aggregated functions that together comprise a unique function. The green cluster, for example, shows how mode management consists of a set of mixed human and cobot functions from which the joint behavior or distributed cognition eventually will trigger the physical performance of the system. The green cluster functions represent the elements for the mode conditions of Table 5. The blue cluster represents human or cobot commands that are necessary to instruct a subsystem to execute a task, including physically hand guiding the cobot. The yellow cluster consists of the physical outcomes (e.g., drilling, mobile platform navigation) that result from command instructions, possibly altered by mode changes, whereas the orange cluster bundles the sensor functions. This cluster is the only one that consists of cobot functions only.

In this FRAM model, the function <Operator provides hand guiding movements> belongs to two clusters simultaneously as physically guiding the swing arm (yellow) to a particular position instructs the mobile platform to follow the operator (blue), when particular aspect conditions are met. Physically hand guiding the cobot per definition activates the enabling device through hand contact <Sense enabling device> in the sensing cluster (orange).

Figure 6 presents the same system control propagation from guiding the manipulator's arm with two hands, which we have already explored through STAMP, but now in the form of downstream propagation. Even if both the STAMP and the FRAM approach usually refrain from making models to represent the physical design, the functional propagation perspective provides a complementary perspective to the HCS. We have highlighted the downstream aspects from functions <Operator provides hand guiding movements> and <Sense enabling device> in Figure 6 to show the aspects generated by these two inherently related functions. They both originate from a single physical operator action (hand contact) and reverberate to a myriad of other functions throughout all clusters. The question of what it means to be in control from a FRAM perspective results in a plot of distributed control, represented as interdependencies in the work system.

Different mode management conditions from Table 5 (not highlighted in Figure 6) are depicted by difference in aspects that arrive in <Activate autonomous AGV navigation>, <Activate drill restricted AGV navigation>, and <De-activate AGV navigation> such as the pre-condition |enabling device activated|, |enabling device de-activated|, |drill armed/activated|, |collaboration mode on|, or |collaboration mode off|. These aspects are generally not restricted to mode management but are interrelated to several other functions that use these aspects as a resource, control, or precondition.

Further examples of contextual negative functional resonance can arise when for example an <Obstacle emerges (human or artifact)> (Figure 5) as the consequence of a falling object or an object overlooked in a previous work task. Alternatively, the previously mentioned negative propagation of drill dust on the safety sensor (Section 4.1) can be traced downstream of the <Sense obstacle> function. In terms of functional propagation, the output of this function is connected to the input <Lock AGV>, which is identical to the stop authority feature in the HCS representation from the STAMP perspective. It is needless to say that other socio-technical system variabilities are contained in this data and deserve to be explored in a full-fledged analysis.

4.3 | EAST application

Even if EAST is best suited to analyze multiagent networks with the simultaneous engagement of multiple human operators and cobots, the EAST scenario used in this study stays restricted to the joint behavior of an individual operator's inputs and a mobile platform with an integrated manipulator (cf. 4.1 and 4.2) and drilling extension. This restriction of scope enables the comparison of three systemic methods through a similar restricted case study. The reader should keep in mind that a full analysis of real-world variables with multiple agents will yield other results than represented in this article and would even influence the centrality and distance measures that resulted from this restricted case study. We also want to emphasize that we applied this shortened data collection process for demonstration of the method only. A full-fledged EAST analysis requires researchers to corroborate between observational data and collection of information from subject matter experts, for example, by applying the Critical Decision Method.

In practical terms, we generated the information, task, and social network data with KUMU, an online network analysis tool with built-in SNA capabilities and versatile graphical network options (KUMU, 2021). We started by building an information network, which is represented by the circled network elements in the integrated network representation in Figure 7. We applied the JCS approach by combining both human and technical agents in a non-hierarchical perspective.

