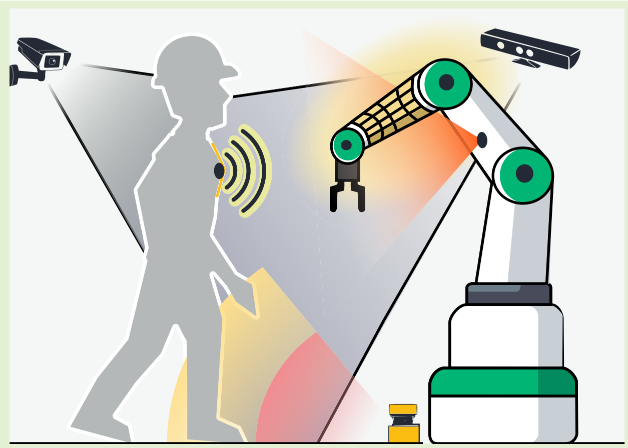
Sensor-Enabled Safety Systems for Human–Robot Collaboration: A Review

Constantin Scholz, Hoang-Long Cao, Emil Imrith, *Member, IEEE*, Nima Roshandel, Hamed Firouzipouyaei, Aleksander Burkiewicz, Milan Amighi, *Graduate Student Member, IEEE*, Sebastien Menet, Dylan Warawout Sisavath, Antonio Paolillo, Xavier Rottenberg, Peter Gerets, David Cheyns, Marcus Dahlem, *Senior Member, IEEE*, Ilja Ocket, *Member, IEEE*, Jan Genoe, *Member, IEEE*, Kathleen Philips, Ben Stoffelen, Jeroen Van den Bosch, Steven Latre, and Bram Vanderborght, *Senior Member, IEEE*



***Abstract*—Sensors are integrated into collaborative robot systems to ensure the safety of human workers by allowing them to perceive their environments, detect human presence, and adjust their actions accordingly. This preferred reporting items for systematic reviews and meta-analyses extension for scoping review (PRISMA-ScR) focuses on current sensor-enabled safety systems for human–robot collaboration (HRC) in the manufacturing industry based on both scientific papers and patents. From the initial search of 6669 references, 281 underwent full-text review and segmentation based on the sensor technology, installation location, and safety operating mode according to the ISO/TS 15066 standard. In the last decade, there has been a clear trend of increasing sensor-enabled safety systems. The dominant sensors used are infrared (IR)-structured light, capacitive, light detection and ranging (LiDAR), resistive, stereo/depth camera, RaDAR, and laser scanners. The primary safety operating mode identified was speed and separation monitoring (SSM). Some systems integrate multiple sensor types, with the most common combinations being LiDAR with stereo cameras or LiDAR with capacitive sensors, and laser scanners with RaDAR. We suggest multisensor integration and standardized benchmarks for future development. This review is among the few that employ the PRISMA-P protocol to study sensor technologies and contribute to a more systematic understanding of the current state of the art in this area.**

***Index Terms*—Collaborative robots, human–robot collaboration (HRC), perception systems industry 50, safety systems, sensors.**

I. Introduction

THE manufacturing industry has undergone a significant transformation in recent decades, driven by the integration of robotic systems and smart sensors. This paradigm shift, known as Industry 4.0, has resulted in network interconnected machines, improved speed, enhanced quality, and increased productivity [1], [2], [3]. Industry 4.0 has also enabled real-time supply management, demand forecasting, autonomous quality control, predictive maintenance, and optimal asset utilization [4], [5].

Human interaction with robotic systems was previously hindered by physical barriers within enclosed robotic work cells [6], [7], [8]. The introduction of collaborative robots (cobots) enabled by variable-impedance actuators has revolutionized this landscape by allowing close collaboration between humans and robots within a shared workspace [9], [10], [11]. Cobots offer increased flexibility, high-speed actuation, rapid programming, and the ability to be deployed in dynamic and flexible workstations, thereby providing a quick return on investment [12], [13], [14], [15]. However, despite their potential benefits, the adoption of collaborative robots remains relatively low and complex [16]. This can be attributed to factors, such as the complexity of performing

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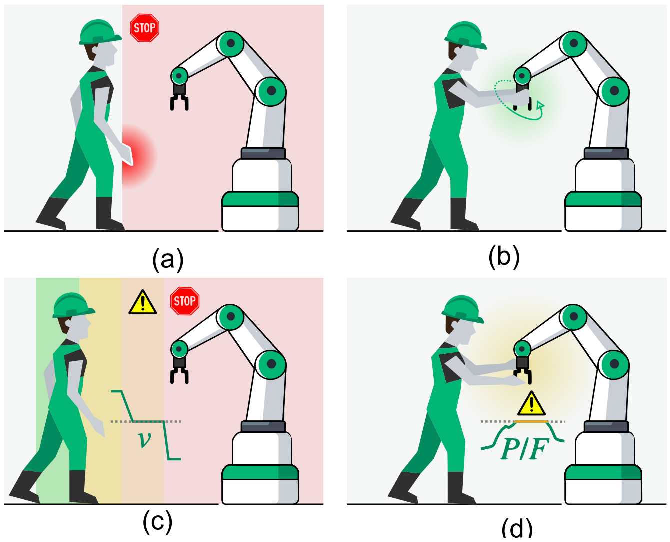

Fig. 1. Four types of operating modes in HRC according to the ISO/TS 15066 safety standard are used to classify the sensor-based safety system in this scoping review. The worker image is designed by Freepik. (a) SRMS. (b) HG. (c) SSM. (d) PFM.

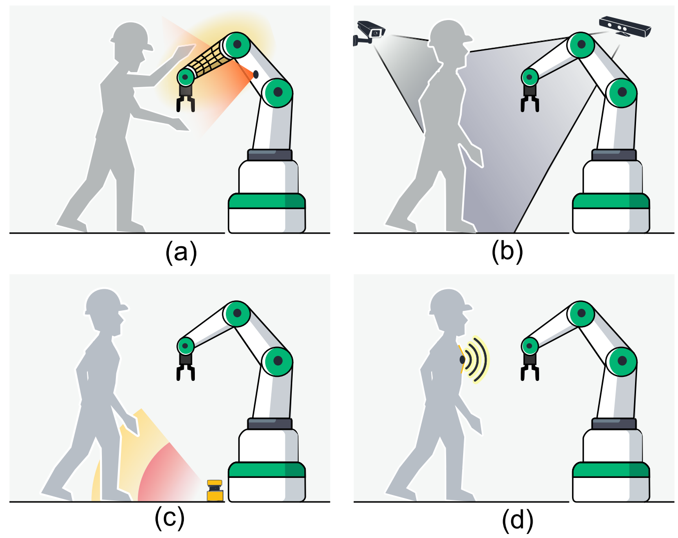

Fig. 2. Installation locations of sensors for safety: on-robot, external, close to robot, and on-human. The worker image is designed by Freepik. (a) On robot. (b) External. (c) Close to robot. (d) On human.

system risk analysis [17], limited knowledge about operating cobots safely [18], concerns regarding worker acceptance and perception and understanding of cobot operations [19], [20], [21], [22], and actuation strategies during a collision of the robot that instead could have been prevented through a sensing system that matches the requirements of the deployed application. Moreover, factors such as reduced speeds and payloads in collaborative human–robot interactions can lead to usability and productivity challenges [23], [24], [25].

The field of robotic safety follows established standards such as ISO 10218-1&2 and ISO/TS 15066, which govern the safe operation of industrial robots [26], [27], [28], see [29] for a review. ISO/TS 15066 defines four operating modes, as illustrated in Fig. 1: safety-rated monitoring stop (SRMS), hand guiding (HG), speed and separation monitoring (SSM), and power and force limiting (PFM). These modes enable different levels of robot interaction and collaboration within shared workspaces. In SRMS, the robot initiates a controlled stop when a human enters a predefined safety zone, resuming operation only once the area is clear and preventing unintended movements. The HG mode allows an operator to control the robot's motion by holding onto it directly, with the robot stopping movement when the operator releases it, thus enabling precise control only under direct human guidance. In SSM, the robot continuously adjusts its speed based on its distance from the operator, thereby ensuring a safe separation distance. This mode is primarily used to slow down and stop the robot when the separation distance is insufficient, although more advanced implementations can modify the robot trajectory to dynamically maintain minimum safe distances. Finally, the FL mode limits the power and force of the robot, thereby allowing safe contact with humans. If the robot collides with a human, it halts operations until the contact is released or reset, depending on the application.

To enable fenceless robot operation and safe human–robot collaboration (HRC), it is crucial to implement *sensor-enabled safety systems*. These systems use different types of sensors to detect and perceive possible dangers, and then activate safety measures to ensure the safety of both humans and objects within the robot's workspace and surrounding area. These sensors can be installed at different locations, as illustrated in Fig. 2: *on-robot*, *external*, *close to robot*, and *on-human*. For instance, many cobot arms are equipped with compact internal force/torque sensors that measure torque at rotational pivot points. When the torque exceeds predetermined limits due to contact with the surroundings, these sensors initiate a safety-rated protected stop to prevent worker injuries [30], [31]. Similarly, external safety pads attached to cobots monitor the impact on workers' bodies or surrounding obstacles by measuring pressure changes in the pads and indicating a collision [32]. While these measures are essential for ensuring safe collaboration, they may also affect productivity by reducing operating speeds.

A new industrial movement is currently leading the worldwide development of Industry 5.0 [33], a vision that prioritizes the well-being of workers at the heart of the production process [34], [35]. Industry 5.0 aims to leverage advanced technologies to enable hypercustomization by enhancing workers' skills and focusing on tasks that cannot be automated, while robots will handle more routine and less cognitively demanding operations. This approach will help address the staffing shortages prevalent in the challenging global labor market, particularly in the manufacturing industry in the member states of the European Union, Norway, and Switzerland [36]. By utilizing cobots, Europe can address productivity bottlenecks caused by shortages of plant and machine operators as well as assemblers. In addition, the concept of circular production models and the upgrading of the existing technology suggest the retrofitting of current industrial robots with safety technology to enable closer collaboration between humans and robots, utilizing existing assets to blur the line between two extremes: cobots, which are safe but slow, and traditional industrial robots, which are fast but unsafe.

Previous reviews examined various aspects of safety and collaboration in robotics. A systematic review conducted by Arents et al. [37] utilized the preferred reporting items for systematic reviews and meta-analyses extension (PRISMA) framework and provided insights into global safety systems and general trends in HRC. However, this review did not extensively explore the technicalities of different sensor modalities used in the identified papers. Moreover, the search was limited to specific terms related to smart manufacturing, smart factories, and industrial environments, which may have restricted the scope of the findings. Another review by Robla-Gómez et al. [38], although not following the PRISMA approach, provided valuable insights into the subject. However, it did not encompass recent developments over the past five years. Finally, Navarro et al. [39] conducted a review that focused not only on proximity sensing for distance but also on proximity sensors for grasping and exploration. While briefly covering sensors applicable to the industry and related safety systems, this review did not extensively address the trends in sensor development and the sensors used or investigated the patent literature [39].

This PRISMA-ScR scoping review aims to provide an updated overview of sensor-enabled safety systems for industrial robots and cobots, specifically focusing on HRC in the manufacturing industry. Moreover, the findings can be translated to other robotic systems, such as humanoids, drones, autonomous vehicles, medical robots, agricultural robots, warehouse automation systems, and service robots. By examining the research and patent literature, this review aims to present the current state of safety systems and provide insights into the expected design of future robotic safety systems. Importantly, this review builds on previous studies by including the patent literature and using a top–down approach to categorize sensor-enabled safety systems. References included in the categorization are available via an interactive online database that allows customized filtering.

