Article:

Sanders, N.E., Sener, E. orcid.org/0000-0001-5159-0870 and Chen, K.B. (2024) Robot-related injuries in the workplace: An analysis of OSHA Severe Injury Reports. Applied Ergonomics: Human Factors in Technology and Society, 121. 104324. ISSN 0003-6870

https://doi.org/10.1016/j.apergo.2024.104324

Robot-Related Injuries in the Workplace: An Analysis of OSHA Severe Injury Reports

Abstract

Industrial robots are increasingly commonplace, but research on prototypical accidents and injuries has been sparse, hindering evidence-based safety strategies. Using Severe Injury Reports (SIRs) from the U.S. Occupational Safety and Health Administration (OSHA), we identified 77 robot-related accidents from 2015-2022. Of these, 54 involved stationary robots, resulting in 66 injuries, mainly finger amputations and fractures to the head and torso. Mobile robots caused 23 accidents, leading to 27 injuries, mainly fractures to the legs and feet. A two-stage deductive-inductive thematic analysis was performed using text data from the final narratives in the reports to discover patterns in tasks, precipitating mechanisms, and contributing factors. Findings highlight the need for guards and collision avoidance systems that detect individual extremities. Post-contact strategies should focus on mitigating finger amputations. More structured and detailed narratives in the SIRs are needed.

Keywords: Industrial Robot-Related Injuries and Accidents, Occupational Safety and OSHA Reports, Human-Robot Interaction and Injury Prevention

1. Introduction

One of the principal expressions of the will to automate is the steady increase of robots in the workplace. In 2020, there were approximately 300,000 robots in the United States, a 7% increase from the previous year (Heer, 2020). The International Federation of Robotics has reported a 9% average annual increase in robot density (robots per worker) in the U.S. since 2014, a trend driven mostly by the automotive and electronics industry (IFR, 2020). The U.S. ranks third behind China and Japan in new robot installations per year (Heer, 2020), and adoption of robots in the workplace is expected to increase (NIOSH, 2019).

As the integration of powerful robotic technology into the workplace advances, it has, perhaps inevitably, led to an increase in robot-related fatalities. According to Stowers et al. (2016), the first recorded incident of a robot-related fatality occurred in 1979 when a person was hit in the head by a robotic arm at an assembly line in the U.S. Another death occurred two years later in Japan when a worker was crushed by a robotic arm while he was repairing it (Stowers et al., 2016). In 1984, an experienced die-cast operator bypassed a safety system to enter a robot's work envelope and was struck from behind and pinned against a pole, which prompted one of the first publicly available case studies of a robot-related fatality in the U.S. (Sanderson et al., 1986). A recent study reported 41 robot-related fatalities in the U.S. between 1992 - 2017 (Layne, 2023). Another study, outside of the U.S., reported that industrial robots accounted for about 5% of work-related deaths in South Korea from 2014 – 2018 (Kim et al., 2021).

While these reports and case studies provide insights into fatalities, non-fatal *severe injuries* are not as well documented (NIOSH, 2019, 2023). However, some work has been done. For example, Jiang and Gainer (1987) analyzed 32 reports from Germany, Japan, and Sweden in the late 1970s through the mid 1980s, finding that most mishaps involved pinch-point injuries of front-line workers caused by poor workplace design. Malm et al. (2010) analyzed 25 robot-related severe injuries which occurred in Finland during the period spanning 1987 to 2006. They found that most injuries involved the hands, and more than half occurred during maintenance or repair operations. Gihleb et al. (2022) found that greater robot exposure in the US and Germany during the period of 2005 - 2011 was associated with an overall reduction in the rate of work-related injuries – but not the most severe injuries.

These findings notwithstanding, occupational surveillance data on robot-related injuries in the U.S. has been relatively limited (NIOSH, 2023). Because of this, the NIOSH Center for Occupational Robotics Research emphasizes the need to identify and monitor robot-related injuries and risk factors, to quantify the burden of occupational injuries using existing data systems, and to develop new surveillance methods and analytical techniques (NIOSH, 2024). In line with this, more comprehensive data for the US began to be recorded in 2015 when the Occupational Safety and Health Administration (OSHA) started requiring employers to report any severe injury that resulted in a hospitalization (Michaels, 2016).