Each element produces an information token that is connected to another element. Links between elements, also called nodes, can be uni-directional or bidirectional depending on the way information is emitted to or received from neighboring elements. The two "system behavior" functions in the middle of Figure 7 produce the observable behavior by the cobot navigation and the cobot manipulator. Together they produce the salient cues for the human operator in terms of expected or nonexpected system cobot movements in space and time. Two other networks are superimposed on the information network. First, the task network can be interpreted from the boxed labels, which also correspond to the colors of the circled elements. Information elements that belong to the same task are grouped together in clusters. The reason for the multicolor taxonomy for the two elements that concern "system behavior" can be found in the
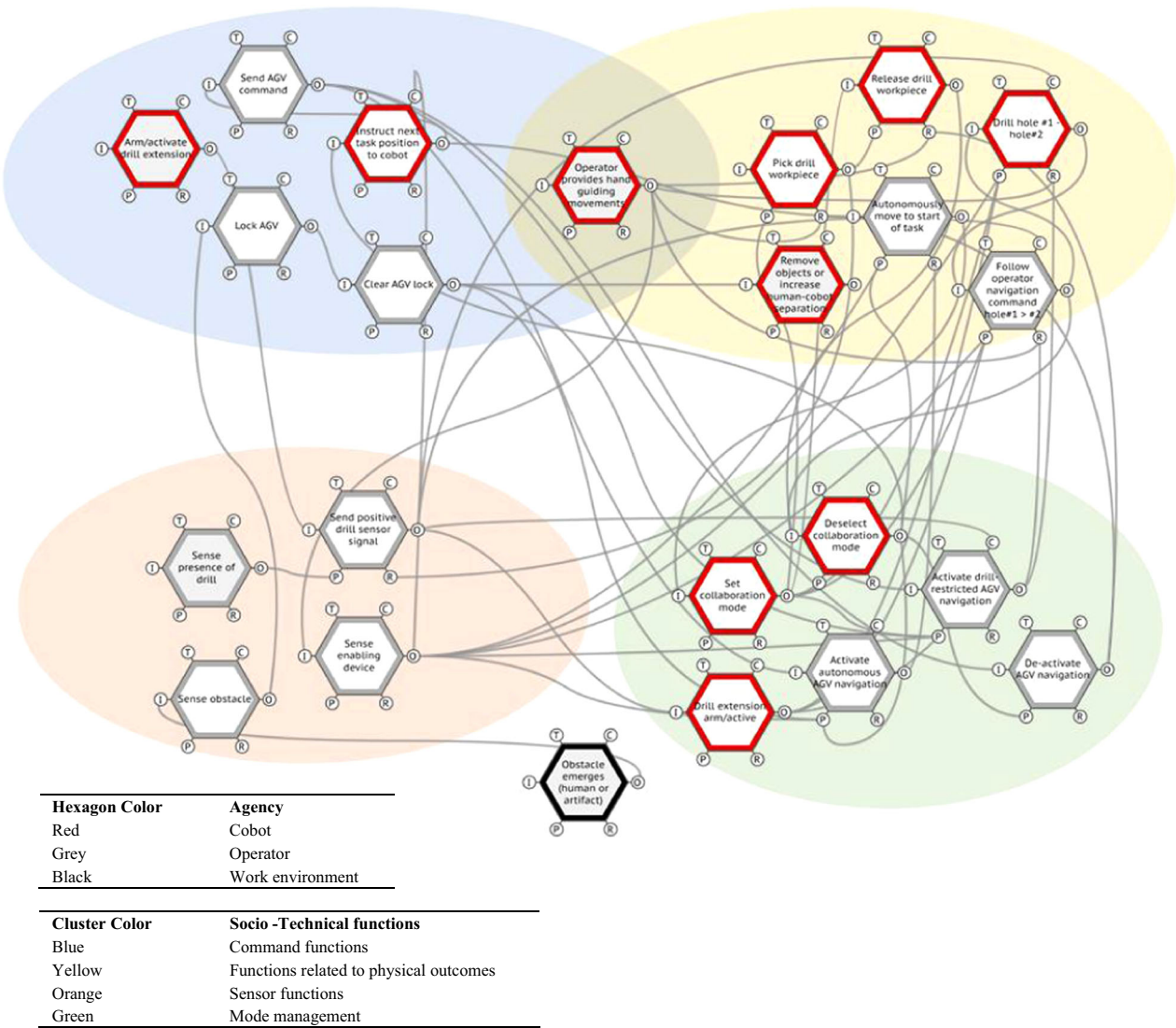
FIGURE 5 FRAM model from the functions related to drilling with mobile cobot support (hypothetical). FRAM, Functional Resonance Analysis Method

fact that they emerge from multiple task clusters. Second, the social network coding can be derived from the additional color-coded elements attached to the information elements (cf. legend social network in Figure 7). Some information elements involve multiple agents. One example is where increased human-cobot separation is produced as the dynamic outcome of both the human agent's and the cobot navigation's reactions to physical separation. Figure 8 presents another perspective on coding by agents, being the graphical representation of which agents are conjointly involved in the execution of a specific task.

Additionally, Figure 8 graphically represents some of the SNA metrics produced by the task network. Ranking numbers and values have been assigned to the tasks, with the information network links taken into account for the calculation of the metrics. Table 6 produces the quantitative results. While a limited number of metrics are graphically displayed by element size in Figure 8. Because of the limited data involved in this restricted case study, care should be

taken in interpreting the absolute numbers in isolation. The ranking of the metric values provides an easy way of comparing the element scores relative to each other.