II. Methods

The scoping review was conducted using a comprehensive five-stage methodological framework: 1) identification of the research questions; 2) identification of relevant records; 3) selection of eligible records; 4) data charting; and 5) collation, summarization, and reporting of the results [40]. The review adhered to the PRISMA for scoping review (PRISMA-ScR) checklist, which was developed to increase the clarity, transparency, quality, and value of reports [41], [42]. A protocol for the scoping review was developed and is available on the Open Science Foundation website at: https://doi.org/10.17605/OSF.IO/YTJVS following the PRISMA-P and PRISMA-S extensions [43].

A. Research Questions

The research questions addressed in this scoping review were formulated based on the problem–concept–context (PCC) framework adapted for engineering [44]. *Problem:* Ensuring safety in HRC. *Concept:* Sensor-enabled safety systems and technologies. *Context:* For applications in the manufacturing industry. This resulted in the following questions.

Q1: What sensor technologies are used in safety systems to achieve HRC in the manufacturing industry?

Q2: What operating modes, according to ISO/TS 15066, do the technologies enable?

Q3: Is there a trend toward combining sensor technologies?

B. Identification of Relevant Records

1) Eligibility Criteria: The eligibility criteria for the scoping review paper include three phases: identification, title-abstract screening, and full-text screening. In the *identification phase*, scientific papers must be written in English or have an available English translation, be journal articles or conference proceedings, and not duplicates. Patents should be in English or have an English translation, be active, pending, or expired but not abandoned or rejected, and not be duplicates under different international patent numbers.

In the *full-text screening phase*, scientific papers should not be review papers and should discuss the design, testing, or usage of a sensor-enabled safety system for HRC. Patents should propose the design of a sensor-enabled safety system for HRC.

In the *full-text screening phase*, scientific papers should propose or evaluate a sensor-enabled safety system that enables or implies enabling one or more operating modes of the ISO/TS 15066, or a combination of these modes or additionally intelligent trajectory (IT) planning. Similarly, patents should propose a sensor-enabled safety system that enables one or more of the mentioned operating modes. In addition, exclusion criteria were defined to provide transparency for excluding certain papers or patents. These include papers or patents that focus solely on algorithm design for sensor data processing, do not propose or evaluate a sensor or system in the context of safety, or do not propose or evaluate a safety sensor or system in the context of safety.

2) Information Sources: For scientific papers, the identified papers were collected from *Scopus* and *Web of Science* databases and exported to RIS files and EndNote format, respectively. The identified patents were collected from *Orbit Intelligence*, a global intellectual property intelligence platform, and exported as an XML file. The last search date was September 16, 2024. All identified papers and patents were imported into *Covidence* as the review management platform.

C. Search Strategy

The following search strings were used to collect scientific papers and patents. For Scopus: `TITLE-ABS-KEY [("SAFE*") AND ("SENS*") AND ("ROBOT*" OR "COBOT*") AND ("INTERACT*" OR "COLLABORAT*")) AND (LIMIT-TO(DOCTYPE, "CP") OR LIMIT-TO(DOCTYPE, "AR")) AND (LIMIT-TO(LANGUAGE, "ENGLISH")].` For Web of Science: `TS = (("safe*") AND ("sens*") AND ("robot*" OR "cobot*") AND ("interact*" OR "collaborat*")).` For Orbit Intelligence: `Safe+ AND (Sens+) AND (Robot+ OR Cobot+) AND (Interact+ OR Collaborat+)).`

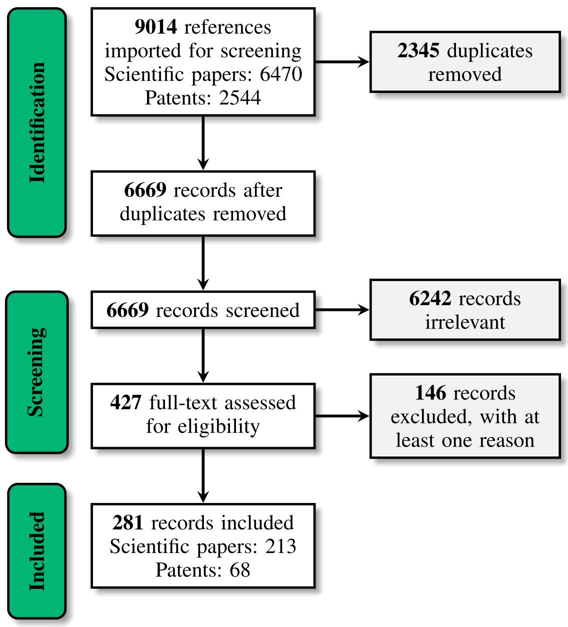

Fig. 3. PRISMA flow diagram for the systematic review.

III. Results

A. Selection of Eligible Records

The selection process for the records is shown in detail in the PRISMA flow diagram in Fig. 3. A total of 9014 references were imported for screening. After removing 2345 duplicates, 6669 records were screened against title and abstract. The records were independently screened by two reviewers, C.S. and H.L.C., with the option of further input from other review team members to resolve any disagreement. The 6242 records were excluded, leaving 427 records assessed for full-text eligibility. Of these, 146 records were excluded for at least one of the following reasons: 27 were related to internal force/torque sensors, 25 had inadequate technical details, 17 were related to safety systems for mobile robots only, 33 had no safety context, 13 had no human involvement, 12 only described algorithms and not sensors, four only had an abstract available, five only described communication interfaces, one was a benchmark proposal, one was related to safety systems for drones, seven was related to grant applications, and one was a video abstract. It is worth noting that a study could be excluded for multiple reasons, but the reported reason was the strongest and with the consensus of the two independent reviewers. Ultimately, 281 records (213 papers and 68 patents) were included in the review.

B. Data Charting

The scoping review table shown in Fig. 4 was structured with information such as the full title of the document, the year of publication, and the type of document (i.e., scientific paper and patent). This was followed by segmentation, which involved breaking down the proposed technology into specific components for analysis. Specifically, the segmentation in a scoping review includes information on the sensor technology (i.e., Stereo Camera, sound detecting and ranging (SoDAR), light detection and ranging (LiDAR) (ToF), RaDAR, Capacitive, Laser Scanner, Pressure pads, or others), sensor installation location (i.e., on-robot, externally in surrounding space, on-human, or a combination), operating mode (i.e., SRMS, HG, SSM, PFM, or a combination), and sensor distribution (single sensor, multiple distributed sensors, skin, and continuous array). Full access to the database and segmentation via an interactive Airtable format is available at: https://bit.ly/PRISMASEG. In our segmentation process, we utilized a weighted sum approach for descriptive statistics. This means that if a system contains multiple properties within a segmentation component, the count for each property is evenly distributed.

C. Collation, Summarization, and Reporting Results

The integration of sensor-enabled safety systems into HRC systems has become necessary in the last 20 years. This trend is evidenced by an increase in the number of publications on the topic, with a steady increase observed annually, see Fig. 5(a), making this topic a significant area of research and development.

1) Q1: What Sensor Technologies Are Used in Safety Systems to Achieve HRC in the Manufacturing Industry?: Various sensor technologies were employed at different locations, as shown in Fig. 5(b)–(d). Most systems use multiple sensor units. Sensors installed directly on the robot are often distributed in the form of skin over the robot's body, whereas external sensors are typically discrete components placed outside the robot. Subsequently, we organized this section to present our findings on sensor technologies based on their installation locations, see Fig. 6.

On-robot sensors refer to those installed on the robot as sensors or sensor skins that cover the entire or parts of the robot body, observing the surroundings looking outwards from the robot body. See Figs. 7–9 for a summary of systems using either touch (tactile) sensors or proximity sensors or both, respectively.

Capacitive Sensors: Capacitive skins have emerged as an integral part of robotic sensing technology, with 34.8% (49 out of 141) of on-robot systems adopting this. Primarily integrated as a robotic skin, capacitive sensing can serve threefold: it can facilitate tactile touch sensing, proximity sensing, or a hybrid of both.

One tactile-sensing methodology employs a dense matrix of intersecting conductive traces. An external object, such as a human hand, disrupts the electric field (**E**) when it physically interacts with the grid. This interaction triggers a change in mutual capacitance (ΔC_{ij}). These capacitance alterations are systematically recorded across the matrix, enabling the system to identify and interpret the object's interaction with the robotic skin. This method utilizes grid-based electrodes [46], [172], which can also be embedded in silicone [45] to simulate the human skin and facilitate touch measurements or trigger retraction reflexes [47]. Given the vast volume of tactile sensor data, an field-programmable gate array (FPGA)-based processing architecture is proposed for the simultaneous processing of sensor data [173].

In addition, scalable and cost-effective capacitive skins have been fabricated using techniques, such as screen printing

#	Key	Title	Year	Author	Operating Mode (S1)	Installation of sens...	Distribution ...	The technology of se...
1	7JLMDSQU	Reactive Planni...	2015	Dumonteil, Ga...	Intelligent Trajectory + SSM	Surrounding space...	Single sensor	IR Structured Light
2	D2ZT2IFC	Effect of active...	2022	Svarny, Petr; Rozlive...	Power and force monitoring	On-robot	Skin	Pressure Pads
3	NC4B9Y9D	HOSA: An End-...	2022	Barbosa, Gibson; Le...	Speed and Separation Monitoring	Surrounding space...	Multiple dis...	Depth Camera (Not ...
4	ZQQWJP9E	Implementatio...	2022	Yang, Kun; Xia, Xink...	Power and force monitoring	On-robot	Skin	Sponge Resistive
5	7MS27AZN	Safe physical h...	2022	Qi, Keke; Song, Zhib...	Speed and Separation Monitoring	On-robot	Discrete se...	LiDAR (TOF)

Fig. 4. Screenshot of the scoping review table. Full charting is available in an interactive filterable Airtable format is available at: https://bit.ly/PRISMASEG.

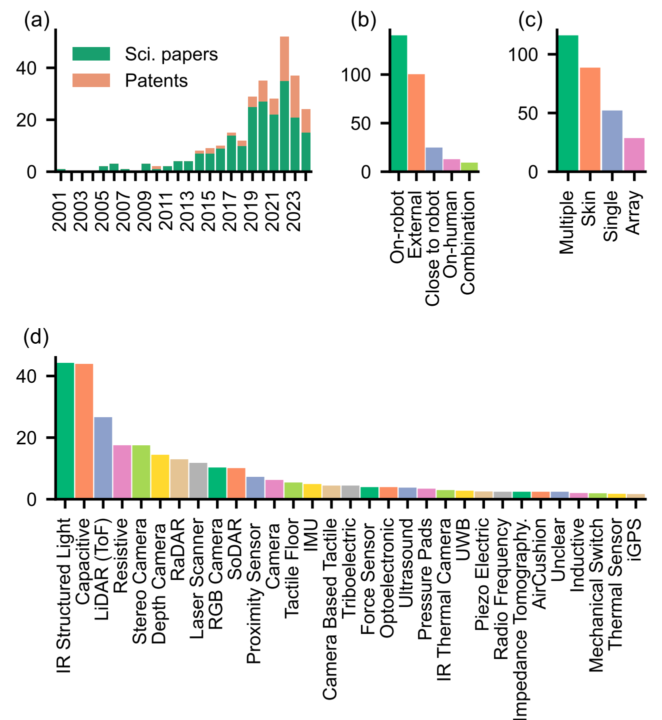

Fig. 5. Descriptive statistics of included records. (a) By publication years. (b) By installation location. (c) By sensor distribution. (d) Major sensing technologies used in safety systems, with a weighted sum greater than 1.