These Severe Injury Reports (SIRs) are a potential boon to understanding robot-related accidents because they include written narratives in addition to coded variables. By augmenting the original codes with information from the narratives, it becomes easier to identify recurring hazard patterns (Drury and Brill, 1983). Inspired by a scene synopsis in theater or film, a *scenario* describes a prototypical accident in terms of the actors (victims), the props (products), the scene (environment), and the action (task) (Drury and Brill, 1983; Lincoln et al., 2004). Lincoln et al. (2004) showed that a thematic analysis could be used to discover patterns by analyzing the tasks, precipitating mechanisms, and contributing factors from narrative reports. One of the aims of this paper is to identify hazard patterns via thematic analysis of the final narratives in the SIRs using the categories of Drury and Brill (1983) and Lincoln et al. (2004).

Accident prediction does not necessarily depend on retrospective analysis (Grant et al., 2018), and considerable work has already been done to anticipate pre-collision scenarios and post-collision injuries in order to develop collaborative robots (Vasic and Billard, 2013; Hentout et al., 2019; Villani et al., 2018; Robelski and Wischniewski, 2016). Collaborative robots, or "cobots", are a type of robot designed to work alongside humans in a shared workspace. Unlike traditional industrial robots that operate in guarded areas away from human workers, cobots are built with features and functionalities that allow them to (more) safely interact with human operators. The ISO/TS 15066 technical specifications for safety of collaborative robots delineates different types of collaboration, including speed and separation monitoring (SSM) as a means to prevent collisions, and power and force limiting (PFL) to mitigate the severity of post-collision injuries (Kumar et al., 2021). Due to the dearth of detailed data on robot-related injuries, controls such as PFL have turned to domains outside of human-robot interaction, such as automobile crash-testing, for guidance on robot-related injury criteria (Haddadin, 2014). As a result, the focus has been on injuries to the head, neck, and chest, with lower extremities excluded due to their assumed reduced relevance for robotics (Haddadin, 2014). Some researchers contend that automotive injury assessment tools may not be suitable for robotics, because high-speed collision criteria may not accurately represent lower-speed human-robot interactions (Robla-Gomez et al., 2017). In addition, the focus on the head and torso to the exclusion of the extremities may not accurately reflect the empirical distribution of robot-related injuries on the body. More detailed and differentiated measures of injury severity for human-robot interactions are needed based on real occupational surveillance data (Haddadin, 2014).

1.1. Research Goals

The first goal of this study (Goal 1) was to assess the Severe Injury Reports (SIRs) in terms of their utility as a resource for safety research and surveillance, in line with the NIOSH Strategic Plan (NIOSH, 2023). A mixed-methods approach was employed to quantify the proportion of narratives containing the data elements of Drury and Brill (1983) and Lincoln et al. (2004), as well as the inter-rater reliability of the coding process. Our chosen methods and their pitfalls are discussed, and we propose enhancements to the SIRs to increase their value to future researchers.

The second goal (Goal 2) was to identify common hazard patterns preceding accidents through thematic analysis. Evidence is presented for tentative hypotheses about hazard scenarios - the recurrence of specific combinations of tasks, contributing factors, and precipitating mechanisms - and possible pre-collision hazard controls are discussed.

The third goal (Goal 3) was to describe the physical consequences of robot-related accidents, specifically how injuries are distributed across the body. Utilizing the OIICS codes for injury nature and body part, descriptive statistics and visualizations are presented for each type of robot and contact event. The findings are discussed in relation to robot-specific injury criteria and post-collision mitigation strategies.

2. Methods

2.1. Data Source

The U.S. Occupational Safety and Health Administration (OSHA) has required employers to report severe work-related injuries since January 1, 2015 (OSHA, 2023). As defined by OSHA, a *severe injury* is an amputation, in-patient hospitalization, or loss of an eye (OSHA, 2023). The reports are freely available for download on the OSHA website (OSHA, 2023). Since the SIRs only include incidents under federal OSHA jurisdiction, reports from the 22 states with their own OSH plans covering private sector employees were not included in the present analysis (OSHA, 2021). The database was downloaded in November 2022 and included reports from January 1, 2015 through April 30, 2022.