The list of SNA metrics is not comprehensive. We have instead concentrated on those metrics that are useful in the context of this case study to meet our demonstration purposes. First of all, we did not include metrics that concern the whole network such as size, density, or cohesion, as these metrics are calculated concerning the total number of elements. They would therefore not produce meaningful results in a restricted demonstration case study with a limited scope. For similar reasons, an individual node metric like sociometric status has not been included because it also relies on the total number of nodes in the network. Eccentricity has not been included because describing the largest number of hops an agent has to make from one side of the network to the other side has little meaning in networks where both human and technical agents are involved, as both agent types are unevenly affected by eccentricity

Hexagon Color	Agency
Red	Cobot
Grey	Operator
Black	Work environment
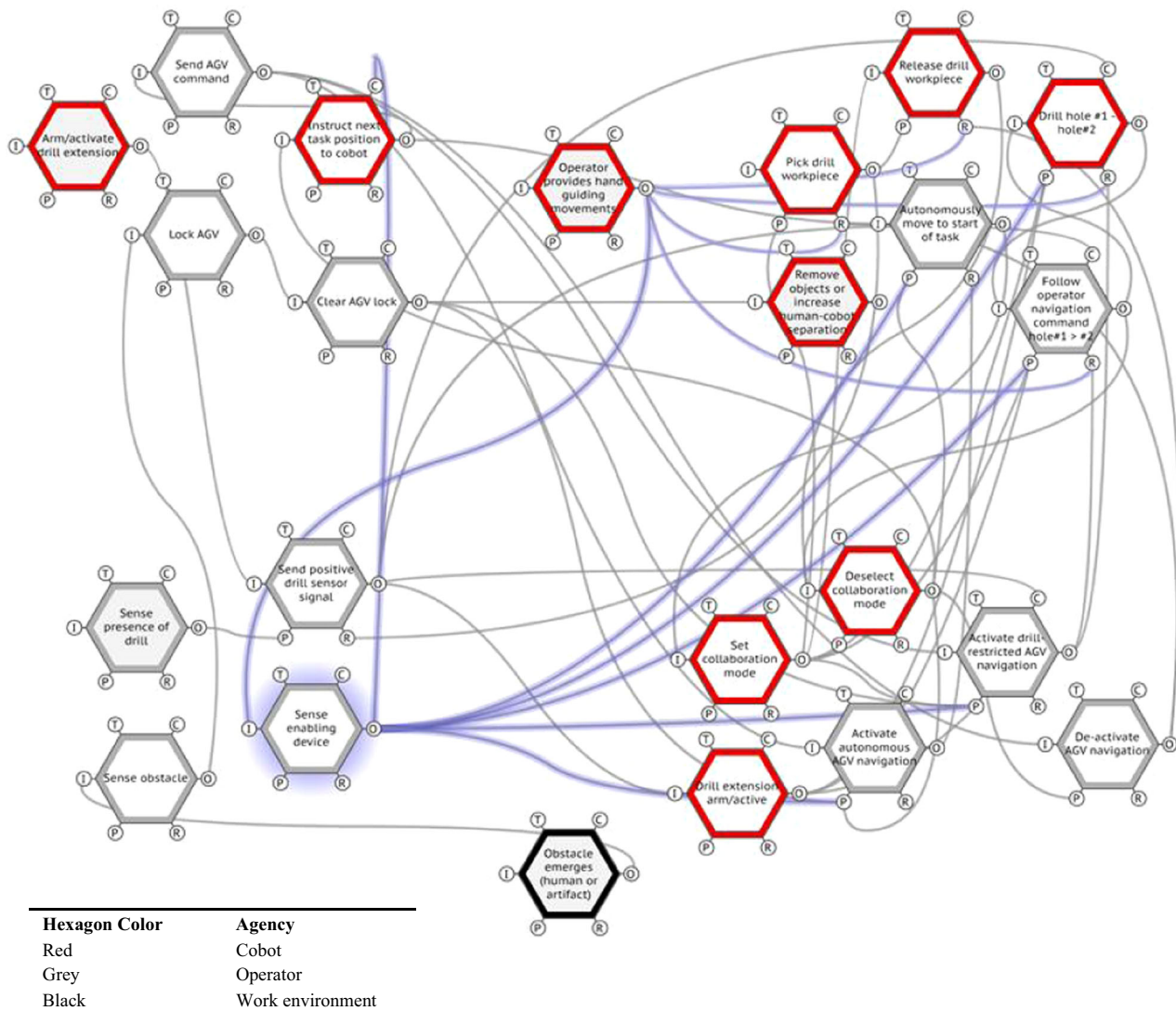
FIGURE 6 Downstream propagation of two inherently linked functions <Operator provides hand guiding movements> and <Sense enabling device>

effects. Automated agents have no problem with using a higher number of hops for automated logical links between sub-controllers. Compared to automated agents, human operators are more prone to information loss when hopping many nodes. A filter could be applied to compare separate eccentricity rankings for human and technical agents in larger case studies in the future. The metrics in the next paragraph are more relevant for our case study because they tell something about the potential for failure propagation or the way of element interrelatedness by varying centrality expressions.