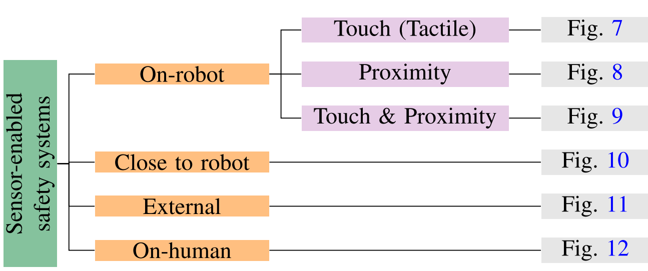

Fig. 6. Classification of sensor-enabled safety systems based on installation locations.

and gel coating. These techniques pave the way for creating highly spatially resolved, super-capacitive skin based on ionic gel-coated microfiber matrices [50]. Moreover, a nonskin-based alternative in the form of hemispherical dielectric elastomer capacitive sensors promotes multidirectional object detection, surpassing traditional x- and y-planar localization [49].

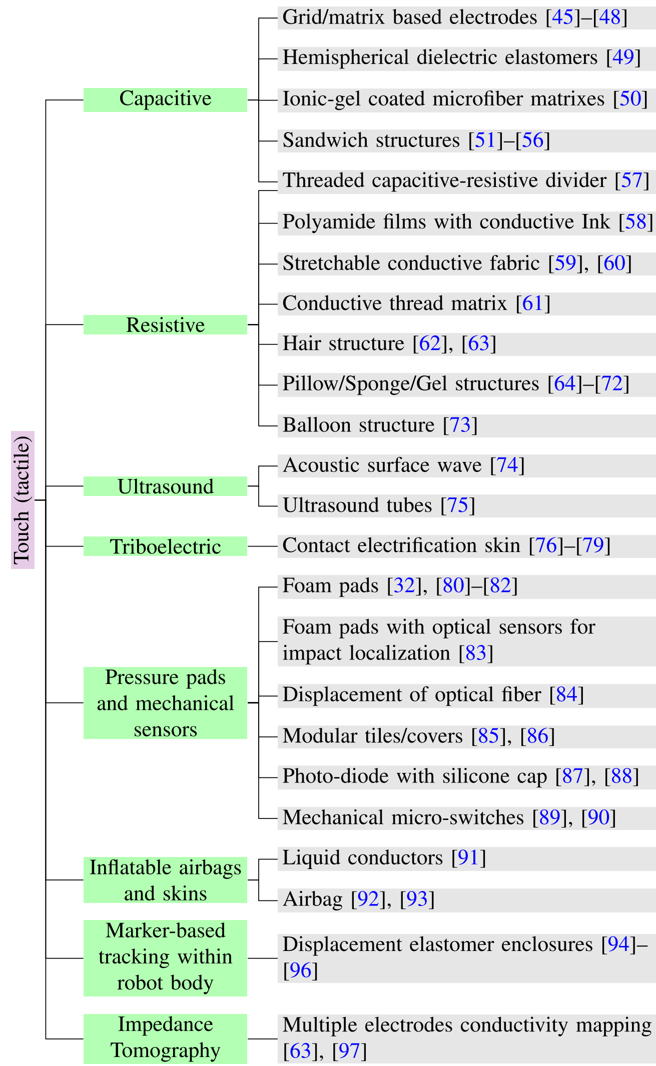

Fig. 7. Classification of sensor-enabled safety systems with on-robot installation using touch (tactile) sensors.

In contrast to grid-based electrodes, another tactile capacitive sensor design employs a sandwich structure comprising two plates. When pressure is applied, the plates' separation is altered, thereby affecting the capacitance [51], [52], [53]. Such sensors can be constructed with irregular planar shapes, with a specially designed conductive line creating a uniform electric field [54] or can be stretchable [55].

These sensors find essential applications in power and force monitoring, providing the robot with the ability to stop upon

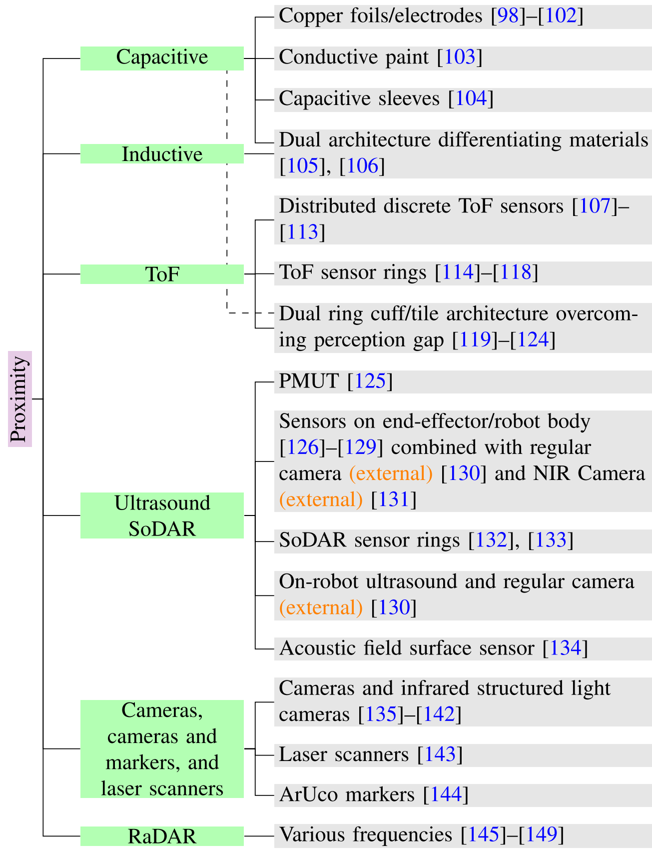

Fig. 8. Classification of sensor-enabled safety systems with on-robot installation using proximity sensors.

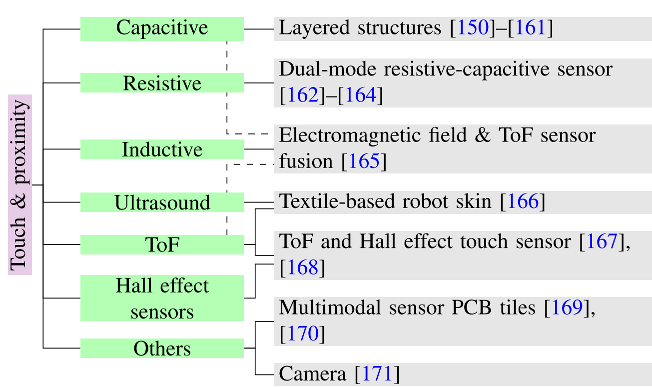

Fig. 9. Classification of sensor-enabled safety systems with on-robot installation using touch and proximity sensors.

contact in safety situations or even simulate a touch sensation over large surfaces, as observed in a handle designed for heavy industrial robot interaction with taxels in a sandwich structure [56], [174].

Furthermore, capacitive skins facilitate proximity sensing with air as the medium, which is indispensable for SSM applications, but have the shortcoming that they can only sense conductive obstacles in their vicinity. Robots can detect nearby objects using copper foils/electrodes dispersed across their bodies, which measure the capacitance against the ground potential [98], [99], [100], [101], [102], [161], conductive paint acting as the sensor has also been proposed [103]. These measurements are translated into a distance proximity value, considering the environmental model, as conductive materials in the vicinity impact sensor readings [175] or are combined with *inductive sensor* elements to differentiate between humans and metal [105], [106]. Progress has also been made in estimating the angle of an object and measuring the sensing quality using an enhanced processing architecture and temperature compensation [176]. Low-cost alternatives using a comb electrode matrix have been suggested and can be integrated with a distributed touch sensor [150]. A control framework using capacitive sensor inputs, such as those from the commercially available FOGALE[1] capacitive skin, has been demonstrated to successfully avert obstacles around a UR5 [104].

Several proposals have been made to amalgamate touch and proximity sensing based on the layering of capacitive sensors [151], [152], [153], [160]. These include modular and interconnected tiles that enable pretouch and touch tracking of human hands [154], sandwich structures ensure that the pressure sensor's capacitance variation does not interfere with proximity perception measurements [155], [156], tiles that facilitate dynamic spatial resolution in both tactile and proximity modes [157], and self-capacitance sensors designed with a curved shape to fit robotic arm housing [158], with added shock-absorbing structures for safer human operator contact [159], or through the combination of a capacitive textile robotic cover with distributed discrete ToF and ultrasound sensors for medium- to long-range proximity detection [166].

Resistive Sensors: Out of 96 systems studied, ten have been proposed that use a resistive sensing approach. This technique involves monitoring changes in the electrical resistance, R, across a pliable, deformable material under strain. This concept is simplified by the equation $R = R_0(1 + (\Delta l/l_0))^2$, where R_0 is the initial resistance, l_0 is the initial length, and Δl is the change in the length.

A multitude of innovative solutions have been put forth in the area of resistive sensing. One such approach involves the creation of an economical, low-resolution, resistive, thin, and flexible sheet composed of polyamide films with electrically conductive ink, which simplifies wiring requirements [58]. To facilitate a snug fit on the body of a robot, skins made from stretchable conductive fabric [59], [60] or sponge materials [72] have been proposed.

Furthermore, a system comprising a conductive thread matrix, separated by a polymer for adjustable spatial resolution, was developed to accommodate various shapes and contours [61]. A unique combination of the threaded resistor divider principles with a capacitive sandwich structure was also used. The resistor matrix determines the location, and the capacitive sensor gauges the impact force with an obstacle [57].

There are also approaches for a hybrid structure designed for large-range proximity and contact force detection, consisting of five layers, including a piezoresistive composite film and copper foil electrodes operating in two modes: capacitive for proximity detection and resistive for contact force detection;

[1] https://perma.cc/9S8S-U3Z2

the transition between modes occurs when the applied force exceeds a critical value [162]. A comparable approach was proposed by Jiang and Sun [163] and Liu et al. [164]. Another approach utilizes skin structures with hair to convert pressure into a voltage signal by means of resistance change [62], [63].

In addition, piezoresistive sensors can be manufactured in pillow-like structures [64], gel structures [71], or a soft substrate sponge structure, which, when combined into an array, allows for spatial resolution [65], [66]. Notably, these structures can be amalgamated with inflatable sponge elements, enabling them to mitigate the impact force during a collision by altering their internal air pressure in real time [67], [68]. Moreover, piezothermic sponges do not only allow the detection of contact force and position [69] but can also be used to measure temperature and can be sandwiched into a capacitive proximity sensor [70].

Finally, a rather abstract approach was proposed involving covering a robot manipulator with a balloon integrated with a laminated crack-based strain sensor. The strain sensors alter resistance when the balloon is compressed, effectively sensing collisions [73].

Ultrasound (SoDAR) Sensors: Ultrasound waves can be utilized for ranging and obstacle detection, similar to time-of-flight (ToF) light ranging. The advantage of ultrasound over light ranging is its resilience to light conditions, such as fog or smoke, and its ability to detect reflective and transparent objects without difficulty. One shortcoming is that the speed of sound can be influenced by ambient temperature and humidity, which are variables that can be measured and actively compensated for through proper sensor characterization. An air-coupled ultrasound transducer, capable of both receiving and transmitting, is composed of a material with piezoelectric properties that when a voltage V is applied to or vibrates and emits an ultrasound wave. This wave is transmitted through air, reflects off an object, and returns to the receiver. The distance d to the object is calculated by dividing the time t taken for the ultrasound wave to return by the speed of sound v_{sound} (343 m/s), and then by 2, i.e., $d = (v_{\text{sound}} \cdot t/2)$.