Each report contains a narrative description of the mishap, as well as Occupational Injury and Illness Classification System (OIICS) codes. There are four OIICS code categories: Nature of Injury or Illness, Part of Body Affected, Source (and Secondary Source), and Event (U.S. Department of Labor, 2012). Definitions of these categories are provided in Table 1.

2.2. Record screening procedure

Figure 1 depicts the flow of information through the different phases of the screening procedure, which was based on the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) statement (Page et al., 2021). When the OSHA SIR database was accessed, it contained 73,254 reports. Because there are no robot-specific OIICS codes, the text of the final narratives was used to identify robot-related injuries. Forty-eight regular expressions (regex) patterns were developed to identify mentions of robots (Table A.10). These targeted key terms and included synonyms, variations, and misspellings, for example, `(?\i)robo(t|ts|t’s|ts’)?` and `(?\i)rbt|robt|rbot|robutt|robit`. This initial search returned 204 reports.

The operational definition of robots is based on ISO 8373: A *robot* is an automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, either fixed in place or mobile for use in industrial automation applications. A *mobile robot* is defined as a robot able to travel under its own control, including a mobile platform with or without manipulators. Automated guided vehicles (AGVs), laser guided vehicles (LGVs) and automated material transfer carts were included in this definition. Eighty-seven reports remained after non-robots were excluded. False positives included many instances of all-terrain vehicle (ATV) accidents.

The remaining records were only included if the robot in question was a primary or secondary source, according to the definitions in Table 1. Ten