Table 6 lists emission and reception (cf. 3.3) as the number of ties departing and arriving in each agent in the network. Nodes with high emission have the potential of a high-risk propagation when a single element fails (KUMU, 2021). This propagation remains valid for human agents, technical agents, or mixed agent types. In this case study, "mode management" has the highest number of outgoing links in terms of emission. "Mode management" drives many other functions and will have an important role when applying a broken link approach

in predictive risk assessment. A high degree of emission does not necessarily need to have a negative influence under normal operating conditions when multiple outputs are anticipated but high emission also indicates more possibilities for failure propagation. A scenario in which the automation mode is incorrectly managed upstream will indeed lead to a wrong automation mode output and undesirable mission performance. In our scenario, the highest rank for reception is assigned to the tasks related to the handling of the cobot manipulator and the drilling task, from which many elements involve handling from human operators. Other than technical components that are often designed to handle multiple information and configuration inputs in real-time, human operators might be overloaded by multiple and synchronous inputs, and therefore the reception metric can be used to indicate bottlenecks in a safety analysis. The tasks in which human operators have the final authority like handling of the cobot manipulating arm and the drilling function are the most connected in terms of reception. Closeness, being the inverse of the sum
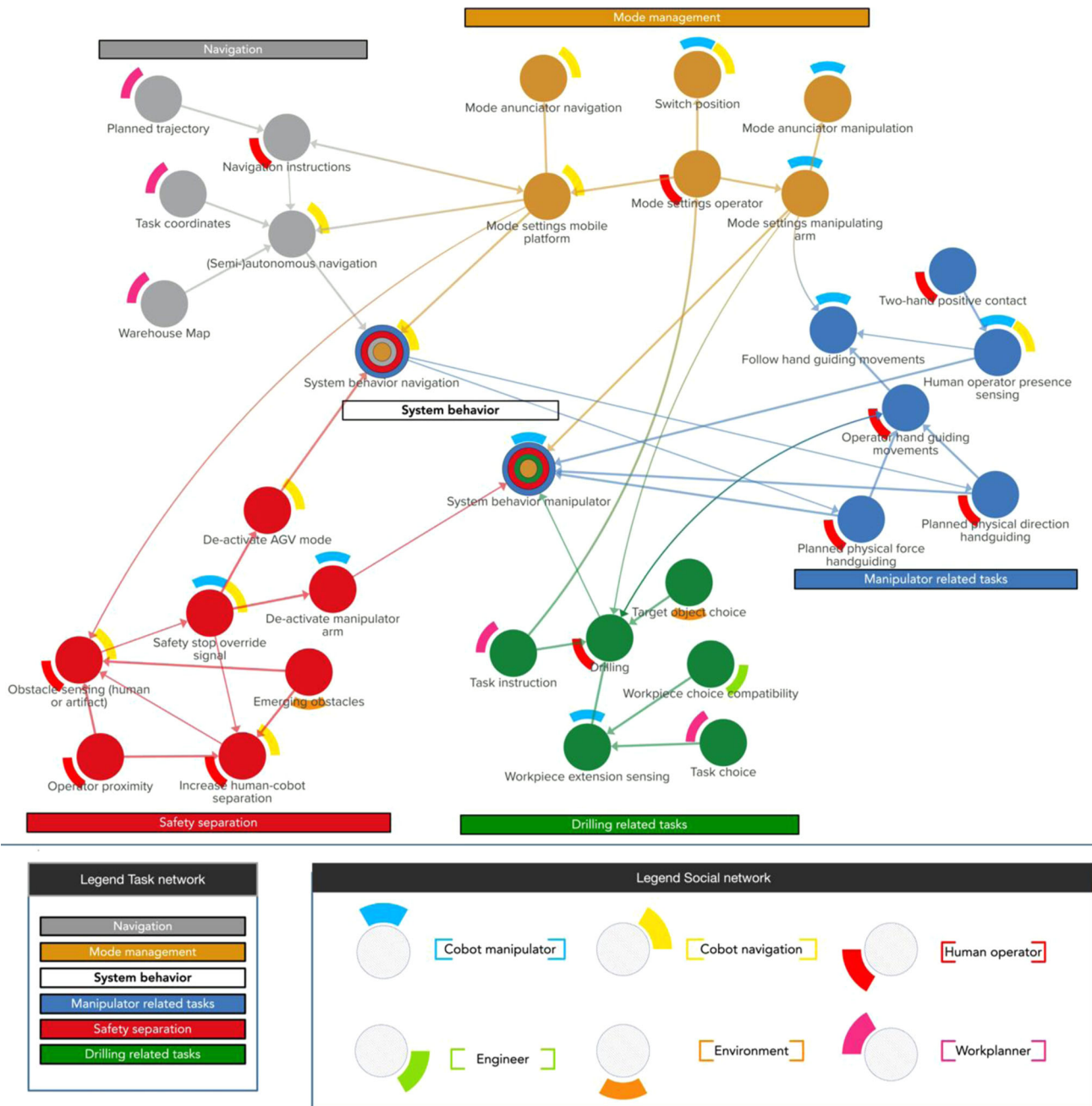
FIGURE 7 EAST integrated information, task, and social network model. EAST, Event Analysis of Systemic Teamwork

of the shortest distances tells something about control of access to information through the network and its members. It is an important measure to tell how well an element is indirectly connected to others. With "mode management" at the highest-ranked position, this task displays a critical role for being related to many other tasks, showing similar undesirable "mode management" consequences as those explained for emission. Farness, not explicitly added in Table 6 is the mathematical reciprocal of closeness (Bavelas, 1950).