The simplest application of ultrasound transducers is in the pitch and catch mode. Here, the transmitter emits a sound pulse that is subsequently received by the receiver. This technique is used in commercial robot safety systems, often used near the tool center point (TCP) [126], on the robot body [127], or in 360° sonar sensor rings [132], [133]. Some proposed systems distribute several transducers across the entire robot body, instead of using a single set of individual transducers [128]. Single ultrasound transducers lack spatial resolution, to overcome this shortcoming several transducers with overlapping field of views (FOV) can be used to estimate the angular location of an object. In addition, by comparing the calculated distances and angles over time, Glowa and Schlegl [129] proposed an algorithm that could differentiate between static and dynamic objects. This information is then used to adjust the trajectory of the manipulator and ensure operator safety. An alternative to traditional bulky piezoelectric ultrasound transducers has been developed in the form of a piezoelectric micromachined ultrasonic transducers (PMUTs) array. This array can be manufactured on flexible printed circuit boards and has a flat form factor, facilitating ergonomic integration into the robot body [125].

While the majority of systems focus on proximity sensing around the robot, SonicSkin takes a different approach. It employs a pair of flat piezoelectric transducers strategically positioned and spaced apart on the robot. The transmitter within this pair emits an acoustic surface wave (ASW) across the entire link, effectively transforming it into a large-area sensor. When a human comes into contact with the body of a robot, the surface signal experiences a dampening effect. This change, denoted by ΔS, can be measured to accurately determine the touch location on the body surface of the robot [74]. AmbiSense is an acoustic-field-based sensing system that generates vibrations across a robot's surface using low-cost piezoelectric transducers. It creates an acoustic field that detects proximity and direction by analyzing interference patterns from reflected sound waves, thereby providing a vision gap-free, reliable sensing solution for safe human–robot interactions [134], [177]. In contrast, the SMAUS system utilizes viscoelastic tubes equipped with ultrasound transmitters at one end and receivers at the other end. These tubes, wrapped around the robot body, deform upon contact and distort the emitted ultrasound signal. The receivers at the other end of the tube detect this distortion and signal a collision [75]. Furthermore, a system has been developed that combines a tactile hair sensor skin with embedded ultrasound transducers. This combination enables the detection of objects before they come in contact with the robot, thereby enhancing safety and operational efficiency [178].

Triboelectric Skins: The triboelectric effect represents a promising avenue for tactile sensor skins, functioning through the principles of contact electrification and electrostatic induction. When an external force is applied, the two films come into contact, consequently generating triboelectric charges [78], [79]. Upon separation of the films, these charges induce an electric potential difference, resulting in current flow. Each application and release of force subsequently triggers this cycle, thereby enabling the sensor to effectively detect touch.

Regarding manufacturing, the roll-to-roll UV embossing process proves advantageous for creating such sensors [76]. Furthermore, innovative approaches continue to be used in this field, such as the proposed skin design that integrates an electrochromic pigment layer. This distinctive layer exhibits a color shift from light green to dark blue upon experiencing an applied force, adding a visible indicator to the tactile sensing capability [77].

Pressure Pads and Mechanical Sensors: Foam pads are increasingly utilized for power and force limitation, serving to mitigate collision impact. Impact reduction can be achieved using various methods. One prevalent approach involves the use of foam cushions that trigger an air vent upon compression, such as air skin, a commercially available product [32], [80], gyroid infill-based robotic skin [81] or matrix structure pneumatic robot skin [82] with tactile resolution to identify the touch location.

Two primary methods were employed to indicate the region of impact based on the degree of pad compression. The first involves the integration of LEDs and light-to-voltage sensors within foam pads. These sensors measure the displacement between each other, thereby enabling estimation of the impact and consequent deformation [83]. The alternative strategy encompasses embedding multiple force sensors underneath a rigid bumper cover connected to the robot link. This arrangement facilitates the identification of the impact region based on force measurements [85]. It is worth noting that proximity covers can be strategically used in close proximity to the end-effector of large industrial robots, particularly to ensure safety within the access portion of the work cell [86].

An inspiration from keyboard technology was drawn to identify the region of impact. For instance, small mechanical microswitches have been implemented as a means of detecting force impact [89]. Furthermore, mechanical pressure and proximity-sensing skin have been proposed, with the added capability of light emission for impact region identification [90].

Moreover, tactile skin alternatives such as optical fibers embedded in a polymer have been explored. These fibers measure the shift in wavelength in response to the force applied, thus functioning as an effective tactile skin [84].

Rather than employing large-scale foam pads for force measurement, the approach in [87] entails the design of a rigid, conformal PCB skin patch. This design utilizes a light-emitting diode covered by a deformable silicone cap-forming taxel. When pressed, variations in the reflected light can be converted into corresponding impact force data.

This skin can also function without the silicone cover. The intensity of the light received upon reflection by the phototransistor can be used to calculate the distance to an object based on the resulting photocurrent [88].

Further advancements have led to the development of modular tiles that can be interconnected to create a larger skin. This skin allows for the ability to sense a range of parameters including proximity, force, acceleration, and temperature. Each tile is equipped with a microprocessor that only transmits new values in an event-driven manner, enhancing the system's computational load [169], similar to TacSuit, which allows for pressure, proximity, vibration, and temperature sensing through modular tiles [170].

Inflatable Airbags and Skins: Efforts to prevent serious human injuries resulting from physical collisions with robotic manipulators have led to the development of inflatable solutions [92], [93]. One such solution is an end-effector airbag designed to inflate around the end-effector, whenever the robot undergoes unsafe motions. This preventive measure shields the end-effector in the event of a collision, whereas a torque sensor detects the impact and prompts the robot to cease operation.

In addition, Kim et al. [91] presented a dynamic inflating solution designed to absorb impacts. This solution features liquid-filled microfluidic channels embedded within the robot's skin and is capable of detecting not only the magnitudes but also the precise locations of external forces, regardless of their shape and size. This unique capability is attributed to the continuous nature of the liquid conductor embedded in the inflatable elastomer.

Marker-Based Tactile Sensors Tracking Within Robot Body: An alternative approach to tactile sensing involves the use of a camera system housed within a flexible cylindrical elastomer casing. Inside this casing, markers are symmetrically distributed and captured by the camera. A computer vision algorithm measures the distribution of these markers. When the casing is deformed by an impact, the markers are displaced. This displacement is mapped by a computer vision algorithm to a ground truth to pinpoint the location and force of the impact [94], [95], which can also be enhanced by a thermal layer for a warm touch sensation [96]. However, this technology raises questions about the placement and integration of the robot's electronics and mechanical structures, such as motors, shafts, and electronics, which are usually found in the inside space where the markers are being projected. Building upon this, Luu et al. [171] propose the surface transparency to be controllable to also allow for proximity sensing through the housing. We contend that at this stage, these markers are more of a theoretical exploration than a feasible solution.

Impedance Tomography: Measures changes in electrical conductivity across a surface using multiple electrodes to create a conductivity map, enabling large-area, volumetric tactile sensing. Unlike capacitive sensing, which detects surface-level changes in electric charge, it can detect the direction and distribution of pressure in robotic skins [48], [97].

ToF (LiDAR) Sensors: The second most prevalent sensor technology implemented on robots is based on ToF sensors, specifically LiDAR, with approximately 17.0% (24 out of 141) of on-robot systems utilizing this approach.

ToFis used to measure the distance between the sensor and an object, functioning by emitting a light pulse, commonly very narrow infrared (IR), toward the object and subsequently measuring the time taken for the pulse to return after being reflected by the object. The distance (d) can then be computed using the equation $d = (c \times t/2)$, where d represents the distance from the sensor to the object, c denotes the speed of light (3×10^8 m/s), and t corresponds to the round-trip time of the light pulse traveling from the sensor to the object and back. The division of the equation by two accounts for t representing the round-trip time. Apart from the ToF method, there is a triangulation method that calculates the angle of reflection that arrives at the charge-coupled device of the sensor.

In its most rudimentary form, IR light-emitting diode sensors are distributed as individual spots [107], [108] or interconnected I2C sensor arrays [109], [113] across the entire robot body, or merely on the end-effector [110], [111]. This arrangement facilitates obstacle detection in the surrounding space and, for instance, the execution of an evasive action to ensure human safety [112].

Instead of distributing individual sensors across the robot body, modular outwards-looking ring arrays of ToF sensors have been proposed [114]. These are based on calculating the optimal sensing volume coverage on the robot [115] and have been successfully used to implement a trimodal SSM. This model leverages both the measured relative human–robot speeds and the separation distance to result in more consistent and smoother robot movements [116]. Close-range detection can be achieved using double sensor rings mounted at opposite ends between a robot link, which can detect imminent collisions over a large coverage area and trigger a safety-rated monitored stop (SRMS) [117].

However, ToF sensors have limitations in the close range, including minimum measurable distance, signal interference, dispersion/absorption effects, and sensitivity/resolution constraints. To overcome these limitations, a ring cuff featuring wide-area capacitive sensing covers has been proposed, which bridges the perception gap, enabling path deviation in a short range, and thus improving the overall obstacle avoidance of the robot arm [119], [120]. Another hybrid approach combining capacitive and ToF sensors [124] has been demonstrated in developing modular skin-like sensor tiles that can be distributed on the entire robot body and stream their data via a serial bus [121], [122], [123].

An alternative multimodal sensor array has been proposed to enable tactile sensing and proximity sensing. This array alternates between the ToF sensors and the *Hall effect sensors* covered by a silicon layer with embedded magnets. When the silicon layer touches or deforms, it induces a change in the magnetic flux density (ΔB), which is converted into force (F), thus enabling contact detection [167], [168]. Another system integrates modular tiles by combining ToF sensors for long-range proximity detection, capacitive sensors for wide-field proximity coverage, and inductive sensing for tactile perception [165].

For a more intuitive human–robot interaction, ToF proximity sensors have been integrated into a modular ring with gesture sensors. These sensors interpret patterns of proximity and hand motion and recognize gestures such as up, down, left, and right [118].

Cameras, Markers, and Laser Scanners: In order to track specific objects and mitigate collision risks, Liu et al. [144] and Shi and Hu [179] demonstrate the usage of 2-D ArUco Markers, akin to QR codes, which are tracked by a camera, not feasible for industry since not all elements can be labeled. Alternatively, some solutions employ a Kinect Camera on the robot, which is capable of automatically tracking the skeleton positions of up to six people within the surrounding space [135].

A more focused approach is the depth camera-in-hand method, which is mainly used to track the operator's hands or objects in the space [136], [140], [141], while another approach is to use a co-moving 3-D camera installed on link 3 to compensate for occluded areas [142]. This methodology is deployed by Bdiwi [137] in conjunction with a Kinect structured light camera, providing a depth frame to segment the observation of the workspace. This enables the system to track the operator's arm and workpiece and halt collaboration if other parts of the human body are too close. To ensure safety, the robot operates only if the operator's face is detected within its FOV, which limits the productivity of the robot. Furthermore, an additional ToF safety sensor skin is integrated to maintain safety, even when the human is not in the FOV because of its limited view or occlusions it might face.

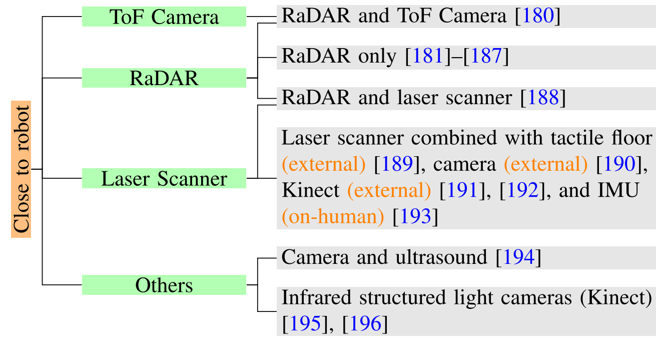

Fig. 10. Classification of sensor-enabled safety systems with close to robot installation.

In another system, Kinect cameras were used on a manipulator's mobile platform to distinguish between the manipulator and surrounding objects within the workspace [138], [139]. This mobile platform employs a laser scanner to monitor the surrounding space. Stopp et al. [143] also utilize several laser scanners, albeit distributed across the entire mobile platform in a bulky configuration.