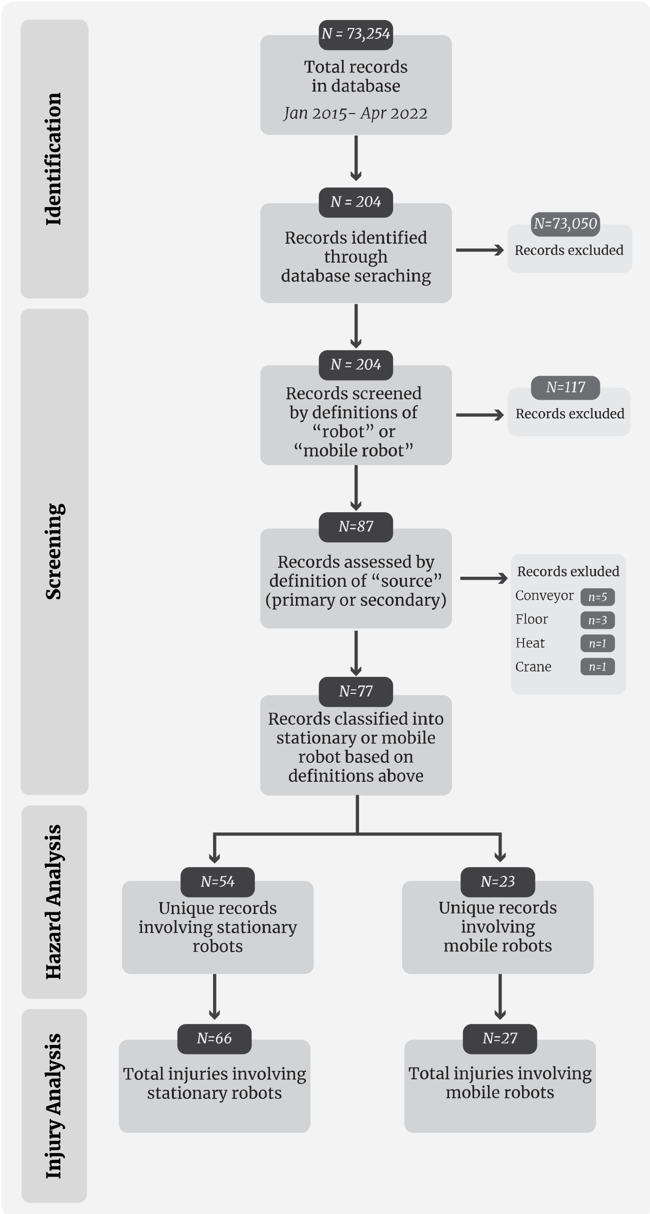

Figure 1: PRISMA flowchart for record screening process

records were excluded on these grounds. Ultimately, 54 unique records involving stationary robots and 23 records for mobile robots were included for analysis. False positives involved incidents where a robot was present in the environment and mentioned in passing, but was only incidental to the accident – it neither directly produced the injury nor generated the source that produced the injury.

CONCEPTUAL CODES AND DEFINITIONS	
Activity	The type of broad activity the injured person was engaged in when the injury occurred
Task	The specific activity engaged in when the injury occurred providing additional detail
Contributing Factor	The key element that increased the risk such that what is normally completed without incident resulted in injury
Precipitating Mechanism	The cause that initiated the chain of events leading to the injury; those mechanisms involved at the start of the injury event
Primary Source	The object, substance, bodily motion, or exposure that directly produced or inflicted the previously identified injury or illness
Secondary Source	The object, substance, or person that generated the source of injury or illness or that contributed to the event or exposure. Not all mishaps involve a secondary source
Injury Event	The principal characteristic of the injury or illness
Injury Nature	The part of the body directly affected by the nature of injury
Body Part	The way the injury or illness was produced or inflicted by the source of injury or illness

Table 1: Conceptual codes (data elements) and their definitions

2.3. Application of Trustworthiness Criteria for Thematic Analysis

The qualitative analysis was performed by the first two authors. Trustworthiness was established via the criteria defined by Guba and Lincoln (1982), Tobin and Begley (2004), and Nowell et al. (2017). Trustworthiness is composed of four elements:

Credibility. Credibility is analogous to internal validity (Tobin and Begley, 2004). It addresses the fit between the actual events and the OSHA investigators' written accounts, versus the researchers' interpretations of those accounts. Credibility is typically established via member checks, where the researchers confirm their findings by following up with the respondents. In this case, the authors did not have access to either the investigators or the victims – only the text itself. Therefore, the authors established credibility by comparing their interpretations via inter-rater reliability calculations (described in Section 2.4.1).

Transferability. Transferability is analogous to external validity and concerns the generalizability of results (Tobin and Begley, 2004). This was achieved in the Discussion (Section 4) by integrating and comparing present findings with similar studies, showing how the results align with or diverge from previous research. In the Results and Discussion, "thick descriptions" and extensive quotations are provided to create more context for readers to assess the transferability of the findings.

Dependability. Dependability is analogous to reliability and refers to whether the research method is logical, traceable, and clearly documented (Nowell et al., 2017). The authors created an auditable trail of their decisions, which included the R Markdown notes documenting the data screening procedure, the code-book documenting the thematic analysis, along with contemporaneous notes and memos.

Confirmability. Confirmability is analogous to objectivity and is concerned with establishing that the results are clearly derived from the data and not the researchers' imaginations or biases (Tobin and Begley, 2004). We therefore provided as much raw data as possible in the form of actual text extracts to support our conclusions.

2.4. Thematic Analysis

To address Goal 2, identifying common hazard patterns preceding accidents, a thematic analysis was performed using Dedoose 9.2. *Thematic analysis* is "a method for identifying, analyzing, organizing, describing, and reporting themes found within a data set" (Braun and Clarke, 2006). A *theme* "captures something important about the data in relation to the research question, and represents some level of patterned response or meaning within the data set" (Braun and Clarke, 2006). In this study, themes refer to patterns within the higher-level conceptual categories (a.k.a. data elements) of Task, Contributing Factor, Precipitating Mechanism, etc. defined in Lincoln et al. (2004), which were established *a priori* before the analysis began (see Table 1).

A two-stage deductive-inductive coding approach was performed (Fereday and Muir-Cochrane, 2006). The deductive stage began with a set of *a priori* conceptual codes (Table 1) which were applied to the data. The inductive stage involved abstracting new categories (themes) that were not pre-defined.