Figure 8 graphically supports two different results from Table 6 applied to eigenvector and betweenness, selected as two metrics that are less intuitive to interpret. Whereas eigenvector is an index

measure of the influence of a node in terms of being connected to other well-connected nodes (Falegnami et al., 2020), betweenness (cf. 3.3) on the other hand provides a measure for the number of times an element stands on the shortest path between two other elements, which can also indicate a potential for failure (KUMU, 2021). "System behavior" shows low centrality in terms of betweenness but has a high eigenvector value. "Mode management" in our case study shows the opposite result. The fact that "system behavior" shows a high value on eigenvector can be explained by the fact that the observable cobot behavior emerges as the product from all tasks. Manipulator-related tasks also score high because these too

FIGURE 8 EAST task network model coded by agents. EAST, Event Analysis of Systemic Teamwork

Element size is proportional to Eigenvector values

Element size is proportional to Betweenness values
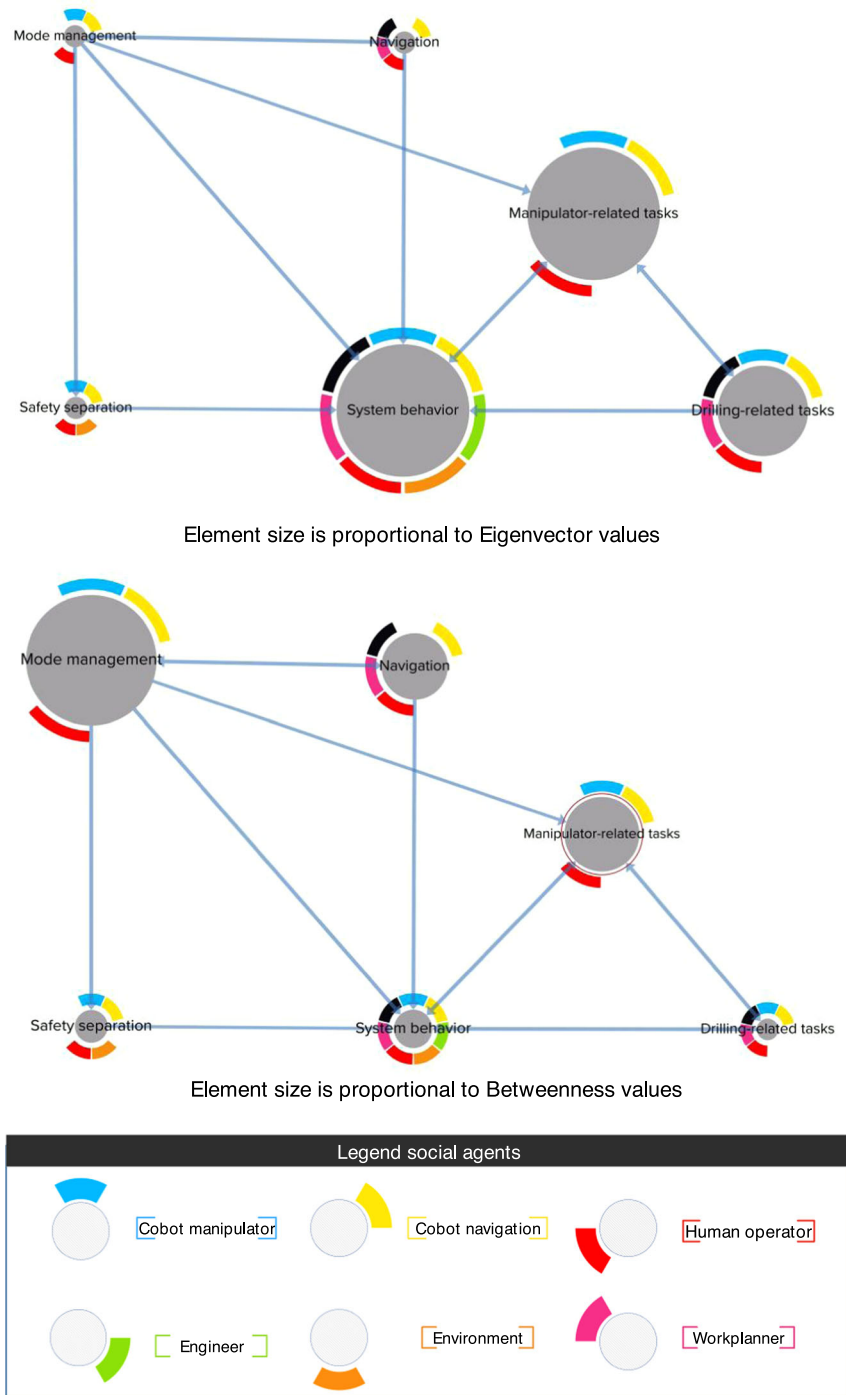
are connected to other well-connected nodes. The "mode management" task, which is a shared responsibility between the human operator, the cobot navigation, and the cobot manipulator agent is central in terms of betweenness because it is often involved in many other short element paths. Correct or incorrect "mode management" will indeed immediately affect all neighboring functions for both navigation and the manipulator handling as a direct consequence of system layout in which "mode management" plays a fundamental role. Hence, the graphical support of differently sized elements in terms of specific metric values helps to understand differences in centrality value interpretations for a metric like, for example, eigenvector and betweenness.