RaDAR: RaDAR uses the principles of electromagnetic wave propagation and reflection to detect, locate objects, and measure their velocity and through that can be utilized to detect static and nonstatic obstacles. Leveraging 160-GHz radar technology, Geiger and Waldschmidt [145] introduced flexible antennas distributed on two dielectric waveguides, providing extensive coverage and flexibility in sensor positioning on the robot's surface. Moreover, Kim et al. [146] identified that utilizing RaDAR sensors on the robot can decrease the cycle time and floor shop space required to perform a task when compared to a close to robot placed laser scanner. Several patents claim the integration of radar technology onto robotic manipulators, which is a challenging task [147], [148], [149], particularly when the radar is mounted on the end-effector rather than statically on the base, owing to both the source and target being in motion, for example, when a human navigates around a moving robotic manipulator, which requires advanced RaDAR processing algorithms.

SENSORS CLOSE TO THE ROBOT refer to those positioned in near vicinity to the manipulator, looking outwards to observe the space, see Fig. 10 for a summary.

RaDAR: RaDAR has been proposed for use in robotic work cells to enable SSM [181], [182]. A frequency modulated continuous wave radar (FMCW) radar sensor can be installed close to the robot base, allowing for the estimation of the separation distance between the operator and the robot. This functions effectively under strong light, direct exposure, or dust, overcoming the limitations of laser scanners, although it has a lower angular resolution. The FMCW radar technology utilizes continuously varying frequencies to accurately calculate the target distance and velocity. A novel speed control architecture has been introduced that uses tracking radar to estimate object range and classification radar to distinguish between humans and mobile robots [183]. A prominent commercially available RaDAR platform is the IWR6843AOP developed by Texas Instruments, which was evaluated for its suitability in measuring worker proximity without invading privacy [184]. To avoid false detections, asymmetric Kalman filters have been proposed [185], and techniques to detect human hand intrusion have been explored [186], [187]. Some methods combine RaDAR with ToF cameras [180] and laser scanners to enhance spatial perception [188].

Laser Scanners: Laser scanners, in combination with an inertial measurement unit (IMU) on the operator, can define the relative position of the torso and upper body configuration, enabling collision avoidance through customized methods like potential fields [193]. To ensure safety redundancy, laser scanners have been combined with tactile mats [189] and vibrotactile bracelets have been added to indicate the proximity of the robot [197].

Camera and Ultrasound: A direction-sensing platform utilizing several 2-D Cameras around the robot base has been proposed by Gradolewski et al. [194]. It detects a person in its FOV based on image segmentation and then uses an ultrasound SoDAR sensor to measure proximity. The issue with this system is that it suffers from occlusions when the robot moves over the sensors, thereby limiting the robot's vision at a certain angle.

IR Structured Light Cameras: On a mobile manipulator platform, Kinect Sensors have been implemented for capturing 3-D point clouds and enabling dynamic safety zoning or SSM [195], [196]. For high-accuracy hand tracking, including fingers, leap motion sensors have been placed on the work-cell table, overcoming the limitations of externally installed Kinects [198].

EXTERNALLY INSTALLED SENSORS refer to those positioned around the robot's workspace, observing it externally and not being placed on the robot's body, see Fig. 11 for a summary.

IR Structured Light Cameras (Kinect Sensor): One of the most widely used sensors for external safety systems is the Kinect sensor by Microsoft. This sensor is based on an amalgamation of an IR structured light projector, depth camera, RGB camera, and an intricate processing suite. The underlying technology for depth sensing such as the Kinect is structured light, a technique that uses a light projector to emit a specific pattern, such as dots, onto a scene or object. When this projected light encounters various surfaces, it distorts based on the distances and orientations of those surfaces. The IR-sensitive camera captures images of the scene with a distorted pattern. By analyzing the disparities between the known projected pattern and the captured distorted pattern, the system computes the depth information for each point in the scene, leading to the creation of a 3-D representation known as a depth map.

Ensuring safe operations around a selective compliance assembly robot (SCARA) robot, which is popular in areas such as packaging applications, has been tackled with the installation of a Kinect camera overhead of the workspace [199]. Positioned to look at the operator and robot from above, the Kinect captures a depth image stream that is then processed through distance limitation filters and edge detection to segment the image for the robot and the operator's upper body. This allows for the calculation of the closest distance based on 2-D edge pixels; the robot's trajectory is immediately halted

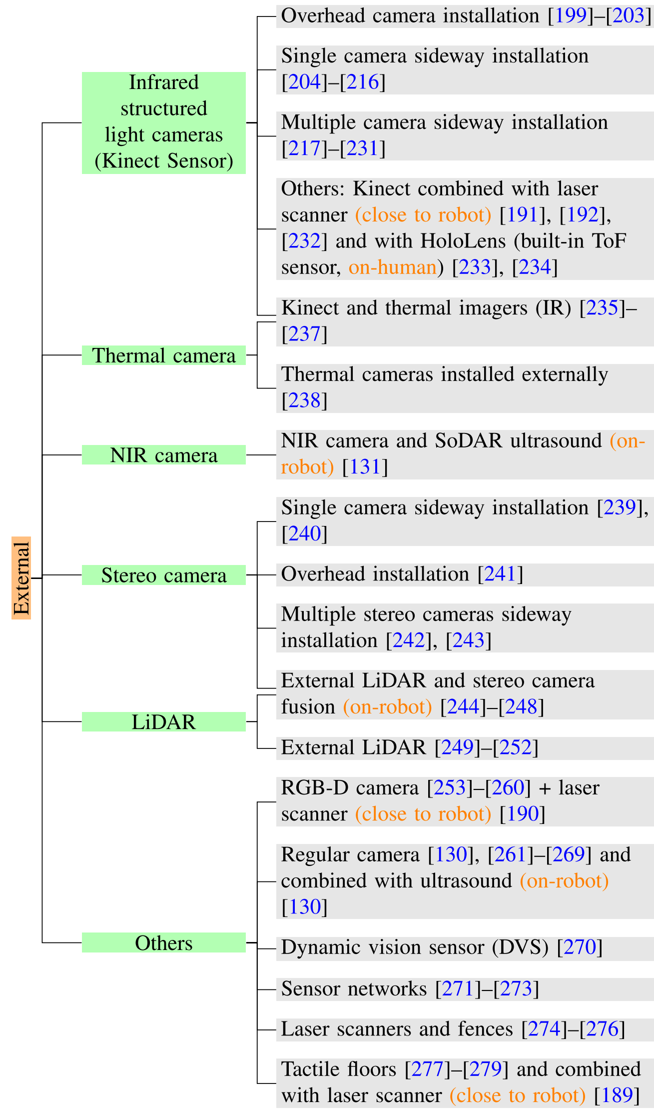

Fig. 11. Classification of sensor-enabled safety systems with external installation.

if the danger criterion is met. The work by Andres et al. [200] employ a similar filtering approach to enable static–dynamic SSM, outperforming the static implementation. Furthermore, a fuzzy logic approach considering the human head and upper body orientation has been developed for risk estimation, complementing estimations made in accordance with ISO 12100 [201].

The approach of tracking human operators' X–Y positions with Kinect, looking downward from above [280], [281], has also been harnessed in conjunction with safety-critical laser scanners. This combined system can trigger a SRMS if the dynamic SSM with Kinect fails or processing lags [191]. Laser scanners combined with Kinects can also enable a layered, redundant safety architecture in a work cell [192]. In addition, [202] demonstrated that collaborative scenarios can also be supported. In this approach, the overhead system identifies and tracks the worker's hand by strategically placing a work piece at its center to facilitate an object handover.

In addition to overhead installations, various proposals exist for single-Kinect camera setups that observe the operator and robot from a sideways perspective. Some approaches leverage occupancy mapping for collision avoidance and safety measures [203], [204], [205], [206]. Others employ skeleton tracking, calculating the distance between humans and the robot to enable real-time speed alterations. These systems may model robots and humans using ellipsoids to swiftly detect collisions [207] or implement reactive, collision-free path planning [207]. For example, Flacco et al. [208] and De Luca and Flacco [209] suggest generating repulsive vectors to obtain smooth and feasible joint velocity commands that help the robot avoid obstacles in a depth space. Du et al. [210] enhance the approach by using larger bounding cylinders around the human skeleton, planning paths in real time that allow robots to bypass operators. In addition, a combination of human skeleton tracking with facial recognition algorithms has been explored. This system can distinguish between a trained robot operator and others, significantly slowing down the robot if the trained operator is not within the FOV of the sensor [211]; moreover, Liu [212] also add a gesture and voice recognition module to the workspace to control the robot.

Several proposals have focused on specific operational scenarios. For instance, contact-point sensing with a Kinect sensor has been suggested as a means to pause and later resume tasks at the exact contact-point position [213]. Furthermore, when obstacles occlude the robot and are situated between the Kinect and the robot, Nascimento et al. [214] recommend extracting the robot from the depth image using the proprioceptive kinematic model. This facilitates the identification of the closest obstacle, allowing the implementation of collision avoidance strategies such as distancing and dodging.

To overcome the occlusions that systems of a single external sensor suffer from, one method involves distributing multiple cameras around the work cell and fusing the depth images together [217] or combining each skeleton model from individual sensors into a single fused estimation of the operator's skeleton [218], [219], [220]. A real-time collision avoidance method capable of handling unknown static and dynamic obstacles was introduced by Liao et al. [221]. This method utilizes artificial potential techniques and repulsive vectors to adjust the trajectory of the robot around the obstacle points identified by depth sensors.

A different strategy filters the operator from the scene by removing the background from the Kinect depth images and applying bounding boxes around the operator. This facilitates minimum-distance calculations for the robot, enabling collision avoidance [222], [223]. Alternative methods generate a convex hull around the operator [224], [225] or use Octrees and Octomaps for distinguishing between the robot model, static objects, and new obstacles in the workspace, and to perform predictive and reflexive robot manipulator trajectory estimation [226], [227]. In addition, detecting the occupancy of space [228] includes a context-aware human pose recognition module that constantly monitors the human operator's assembly poses and triggers a new robot target once a working step has been completed.

A specialized approach proposed by Morales et al. [229] use a detection pipeline that leverages salient RGB detection, maps it to depth, and feeds the data into a PointNet CNN (trained on the RGBD-DHaRIo dataset [230]). This allows for the detection of the number of people in the scene and utilizes a biternion network architecture to calculate the movement trend and orientation of an operator over several frames. To further enhance segmentation, *thermal cameras* are deployed by Yang et al. [235], Costanzo et al. [236], and Katsampiris-Salgado et al. [237]. These imagers, which are insensitive to light, improve edge detection robustness alongside a Kinect depth camera, enabling SSM.

Several developments combine Kinect cameras with on-human mixed-reality headsets, such as *HoloLens*. For instance, Liu et al. [231] perform skeleton tracking with Kinects and visualizes a dynamic risk field, indicating safe and unsafe regions around the robot. Messeri et al. [233] estimate the human wrist position in the workspace to overcome occlusions. Another approach uses Kinects to track the operator and display the minimum-distance calculations in an augmented reality headset [234]. These multifaceted solutions offer promising avenues for enhancing safety and efficiency within the dynamic field of robotic operation.

NIR Camera Sensors: External near IR (NIR) imaging cameras have been deployed to identify and classify humans by examining the spectral signature of skin reflection intensity at extended distances. This technology has been synergistically integrated with a SoDAR ultrasound array mounted on the robot, granting it the capability to discern obstacles at mid-range distances. To complement this, an NIR point sensor was specifically implemented on the robot to detect human presence near a TCP point in close proximity. These diverse sensor signals are collectively processed using a redundantly configured central control unit [131].