2.4.1. First-Stage Deductive Coding Procedure

The first two authors began by independently and systematically parsing each narrative report, highlighting selections of text (referred to as *excerpts*) and applying a conceptual code to each excerpt according to the procedure described by Guest et al. (2012). Ultimately, 342 coded excerpts were generated by Rater A and 337 by Rater B. Table 2 shows an example of one report, and how the text was excerpted and coded by the two raters. Not every narrative contained enough information for every code to be applied, and the two raters did not always agree on how to excerpt and code the text. Before moving on to the inductive second-stage of the analysis, we ensured there was "good" agreement between the raters.

This was done by calculating inter-rater reliability (IRR) via Cohen's Kappa (Cohen, 1960; De Vries et al., 2008). Cohen's Kappa applies to a situation where two or more judges independently assign mutually exclusive nominal categories to a set of independent items. It indexes the proportion of agreement after chance agreement is removed from consideration (Cohen, 1960). In our case, the judges were Raters A and B, and the mutually exclusive nominal categories were the conceptual codes in Table 1. A straightforward IRR calculation was thwarted because the items (excerpts) were not actually independent – each rater created their own set of excerpts. Using

ID: 2016099119
Source: Extruding, injecting, forming, molding machinery, unspecified (3530)
Secondary Source: NA (NA)
Event: Caught in running equipment or machinery during regular operation (6412)
Nature: Cuts, lacerations (132)
Part of Body: Finger(s), fingernail(s), unspecified (4420)
Final Narrative: An employee entered a robot cell through an opening used to remove sand. As the employee attempted to adjust the casting, the saw caught and cut the employee's finger. An interlocked gate was in place at the time.

Rater A	Rater B	Conceptual Code
An employee	employee	**Victim**
robot cell	robot cell; An interlocked gate was in place at the time	**Environment**
regular operation	regular operation	**Activity**
As the employee attempted to adjust the casting	attempted to adjust the casting	**Task**
through an opening used to remove sand; An interlocked gate was in place at the time.	N/A	**Contributing Factor**
N/A	entered a robot cell through an opening used to remove sand	**Precipitating Mechanism**
the saw caught and cut the employee’s finger	caught and cut	**Injury Event**

Table 2: Example of one record showing coded excerpts as part of the first-stage deductive coding

Table 2 as an example, Rater A excerpted "An employee" to be coded as Victim, while Rater B excerpted "employee". On a semantic level, both raters agreed on the victim, but the two text strings did not match. To obtain a score, 20% of each Rater's excerpts were sampled, stratified by conceptual code category, then randomized and given to the other rater to code. This resulted in two point estimates of Kappa – one for Rater A given a sample of Rater B's excerpts, $\kappa_{A|B}$, and for Rater B given a sample of Rater A's excerpts, $\kappa_{B|A}$. No formal hypothesis testing was done with these estimates. They were used to guide discussion and resolve any discrepancies in how the definitions in Table 1 were interpreted and applied. The entire deductive coding procedure had to be repeated before "good" agreement was finally achieved.

"Good" agreement ultimately depends on the context and judgement of the researchers, and there are a variety of standards proposed by different authors. Fleiss (1971) suggests that .60 to .74 is "good", and .75 to 1.0 is "excellent". Landis and Koch (1977) propose that values between 0.61 to 0.80 represent "substantial agreement" and 0.81 to 1.0 is "almost perfect" agreement. Cicchetti (1994) suggest that values below .70 are unacceptable, between [.70 and .79] are fair; between [.80 and .89] are good, and greater than .90 are excellent. We therefore established a cutoff of 0.70 for this analysis.

2.4.2. Second-Stage Inductive Coding Procedure

Thematic analysis can be used for a wide range of epistemologies (Nowell et al., 2017). Developed for constructivist paradigms in the social sciences, theme discovery and mixed-methods can be applied to both post-positivist and interpretivist epistemologies (Ryan and Bernard, 2003). A post-positivist stance was taken here, where it was assumed that the hazard patterns which preceded the accidents did indeed constitute an objective truth "out there", although the authors recognized that only successive approximations of that truth could be made (Blandford et al., 2016).