The coding from the social agents in Figures 7 and 8 can be used to support the JCS understanding of a socio-technical system. Instead of looking at traditional opposition of human and technical agents, EAST's social agent coding allows one to interpret which agents are jointly responsible for the production of specific tasks. Even subsystems such as the cobot navigation and the cobot manipulator and the effects they have on each other in the context of being related to several tasks and other agents can be immediately derived from their

TABLE 6 SNA centrality metrics for the combined information-task relationship effects on the task network

Rank	Degree Centrality (value)	Betweenness (value)	Closeness (value)
#1	Mode management (10)	Mode management (0.045)	Mode management (0.157)
#2	Manipulator-related tasks (9)	Manipulator-related tasks (0.028)	Navigation (0.110)
#3	Drilling-related tasks (9)	Navigation (0.025)	Manipulator-related tasks (0.057)
#4	Safety separation (8)	System behavior (0.017)	Drilling-related tasks (0.057)
#5	Navigation (7)	Safety separation (0.015)	Safety separation (0.052)
#6	System behavior (5)	Drilling-related tasks (0.012)	System behavior (0.043)
Rank	Eigenvector (value)	Reception (value)	Emission (value)
#1	System behavior (0.045)	Manipulator-related tasks (9)	Mode management (5)
#2	Manipulator-related tasks (0.028)	Drilling-related tasks (8)	Manipulator-related tasks (2)
#3	Drilling-related tasks (0.236)	Safety separation (7)	Drilling-related tasks (2)
#4	Safety separation (0.000)	Mode management (7)	Navigation (2)
#5	Mode management (0.000)	Navigation (6)	Safety separation (1)
#6	Navigation (0.000)	System behavior (5)	System behavior (1)

aggregation in the system's functions, ultimately providing a systems-thinking perspective. This case study only involves few external agents that are further removed from the direct human-robot interaction, like a work planner or an engineer. An increase in the complexity of the distributed cognition or distributed situation awareness architecture when subsequent external agents are added will emerge from the graphical network representation and SNA metrics. Values of SNA metrics can be related to the agents involved in specific tasks or information elements, for which we provided some limited examples in the previous paragraph.

Through this case study, we have demonstrated the usefulness for cobot safety by the analytical possibilities typically applied in EAST. The analysis supports the credibility of EAST as a framework to study distributed cognition networks concerning cobot applications.

5 | DISCUSSION

Each of the methods provided useful insights for the design, implementation, and operation of safe and efficient cobot systems that could not be derived from nonsystemic methods. Traditional safety analysis methods pursue the search for component failures or failure modes, but disregard that safety is also a positive capacity in terms of how mission performance is really achieved. The methods which we have used in this explorative study all put activities from human and technical agents at the center of the analysis. In all three methods, functional outputs are the concretized elements of the system. These functional possibilities have a higher granularity than simple agent exchanges connected through an interface and are not restricted by the properties of a device. By avoiding a reductionist view on component or mere agent interaction, systems can be made safer and more efficient by enabling or constraining functional configurations.

In all three systemic safety methods, "mode management" for example, was considered as an array of functions which was distributed throughout or connected to human and technical agents. Each method highlighted the importance and centrality from mode management for efficient system performance to emphasize but one practical lesson from this case study. Systemic safety methods thereby reveal that mode management does not even have to fail to cause system malfunction, but can simply result from suboptimal systems understanding. STAMP revealed how automation modes are altered as the logic consequence from activation of the two hand-guiding device. The human operator is not even necessarily aware that physically grabbing and directing the manipulator influences mode management and subsequent navigation and manipulating behavior.

The FRAM model similarly showed that this function, this time described as <Operator provides hand guiding movements>, indeed is shared by two functional clusters simultaneously. In the FRAM model it is only two propagations away of resonating with every other functional cluster in the model.

Equally, EAST revealed the same distributed connectivity in relation to the mode management task, but additionally expressed the centrality of mode management as a quantitative measure in several SNA metrics. The power of all our methods for safer and more efficient design and operation of cobot systems lies in revealing the distributed and emergent result from joint actions. Without the application of STAMP, FRAM or EAST, the exact distributed nature of functional system performance would remain obscured to the analyst. Subsequently, automation mode effects in our highlighted example should be made clearly detectable to operators by unambiguous feedbacks, annunciator design and intuitive cobot behavior. Additionally, operators should be trained about the consequences of their actions on automation modes. This observation

reveals that the locus of understanding does not lie in the individual actions, or components, but in the alignment of design, training and operation of future cobot applications.