Stereo Cameras and Other RGB-D Cameras: A stereo camera functions on the principle of stereoscopic vision by using two lenses spaced apart at a distance analogous to human eyes. These lenses capture two slightly different images of the scene. Analyzing the disparity or difference between these images enables depth information extraction through triangulation, thus facilitating the creation of a depth map. However, some papers and patents fail to specify whether a stereo camera has been employed and merely mention the use of an unspecified RGB-D Camera.

For instance, Svarny et al. [239] leverage an Intel RealSense StereoVision Camera to track an operator's skeleton by feeding the depth map into the OpenPose API. This facilitates the extraction of the skeleton to calculate the separation distance for the SSM. At very short distances near the contact, it switches to PFM using the robot's built-in torque sensors to halt the robot on collision. Another proposal involves deploying multiple cameras within the workspace, coupled with an artificial intelligence (AI)-based skeleton tracking layer, to ensure that the safety distance to the operator is maintained [242], cluster the detection into ellipsoids [243] or fusing it with a thermal image provided by a thermal camera to ensure fast and reliable human localization [282]. To distinguish between robots, objects, and operators in the workspace, Antão et al. [240] propose processing detection from a sideways-installed ZED stereo camera into a labeled occupancy voxel-grid. This method differentiates the occupancy of space, permitting its use for topics like predictive control or task recognition. Unfortunately, objects are identifiable only by color. To separate static scene elements from dynamic ones, another method segments the depth map using a sideways-mounted camera [215] or proposes to process the depth map into voxels to use it for real-time motion planning [216].

Similarly, Haghighi et al. [283] and Yang and Zhang [284] developed modules that enhance the data accuracy for body tracking with IMUs on the operator, mitigating limitations in the angle of view, distance, and lighting conditions for detecting gestures and postures. Farsoni et al. [285] primarily employ IMUs to render skeleton tracking redundant and augment stereo vision-based 3-D perception. Calibration and setup of cameras are vital for complete coverage of the workspace, ensuring coverage devoid of shadows and an accurate voxelized representation of the space. Collision detection is accomplished by dynamically swept volumes stepping through voxels to confirm that they are unoccupied [253]. Several overhead camera systems have been proposed for workspace monitoring, such as the patent behind the formerly commercial system PilzEye [241]. Other overhead or sideway camera solutions capture human and robot interactions in the operating environment [254], [286], distinguishing between safe and risk zones [255], [256]. Some solutions even project these zones onto the workspace floor [257] or employ them for collision avoidance [258], [259], [260]. The human-robot safety (HOSA) system additionally verifies whether the operators are wearing personal protective equipment [287]. Another patent, [190], advocates human skeleton tracking and environmental mapping using depth cameras in conjunction with a laser scanner. A similar approach was demonstrated with the movable iMRK platform, which can additionally perform gesture recognition [288].

To enhance the safety around large-scale, high-payload robots, authors [244], [245], [247], and [248] present a dual-tiered collision avoidance strategy. This approach incorporates a global LiDAR system, which provides comprehensive detection of the entire environment, and a local stereo camera to supply more detailed, high-speed, localized information within the known workspace of the human. Such an integration markedly elevates the system efficiency in dynamic SSM, enabling rapid calculation of intrusion distances [246] and adding object tracking functionality to ensure that operators are not lost in the workspace [289]. An entirely LiDAR-based approach is presented by Haifeng et al. [250]; moreover, Podgorelec et al. [249] segment the robot and static obstacles in real time from the detection and enables SSM. A commercial system on the market that uses an external LiDAR (ToF) sensor mounted overhead is the Veo FreeMove system [251].

In summary, Pieskä et al. [290] observe that depth-sensing cameras are typically deficient in features, such as locking mechanisms and adequate protection against dust and water. Such shortcomings render them unsuitable for harsh industrial environments where they may be exposed to misalignment. This article further underscores the necessity for future research to focus on the development and investigation of robust devices explicitly designed for industrial applications that are capable of overcoming these challenges.

Regular Cameras: In lieu of employing an RGB-D depth camera, some proposals favor regular RGB cameras. For instance, Lu et al. [261] outline a work cell where cameras are positioned above the workspace to capture images, segmenting them to identify the blob corresponding to the worker's hardhat. The centroid of the blob is then converted to its line-of-sight in 3-D world coordinates. If the worker is not wearing a hardhat, the microwave sensors still detect the intrusion, consequently shutting off the robot. To perform collision avoidance, Xie et al. [269] utilize a sideways-facing RGB camera to perform skeleton tracking on 2-D images.

To further enhance human tracking within the workspace, Höcherl and Schlegl [130] specifically identifies the operator's hand using an overhead camera, supplementing this identification with a redundancy check via on-robot installed ultrasound SoDAR sensors. Moreover, Dietrich et al. [262] designed an HRC booth employing multiple cameras, implementing a voxel carving method that labels voxels as occupied unless explicitly marked empty by one of the cameras. This allowed the robot to adjust its speed. In addition, Tan and Arai [263] conduct upper body skeleton tracking through overhead cameras, while other works extend it to full-body skeleton tracking [264], [265] or even the analysis of human attributes in the workspace to calculate a risk score [266].

For large-area human tracking, Iwashita et al. [267] advocate a distributed camera network. This approach utilizes the fast marching method, facilitating efficient tracking of an individual's movement within the space.

Furthermore, a multifunctional cell has been suggested by Chen et al. [268], incorporating two cameras specifically tasked with tracking the incoming operators. This cell consists of an entry detection camera coupled with a module capable of both facial and gesture recognition, enhancing human–robot interaction within the workspace.

Dynamic Vision Sensors (DVSs) Stereo: DVS, also referred to as event-based cameras, are bioinspired sensors that detect changes in the logarithmic brightness of a scene. They excel in capturing fast-moving objects while simultaneously ignoring static background elements, thereby minimizing the volume of data required for processing. Steffen et al. [270] introduce a DVS stereo-camera network, where the camera outputs are integrated into a spiking neural network to build an obstacle memory of the robot's workspace. This excludes the robot itself and is designed to conserve older states while responding to new events and maintaining accurate obstacle memories at all times. However, the proposed system is facing issues with the cooperative stereo network, which does not support a fine-grained representation to avoid a drastic increase in the number of neurons and synapses used in the SNN and, thus, the required resource.

Sensor Networks: Proposals for wireless networks include ceiling-mounted Wireless Nodes that track objects such as workers by monitoring the perturbation of the radio field [271]. Researchers have also suggested integrating RF

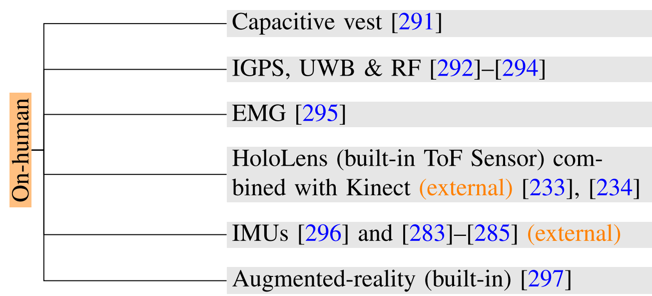

Fig. 12. Classification of sensor-enabled safety systems with on-human installation.

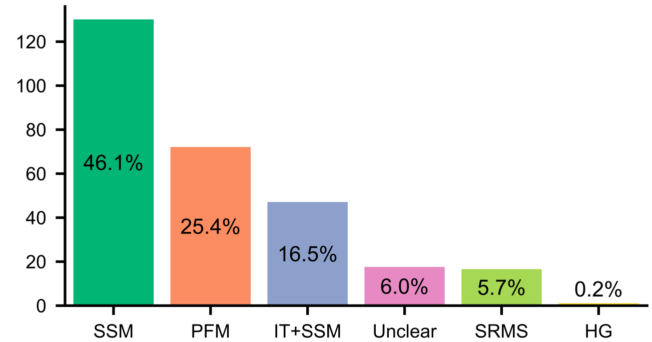

Fig. 13. Operating modes: SSM, PFM, IT and SSM, unclear, SRMS, and HG.

perturbation-based sensing into beyond 5G cellular systems for seamless integration with existing environments, such as factories. They recommend allocating a single symbol in each subframe of the communication system, yielding a 1-kHz sampling frequency for subject tracking [272]. A novel sensor fusion network architecture and detection/localization algorithm is proposed by Minora et al. [273] which combine data from a 122-GHz FMCW radar, 100-GHz imaging camera, and IR array sensors for anonymous perception of workers in the workspace.

Laser Scanners and Fences: The most prevalent method to ensure safety in robotic work cells involves laser scanners, which scan their surroundings and gauge distances using the ToF principle. These are generally positioned close to the floor level for detecting operators [274]. Shackleford et al. [275] blend multiple laser scanners to enable SSM and suggest strategies to mitigate occlusion when several operators are in the workspace. To prevent contact with specific robot parts, laser fences can be deployed to trigger an SRMS until the area is cleared [276] or can be used alongside a Kinect sensor that tracks the skeleton of the operator [232].

Tactile Floors: An alternative method to track an operator's position in a work cell involves the use of tactile floors that respond to applied pressure. This approach enables the tracking of human movement direction and speed. When paired with an overhead projector system, safety-specific features, such as safety zones or process-specific information can be displayed on the floor [277]. This system also serves as user input, such as initiating the next work step via the tactile floor [278]. Peter et al. [279] employ a convolutional neural network (CNN) to classify tactile data, distinguishing between objects such as mobile robots, humans, and trolleys to interpret user intentions.

Thermal Cameras: While previous systems have fused thermal cameras with stereo vision cameras or Kinect sensors, this proposed low-cost system [238] uses a single externally installed thermal camera to monitor access to the workspace purely based on the thermal imaging and a background subtraction algorithm.

ON-HUMAN SENSORS refer to those being worn on the body of the human while working in the vicinity of the robot, see Fig. 12 for a summary.

Capacitive Vest: A capacitive shunt mode vest has been designed, leveraging the principle that the displacement current and capacitance between transmit and receive electrodes decrease when an object enters the electric field generated by the transmitting electrode. This vest can detect metallic objects at distances of up to 18 cm with high resolution, track an object's motion, and provide an accurate estimate of its shape [291].

IGPS, UWB, and RF: Indoor global positioning system (IGPS) and ultrawideband (UWB) solutions have been introduced to offer precise location tracking within indoor environments [292], [293], [294]. By utilizing tags or antennas placed on humans and robots, these systems can monitor their positions and work in coordination with externally installed ultrawideband (UWB) receiver stations. RF-based proposals, such as a wireless earpiece emitter, have also been explored. This earpiece generates a field around the human worker, and the detectors sense disruptions in the field to send commands that alter the robot's operation. The system can even produce sounds that represent the spatial location of the robot relative to the earpiece, thereby enhancing situational awareness.

EMG Sensing: Myoelectric signal sensors, worn on the operator's arm, have been explored to capture the operator's pose and utilize it for human–robot interaction, and amend the robot's operating mode based on the action [295].

IMU: By distributing IMUs on the human operator to track movements and represent them as a skeletal model, Ate,s et al. [296] and Wenming et al. [298] eliminate the need for skeleton tracking cameras.

Augmented Reality Headset (Built-in Sensors): One recent trend emerging is the use of augmented reality headsets and using their built-in sensors to obtain the operator position [297].

2) Q2: What Operating Modes, According to ISO/TS 15066, Do the Technologies Enable?: Segmentation of the safety systems, as depicted in Fig. 13, aligns with the working modes defined in ISO/TS 15066.

SSM is the predominant mode, implemented by approximately 45.1% of the systems, primarily using structured light cameras, such as Kinect sensors. The sensor data stream is then used, e.g., for skeleton tracking and point cloud voxelization for occupancy mapping to dynamically analyze and respond to the spatial environment around the robot. This setup allows for dynamic analysis and response to the spatial environment around the robot. In addition, approximately 16.5% of systems include IT adaptation to enhance SSM, a feature not currently specified in the standard but vital for the future optimization of robotic manipulators, raising the SSM's total adoption to

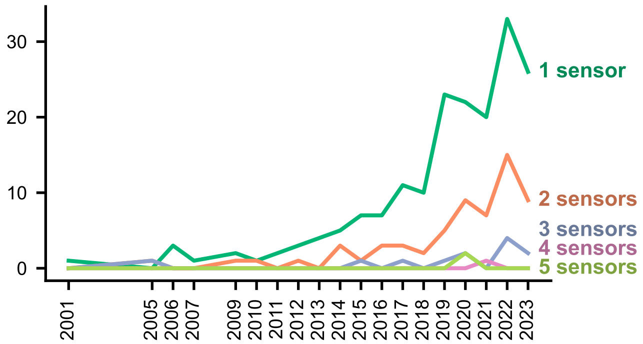

Fig. 14. Publication trend over years by the number of sensor technologies used in the system. Data from 2024 is excluded.

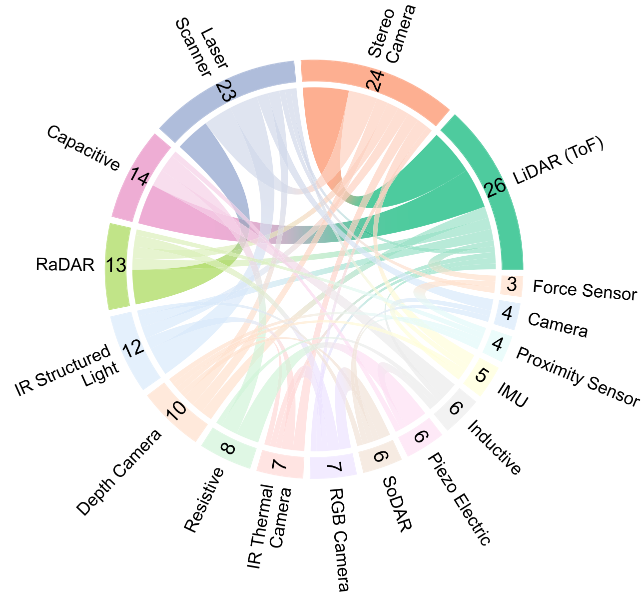

Fig. 15. Chord diagram visualizing interconnections among the most used sensors (with more than five combinations) within a safety system, with the line thickness representing the relative frequency of each sensor pairing. Notably, the connections between LiDAR (ToF) and stereo cameras, LiDAR (ToF) and capacitive sensors, as well as laser scanners and RaDAR, are most prominent, illustrating key sensor synergies.

61.6% and highlighting a strong trend toward this mode. The widespread adoption of SSM coupled with trajectory adaptations would enhance safety and efficiency, marking a shift toward more interactive and autonomous robotic systems in manufacturing.

Power and force monitoring accounts for 25.4% of the implementations, typically through capacitive sensors integrated as "skins" on the robot bodies to detect collisions and sense touch. These skins may also facilitate HG by determining whether the robot is being manipulated, although this application of this operating mode was not evident across the analyzed papers.

SRMS, which simply halts the robot's operations, appears in only 5.7% of the implementations. This basic mode is increasingly being replaced by SSM due to its limited functionality of only stopping the robot, with no dominant sensing technology identified. Ambiguity in defining operating modes was prevalent in some studies, with others omitting these details entirely, suggesting a significant need for stricter adherence to and clearer articulation of compliance or future planned compliance, even at the research level.

3) Q3: Is There a Trend Toward Combining Sensor Technologies?: Analyzing sensor combinations indicates a prominent trend toward the utilization of single-sensor setups in robotic systems, with a growing interest in dual-sensor configurations, whereas configurations utilizing three or more sensors are less common, as depicted in Fig. 14. Fig. 15 further illustrates these interconnections, emphasizing the primary pairings of technologies and their prevalence across the systems.

Of the 281 systems studied, approximately 30.2% use more than two sensor technologies, with LiDAR (ToF) and stereo cameras being the most common combination, occurring in eight instances. This pairing leverages detailed depth mapping from stereo cameras in structured environments while using LiDAR for distance measurements in less feature-rich, unstructured spaces. The second most common combination is LiDAR (ToF) and stereo cameras, occurring in seven instances. The third common combination is laser scanners and RaDAR, appearing together in six instances, often enhancing perception under suboptimal lighting or environmental conditions. In addition, 5.6% of the systems adopt more than three sensor technologies, typically in unique combinations. This distribution indicates a preference for simpler configurations that enhance the safety and performance of robotic systems by leveraging the complementary strengths of different sensors. However, the adoption of configurations with more sensors, which could provide further benefits such as increased sensing redundancy in different spectrums, remains limited.

IV. Implications of the Review and Recommendations for Future Practice

A. Findings

Our scoping review reveals several key findings. First, current safety systems mostly rely on single-sensor technologies, particularly those integrated into SSM mode, using externally installed structured light cameras. While on-robot sensing has improved, the focus remains on tactile skins without shear force capabilities, often accompanied by low-resolution proximity sensors limited to a 30-cm range on the robot arm. Second, there is a trend toward using dual-sensor setups to improve safety and functionality through sensors to increase the robustness and fault tolerance. However, multisensor systems (more than three sensors) are still uncommon, and single-sensor systems continue to be dominant. Third, most existing external systems face challenges such as occlusions, limited spatial awareness, and dependence on fixed installations, which may pose difficulties in implementing robots on movable platforms or in rapidly reconfigurable workspaces, as envisioned in Industry 5.0.

B. Recommendation for Future Research

Future research and development should focus on improving proximity sensors by increasing their accuracy, range, and angular resolution; enhancing tactile sensor accuracy through the shear force sensing; and improving responsiveness to differentiate between various types of physical interactions critical to safety (collisions) and intended control.

Robotic proximity-sensing systems are often constrained by limited frame-rate capabilities. While real-time responsiveness benefits from frame rates of 90 Hz or higher, many current systems operate at 30 Hz or less. This limitation poses significant safety risks in dynamic environments with frequent human-robot interactions. For instance, at a combined closing speed of 3 m/s (robot at 1 m/s and human at 2 m/s), the separation distance decreases by approximately 3.3 cm every 11 ms—the frame interval of a 90-Hz system. Lower frame rates prolong the update intervals, impairing the ability of the system to react promptly.

Processing high frame rates requires computational resources that are capable of handling high-volume, low-latency data streams. Fast, highly parallel, and redundant computing architectures are essential for ensuring processing times across extensive sensor arrays. Integrating adaptive sensing mechanisms allows adjustable frame rates in critical zones, for example, human–robot handover areas. By dynamically allocating higher frame rates to these areas, the system enhances responsiveness and safety without incurring unnecessary computational overheads in less critical zones.

In addition, the perception system must be able to function effectively under varying conditions, such as different lighting, dust, and weather scenarios (e.g., on construction sites), to prevent "vision gap." The system should be fault-tolerant and have low latency to allow swift adjustment of trajectories and avoid obstacles, thereby ensuring high operational uptime. In addition, the sensing system must be lightweight to avoid compromising the robot's payload capacity of the robot and have a small form factor to minimize the risk of self-collision. While emerging large-area electronics and printed and stretchable sensors offer flexible, scalable arrays for robotic surfaces, primarily in tactile sensing, further research is needed to adapt these technologies for high-resolution, real-time proximity sensing. Scaling production through large-area electronics foundries may provide a viable platform approach, enabling cost-effective integrated sensing systems that meet the demands of industrial, collaborative, and humanoid robots, which are on the rise in various sectors.

To advance the next generation of robots and to blur the lines between industrial robots and cobots, robust capabilities for global 3-D environmental mapping, reconstruction, and real-time spatial interpretation are required. This requires accurate differentiation between humans, manipulable objects, and other robots, adaptive resolutions with a high resolution near the TCP for precise manipulation and navigation, and with lower resolution to detect incoming objects in the surrounding workspace. Moreover, perception systems must be capable of recognizing occlusions caused by obstacles and identifying unmonitored areas, particularly when the system is mounted on the robot and detections occur outside the FOV.

In addition, we recommend further research and development of deterministic algorithms across multiple sensor pipelines in various spectra instead of relying only on algorithms based on large annotated datasets for understanding spatial information. This approach should incorporate a late-stage (high-level) fusion of these parallel data streams into a unified representation. Such integration not only enables a clear distinction between static and dynamic objects and their types but also enables effective tracking within the environment, ensuring comprehensive awareness of the area surrounding the robot. As these systems overcome certification challenges and are integrated into the industry for use in humanoid robots, they will gather extensive datasets. Although an AI application layer can be added to enhance functionality, it is crucial that foundational sensor integration and data processing are robust and reliable for mapping the space. As computing power continues to advance, these foundational sensor stacks will enable effective deployment and scaling of AI-based foundational models for more sophisticated spatial interpretations. In addition, multisensor detection systems can be leveraged for dataset annotation, for instance, by aligning thermal images with point clouds generated from depth maps to accurately segment the human operator.

Finally, we recognize several legal and regulatory challenges, particularly regarding liability, that significantly impact the certification and commercialization of robotics safety systems. The robotics landscape progresses slowly, with multi-sensor systems rarely commercialized, except by companies like Neura Robotics.[2] Therefore, researchers should specify the operating modes of their systems. Throughout the papers identified in the scoping review, this was often not entirely clear. Furthermore, standardized benchmarks should be established and linked to a robotics intelligence index designed explicitly to assess robotic safety abilities, enabling a consistent and comparative evaluation of future proposed robotic safety, perception, and autonomy systems.

V. Conclusion

In conclusion, this PRISMA-ScR scoping review systematically evaluated sensor-enabled safety systems for HRC in the manufacturing industry. For stakeholders in manufacturing and robotics, our analysis provides a comprehensive, segmented overview of ongoing developments and trends in this area. It can also support design and decision-making processes for integrating sensor technologies into robot safety systems. We suggest prioritizing the development of advanced proximity sensors with improved accuracy and range, as well as exploring multisensor setups to enhance safety and functionality. Furthermore, establishing standardized benchmarks linked to a robotics intelligence index should be considered for the consistent and comparative evaluation of future robotic sensor-enabled safety and perception systems for HRC.

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Hoang-Long Cao is with BruBotics, Vrije Universiteit Brussel, 1050 Brussels, Belgium, and also with Flanders Make, 3920 Lommel, Belgium (e-mail: hoang.long.cao@vub.be).

Emil Imrith is with BruBotics, Vrije Universiteit Brussel, 1050 Brussels, Belgium.

Nima Roshandel is with BruBotics, Vrije Universiteit Brussel, 1050 Brussels, Belgium, also with the Department of Electrical Engineering, KU Leuven, 3000 Leuven, Belgium, and also with imec, 3001 Leuven, Belgium.

[2]https://perma.cc/3T4W-JVLF

Antonio Paolillo is with the Software Languages Lab (SOFT), Vrije Universiteit Brussel, 1050 Brussels, Belgium, and also with BruBotics, 1050 Brussels, Belgium.

Xavier Rottenberg is with imec, 3001 Leuven, Belgium, and also with the Department of Nuclear Engineering, Université Libre de Bruxelles, 1050 Brussels, Belgium.

Peter Gerets, David Cheyns, Ilja Ocket, Kathleen Philips, and Ben Stoffelen are with imec, 3001 Leuven, Belgium.

Marcus Dahlem is with imec, 3001 Leuven, Belgium, and also with the Khalifa University of Science and Technology, Abu Dhabi, United Arab Emirates.