STAMP, FRAM, and EAST are rooted on quite different theoretical foundations, yet all relying on systems theory. They all have in common that the unit of analysis has shifted toward understanding the interactions between components, instead of simply focusing on individual component failures. Ultimately, STAMP, FRAM, and EAST aim to answer questions related to what it means to be in control, or how cognition is distributed, through different analytical lenses. In STAMP safety is considered a control problem, whereas in the FRAM, safety is understood as the successful management of functional resonance. EAST evaluates systems from a cognitive distribution perspective, relying on both explicit and implicit information transactions. Besides the theoretical underpinnings, the three approaches provide different insights by different modeling representations. STAMP lends itself to a safety control perspective by introducing safety constraints and providing a causation understanding from an HCS perspective. FRAM and EAST are ideally suited to describe the distributed nature of socio-technical control, with nuances between the latter approaches. A single method does often not meet the analytical challenges in isolation (Stanton et al., 2018) and there is merit in using a combination of methods to understand the complexity and diversity of sociotechnical systems (Salmon & Read, 2019; Salmon et al., 2017).

A summary of how the different methods respond to the research questions "What does it mean to be in control in a Joint Cognitive System?" and "How is control distributed across such systems" is provided below in Table 7 and is based on method properties described in section:

In STAMP, dependencies are built up around control actions and feedback which create several control loops within the boundaries of an HCS. Multiple hierarchical control structures can be interconnected and receive external outputs. STAMP inherently labels its connections in terms of control actions (downward arrows), feedbacks (upward arrows), or external inputs (arrows with lateral inputs)

TABLE 7 Methods comparison table

	STAMP	FRAM	EAST
Relation to research question	What does it mean to be in control is based on the systemic distribution and management of control	Understanding how control is distributed precedes what it means to be in control, interpreted as (positive) performance variability	Understanding how control is distributed precedes what it means to be in control, examined through the lens of distributed cognition, information access and information management
Theoretical foundations	Safety as a control problem	Functional resonance	Distributed Cognition/Distributed Situation Awareness
Representation	Hierarchical control structure	Functional analysis representation	Information, task and social network + integrated network of networks
Dependencies	Top-down hierarchical control from a systems-thinking perspective	Nonreductionistic, nontaxonomic method to analyze nonnormative behavior	Nonreductionistic, nontaxonomic method to analyze nonnormative behavior
Dependency features	Control and feedback loops. Inputs and interdependency of loops	Functions connected by six possible aspects, phenotypes for endogenous and exogenous couplings, and assignment of agents	Elements and ties in information, task and social network (agents) and integrated network of networks
Distributed cognition	STAMP maps control and feedback loops by means of socio-technical hierarchy	Nonhierarchical functional analyses (information exchanges and functional exchanges are treated equally)	Nonhierarchical distribution of information among tasks and agents
Outcome	STAMP results in the Hierarchical Control Structure as causation model	Assessment of the aggregated performance variability to manage positive and negative	Quantitative distance and centrality measures
			Qualitative representation of networks
	STPA respectively provides safety constraints	resonance by upstream and downstream resonance	Broken links approach: Assessing "alternative circuits," "short circuits," "long circuits," and "no circuits" for predictive risk assessment
Risk mitigation principle	Controller constraints are the logic result from the methodology	Descriptive system understanding guides understanding and managing risk on a case study basis	Descriptive system understanding guides understanding and managing risk on a case study basis

Abbreviations: EAST, Event Analysis of Systemic Teamwork; FRAM, Functional Resonance Analysis Method; STAMP, System-Theoretic Accident Model and Processes.

(Figures 3 and 4). Contrarily, in FRAM dependencies exist of couplings connecting the six potential aspects of functions (Input, Output, Precondition, Resource, Control, Time) and it is also possible to assign phenotype values to the aspects, which permit to attach a qualitative evaluation of dependencies (e.g., timing, precision, accuracy, etc.). FRAM is thereby the approach that provides more rigidity in defining how dependencies (called couplings) influence system behavior. In FRAM, a precondition for example needs to be satisfied before the next action can start, whereas a resource defines a coupling that is consumed by the next function. EAST, on the other hand, does not distinguish between aspect types, but it essentially provides a difference between information, tasks, and agent networks.

EAST provides an alternative perspective to assess the quality of dependencies (sometimes called ties or edges in EAST, but in most studies simply named relationships) using SNA metrics to assess the centrality, position, or efficiency of a node. This quantitative assessment of the network and its nodes is not offered by the other two approaches. The EAST framework recently introduced the East broken-links approach for predictive risk assessment (Lane et al., 2019; Stanton & Harvey, 2017). In the broken-links extension, EAST assesses series of dependencies through evaluating them in the context of "alternative circuits," "short circuits," "long circuits," and "no circuits," introducing an additional qualitative propagation potential. The FRAM on the other hand verifies to which extent a series of dependencies produces positive or negative resonances with other couplings upstream or downstream of functions under investigation with a strong emphasis on the nonlinear propagation potential. Which method is better ultimately depends on the research subject. EAST can be especially useful in smart factories which contain data information networks in combination with networked technologies. FRAM on the other hand has the advantage of being a method-sine-model (Hollnagel, 2012), which makes it highly adaptable to different contexts.

Concerning the focus of investigation and outcome, one important difference between STAMP and the other two approaches is STAMP's focus on negative outcomes and countermeasures. Contrarily, FRAM has been described to apply a more descriptive resilience engineering perspective (Patriarca et al., 2020) and EAST has similarly been described to take advantage of a "non-reductionistic, non-taxonomic method for analyzing non-normative behavior of systems" (Stanton & Bessell, 2014). Improving system safety through FRAM and EAST approaches depends in great part on gaining a better understanding of distributed cognition and control and exposing the implicit functioning of the system. Safety mitigation is not strictly instructed by the FRAM and EAST methodologies. Contrarily, STAMP provides a top-down model and takes a systems-engineering approach with predefined risk mitigation steps incorporated in its methodology. All approaches acknowledge the role of normal performance in accident causation s (Hollnagel, 2012; Leveson, 2011b; Stanton et al., 2018). FRAM and EAST, therefore, tend to be more suitable for describing operational systems, including emergent relationships initially not foreseen in the design, whereby the hierarchical control structure approach from STAMP can be preferential

for engineering approaches, especially in early design phases, where design is based on the logic of controllers and anticipated contextual parameters. STAMP as a causality model can be complemented with STPA, as a hazard analysis extension. STPA results in system control constraints that result from the HCS by the identification of control actions, unsafe control actions, loss scenarios, and contextual parameters. See Adriaensen et al. (2021) for an extended STPA analysis related to the STAMP analysis from this publication in which the system control constraints for the AGV controller systematically were systematically studied. By applying STPA, we widened the scope to predictive risk analysis, Likewise, we recommend future research to examine cobot applications through the EAST broken-links approach as a predictive risk analysis extension.

In essence, several methods can mutually support the understanding of the system or the scenarios and instantiations under investigation. The functional distribution from both EAST and FRAM approaches can subsequently be verified and contrasted with the control structure of the STAMP representation. Additionally, "the focus" of the three systemic methods differ. STAMP delivers a stepwise approach to derive the HCS from losses, hazards, and system control constraints, which provides an opportunity to demonstrate compatibility with more traditional safety analysis requirements. FRAM has strong theoretical underpinnings that do not prescribe specific data collection methods but require the researcher to represent strong ontological models of the work systems under consideration. In comparison to the other approaches, EAST has a greater focus on a comprehensive data collection framework, which increases the scientific reliability of the resulting models.

The limitations of the article can be found in the fact that an actual case study requires interviews and observational data to build more accurate models with support from subject matter experts. The robust initial data gathering methods from EAST can yield data that can in turn be re-utilized in any of the other remaining systemic methods. Future research could provide full-fledged FRAM and EAST analysis of multiagent networks.

Another limitation is that we used the methods for a limited demonstration case and did not provide a systematic analysis of all data that could be gained from this case study. Future research could also investigate new configurations of the various method strengths to be used in combination. From several possible configurations, at least the combination of EAST and STAMP has been described (Salmon et al., 2018), as well as a combination of network metrics and FRAM (Falegnami et al., 2020). We would also like to point to the fact that we only applied a selection of methods for this study, but ideally future research would draw a full comparison of strengths and weaknesses of several other available systemic methods, such as CWA (Naikar, 2017), system dynamics (Ibrahim Shire et al., 2018), or Net-HARMS (Hulme et al., 2021; 2021) to just name a few. During the writing of this manuscript, one publication in particular deserves attention, because it compares the reliability and validity of, STPA and the EAST broken-links approach (Hulme et al., 2021), with the recommendation to further test extensions to enhance the reliability and validity of these methods in the future.

6 | CONCLUSION

The literature review on collaborative robots presented in this publication revealed a great emphasis on a techno-centric perspective, whereby risk was narrowly defined in terms of uncontained energy, with a typical focus on safety mitigation in terms of speed, kinetic energy, and separation. The contribution from this article is to first draw attention to a paradigm shift from a mere techno-centric perspective toward a socio-technical safety perspective, and secondly to provide and demonstrate the feasibility of different systemic safety analysis methods to complement the traditional energy-barrier perspective for cobots safety analysis. Collaborative robot applications purposefully use the principle of distributed cognition to the advantage of a joint action that is stronger than the sum of its parts, which additionally motivated to examine the problem domain from a JCS perspective. The finding from such an approach can support a systemic human factors design perspective and provide insights about implicit cues and effects that can be important for training purposes. We believe this is the first study to explore the joint possibilities of the three systemic approaches STAMP, FRAM, and EAST or to highlight their specific benefits.

The controller-constraint view from STAMP, the network analyses from EAST, and the variability-resonance perspective from FRAM provide complementary lenses to analyze collaborative work in human-machine collectives. Regardless of the specific approach to be applied, with its respective pros and cons, we believe that a socio-technical research perspective is required to deal with issues referred to modern and future cobot systems.

ORCID

A. Adriaensen https://orcid.org/0000-0002-6002-7593
R. Patriarca https://orcid.org/0000-0001-5299-9993

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