Jan Genoe is with the Department of Electrical Engineering, KU Leuven, 3000 Leuven, Belgium, and also with imec, 3001 Leuven, Belgium.

Jeroen Van den Bosch is with the Department of Management, Strategy and Innovation, KU Leuven, 3000 Leuven, Belgium, and also with imec, Leuven, Belgium.

Steven Latre is with imec, 3001 Leuven, Belgium, and also with the Department of Computer Science, Universiteit Antwerpen, 2000 Antwerp, Belgium.

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Constantin Scholz received the M.Eng. degree in electrical and electronic engineering with management from the Imperial College London, London, U.K., in 2020.

He leads the SAFEBOT Program, a joint initiative between imec, Leuven, Belgium, and also with Brussels Human Robotics Research Center (BruBotics), Vrije Universiteit Brussel, Brussel, Belgium, advancing robot situational intelligence and speed. His research interests include safe human–robot interaction, sensor technology, sensor fusion, electronic skins, human–robot communication, collaborative robotics, and advancements in Industry and Society 5.0.

Hoang-Long Cao received the B.Eng. degree in mechatronics from Can Tho University, Can Tho, Vietnam, in 2010, the joint M.Sc. degree in electromechanical engineering from Vrije Universiteit Brussel, Brussel, Belgium, and Université Libre de Bruxelles, Brussels, in 2013, and the Ph.D. degree in robotics from Vrije Universiteit Brussel in 2018.

He is a Guest Professor and Postdoctoral Researcher with the Robotics and Multibody Mechanics Group, Vrije Universiteit Brussel, and a member of Flanders Make, Lommel, Belgium. His research interests include social robotics, human–robot interaction, and human–robot collaboration.

Emil Imrith (Member, IEEE) received the B.E. degree in electronics engineering from University INTEC, Santo Domingo, Dominican Republic, in 2009, and the M.Sc. degree in applied mathematics from the University of Dundee, Dundee, U.K., in 2021.

He has been working in the field of electronics and system architecture since 2005 and has an interest in self-programmable control systems, artificial intelligence (AI) computer architectures, and theoretical mathematics. Since 2003, he has partnered as a Robotics System Architect with Vrije Universiteit Brussel, Brussel, Belgium.

Nima Roshandel received the bachelor's degree in mechanical engineering from the Amirkabir University of Technology, Tehran, Iran, in 2020, and the M.S. (Hons.) degree in electromechanical engineering from Vrije Universiteit Brussel, Brussel, Belgium, in 2023.

He is a joint Ph.D. Researcher with KU Leuven, Leuven, Belgium, and also with Vrije Universiteit Brussel, with scholarship support from imec, Leuven. His research focuses on sensor fusion and signal processing for robotic applications, computer vision, and machine learning, to advance the perception of robotic manipulators.

Mr. Roshandel received the Full Scholarship for the B.Sc. degree.

Hamed Firouzipouyaei received the bachelor's degree in mechanical engineering from Mechatronics Sharif University of Technology, Tehran, Iran, in 2015, the master's degree in mechanical engineering from Mechatronics Sharif University of Technology, in 2021, and the master's degree in electromechanical engineering-robotics from Vrije Universiteit Brussel, Brussel, Belgium, in 2024.

He is a Researcher and Engineer with specializing in robotics and advanced control systems. With extensive experience in reliability-centered maintenance and collaborative robotics, he is currently working on the SAFEBOT Project at Vrije Universiteit Brussel, and imec, Leuven, Belgium, focusing on real-time path planning and motion control to optimize human–robot interactions for safer, more efficient industrial applications.

Aleksander Burkiewicz received the B.Sc. degree in mechanical engineering from Warsaw University of Technology, Warsaw, Poland, in 2021, and the M.Sc. degree in electromechanical engineering from Vrije Universiteit Brussel, Brussel, Belgium, in 2024.

He is a Ph.D. Researcher in Robotics with Vrije Universiteit Brussel. His current research interests include extended reality interfaces, human–robot communication, teleoperation, Industry 5.0, and collaborative robotics.

Milan Amighi (Graduate Student Member, IEEE) received the B.Sc. degree in electromechanical engineering from the Université Libre de Bruxelles, Brussels, Belgium, in 2021, and the joint M.Sc. degree in robotics, mechatronics, and construction engineering through the Bruface Program from the Vrije Universiteit Brussel, Brussels, and Université Libre de Bruxelles, in 2023.

He is currently a Ph.D. Researcher, focusing on 3-D force sensors for robotic applications in collaboration with Melexis, Ypern, Belgium.

Sebastien Menet is a Ph.D. Researcher with Vrije Universiteit Brussel, Brussels, Belgium, conducting his work within the BruBotics Laboratories in collaboration with Melexis. His research centers on developing innovative robotic skin equipped with magnetic force sensors to detect interactions between humans and robotic arms, aiming to advance safer, more efficient human–robot interactions by overcoming the 0-cm perception gap.

Dylan Warawout Sisavath received the B.E. degree from the Université Libre de Bruxelles, Brussels, Belgium, in 2023, and the M.Eng. degree from Vrije Universiteit Brussel, Brussel, in 2024.

He is currently a Ph.D. Researcher, with research interests in robot vision and grasp preshaping for dynamic grasping.

Antonio Paolillo received the Ph.D. degree from the Université Libre de Bruxelles, Brussels, Belgium, in 2018, focusing on real-time systems and power-aware scheduling.

He is an Assistant Professor in Software Technology with Vrije Universiteit Brussel, Brussel, with expertise in operating systems, embedded real-time systems, and software performance evaluation. He has extensive industry experience, including work with spin-offs, startups, and large companies, where he applied his research to practical software engineering and performance challenges. Returning to academia, he now leads projects in performance evaluation, cybersecurity, and robotics, building a strong team in real-time and embedded software.

Xavier Rottenberg received the M.Sc. degree in physics engineering and the D.E.A. degree in theoretical physics from the Université Libre de Bruxelles, Brussels, Belgium, in 1998 and 1999, respectively, and the Ph.D. degree in electrical engineering from KU Leuven, Leuven, Belgium, in 2008.

He joined imec, Leuven, in 2000, and currently leads wave-based sensing and actuation (WSA) activities, including photonics, phononics, sensors, micro and nanoelectromechanical systems (M/NEMS), and quantum sensing. He is a Fellow of imec. He has over 150 peer-reviewed publications and patents and has lectured at DTIP, EuroSimE, ESoA, and more. He contributed to launching several ventures, including Pulsify Medical and SWAVE Photonics.

Peter Gerets received the Engineering degree in electronics and microelectronics from Katholieke Hogeschool Brugge Oostende, Brugge, Belgium, in 1985.

He has 38 years of experience in industrial environments and high-tech companies. He has innovated across domains like projection systems, display systems, image processing, flat panel technologies, and digital electronics, holding over 40 patents as inventor and co-inventor. He is currently active as the Scientific Director at imec, Leuven, Belgium.

David Cheyns received the M.Sc. and Ph.D. degrees in electrical engineering from KU Leuven, Leuven, Belgium, in 2003 and 2008, respectively.

With over 20 years' of experience in thin-film, large-area technologies, he has co-authored over 50 publications and five patents. He pioneered organic tandem solar cells, perovskite materials, organic light-emitting diodes (OLEDs), colloidal quantum dots, and large-area ultrasound at imec, Leuven. Presently, he is an Research and Development Manager with the "Sensor and Actuator Technologies" Department, imec, Leuven.

Marcus Dahlem (Senior Member, IEEE) received the Ph.D. degree in electrical engineering from MIT, Cambridge, USA, in 2011.

He joined imec, Leuven, Belgium, in 2018, as a Principal Member of Technical Staff and is currently the Program Manager for LiDAR. He has over 140 peer-reviewed publications and has held positions at MIT, IBM Zurich, Zurich, Switzerland, INESC Porto, Porto, Portugal, and Khalifa University of Science and Technology, Abu Dhabi, UAE. He is working with the Optics and Quantum Electronics Group, Research Laboratory of Electronics, MIT.

Ilja Ocket (Member, IEEE) joined imec, Leuven, Belgium, in 1999, working initially on mmWave radar and radio development. He has been the Program Manager for radar and neuromorphic sensing and, since 2023, manages imec's automotive portfolio.

Jan Genoe (Member, IEEE) received the M.S. degree in electrical engineering and the Ph.D. degree from KU Leuven, Leuven, Belgium, in 1988 and 1994, respectively.

He joined the High Magnetic Field Laboratory, Grenoble, France, as a Human Capital and Mobility Fellow before taking on academic roles at KHLim, Diepenbeek, Belgium. He is currently Scientific Director with the Sensors and Actuators Technology Department, imec, Leuven. His major research interests include the combination of novel devices with design in novel technologies.

Kathleen Philips received the master's degree in electrical engineering from KU Leuven, Leuven, Belgium, in 1995, and the Ph.D. degree in electrical engineering from Eindhoven Technical University, Eindhoven, The Netherlands, in 2005.

She had spent over 12 years as a Senior Research Scientist at Philips Research, Eindhoven. She is a VP of Research and Development with imec, Leuven, and the General Manager with the imec Holst Centre, Eindhoven. Since joining imec, in 2007, she has led research in cognitive sensing, millimeter-wave sensors, ultra-low-power (ULP) design, and human augmentation. She has over 60 publications and various patents.

Ben Stoffelen received the bachelor's degree in applied computer science (management information systems) from Katholieke Hogeschool Leuven, Leuven, Belgium, in 2012, the M.Sc. degree in international business and enterprise from the University of South Wales, Cardiff, U.K., in 2015, and the M.Sc. degree in wirtschaftsinformatik from Hochschule München University of Applied Sciences, Munich, Germany, in 2015.

He leads the Connected and Intelligent Sensing Research Group, Artificial Intelligence (AI)&Algorithms Department, imec, Leuven, Belgium, focusing on combining sensor technologies, chip design, and AI for sectors such as health, automotive, and smart industries.

Jeroen Van den Bosch received the bachelor's and master degrees in business engineering from KU Leuven, Leuven, Belgium, in 2012 and 2014, respectively, and the Ph.D. degree in economics from KU Leuven, in 2019.

During his doctoral studies, he was Visiting Researcher at the Questrom School of Business, Boston University, Boston, USA, and Visiting Researcher at IESE Business School, Barcelona, Spain. After his doctoral studies, he did a post-doc between KU Leuven and IMEC, which is a world-wide Research and Development hub on nano-electronics and digital technologies. After his post-doctoral studies, he started as Strategic Development Manager in IMEC and combines this with research activities at the department of Management, Strategy and Innovation at KU Leuven. His academic work is published in academic journals such as Information Systems Research and Small Business Economics.

Steven Latre is a VP of Research and Development Artificial Intelligence (AI) and Algorithms at imec, Leuven, Belgium, leading an interdisciplinary team of over 1000 researchers across AI accelerators, advanced sensors, and machine learning. His research applies to domains such as computing and connectivity systems, life sciences, automotive, greentech, and smart industries. He is also a part-time Professor with the University of Antwerp, Antwerp, Belgium.

Bram Vanderborght (Senior Member, IEEE) received the Ph.D. degree from Vrije Universiteit Brussel, Brussel, Belgium, in 2007.

He has conducted research at the JRL Laboratory, AIST, Tsukuba, Japan, and was a Postdoctoral Researcher with the Italian Institute of Technology. Since 2009, he has been a Professor with Vrije Universiteit Brussel. He is with imec, Leuven, Belgium, as a Scientific Collaborator. He has received an ERC starting grant and coordinated three EU projects on smart and self-healing materials for soft robots. His research interests include human–robot collaboration, focusing on health and manufacturing applications, such as exoskeletons, prostheses, social robots, drones, and cobots.