Stage two was a bottom-up, data-driven, inductive process where themes organically emerged from the data without pre-existing conceptual codes. The authors followed the procedure in Braun and Clarke (2006):

1. Generating initial codes: Each rater independently reviewed the excerpts in each category from the from the previous stage, parsing them one at a time, and abstracting from each specific excerpt one or more tentative codes.

2. Searching for themes: The initial codes were grouped into clusters, along with their excerpts and complete narratives. This was done interactively using manual tools such as whiteboards and sticky notes, but ultimately Dedoose was used to create the code-book.
3. Reviewing themes: The clusters of coded excerpts (i.e., the emerging themes), were considered in the larger context of their narratives and the entire corpus. Adjustments were made based on the two criteria of internal homogeneity and external heterogeneity: data within themes should cohere together meaningfully, while there should be clear and identifiable distinctions between them (Braun and Clarke, 2006).
4. Defining and naming: This was to delineate and clearly articulate the defining characteristics of each emerging theme and to assign it a descriptive name.

Steps 2 - 4 were repeated until we judged the themes fit the data well and the process became one of fine-tuning, at which point we stopped (Braun and Clarke, 2006).

2.5. Re-Coding OIICS Codes for Injury Analysis

Low-level OIICS codes for Body Part were grouped into higher hierarchical levels to facilitate sense-making: The new code *head* comprised the original codes for head, nose, neck, and face. *Torso* comprised the abdomen, ribs, chest, lungs, back, whole body, and internal. *Arm* comprised forearm, upper arm, arm, shoulder, collarbone, and elbow. *Hand* comprised the wrist and hand. *Finger* comprised the finger. *Pelvis* comprised hip and pelvis. *Leg* comprised leg, lower leg, and knee. *Foot* comprised ankle, toes, and foot.

When multiple injuries occurred within the same incident, the OSHA investigators, being limited to only one Nature and Body Part field, were forced to code the incident as "Multiple body parts, n.e.c." ("not elsewhere classified"). In most cases when there were multiple injuries, we were able to use information in the narrative text to code them individually. When multiple instances of the same Nature occurred to the same Body Part (e.g., three fractures to the left tibia), we counted it as a single injury.

3. Results

3.1. Inter-Rater Reliability and the Utility of Narrative Reports

The initial inter-rater reliability test revealed low agreement for Environment, Contributing Factors, and Precipitating Mechanisms. Close inspection of the test results showed that what Rater B labeled as "environment," Rater A often categorized as a "contributing factor." Similarly, classifications by Rater A as "contributing factor" were frequently coded by Rater B as "task," "environment," or "precipitating mechanism."

Table 3: Prevalence of conceptual codes within the corpus of records, and IRR values after the initial and final round of deductive coding. A minimum value of 0.70 was required before proceeding to the inductive stage.

		Rater $A\|B$		Rater $B\|A$	
Code	Prevalence	Initial	Final	Initial	Final
Victim	100%	1.00	1.00	1.00	1.00
Environment	30%	0.32	1.00	0.92	1.00
Activity	60%	0.72	0.94	0.79	0.88
Task	86%	0.77	0.91	0.70	0.72
Contributing Factor	14%	0.54	0.82	0.22	0.90
Precipitating Mechanism	58%	0.28	0.82	0.58	0.80
Injury Event	94%	0.82	0.96	0.85	0.92
Pooled	-	0.70	0.93	0.78	0.89

Upon reviewing the results and discussing the discrepancies together, it became clear that the primary issue was the coding level: semantic/explicit versus latent/interpretive. Rater B's approach was more conservative, focusing strictly on the text's explicit content. In contrast, Rater A engaged in deeper interpretation, attempting to infer broader meanings and implications. For example (Table 2), Rater A interpreted the mere mention of an "interlocked gate" in a report as significant in itself, implying an attempt to communicate the insufficiency of guarding mechanisms. Conversely, Rater B classified it under "environment," noting that no failure of any safety system was explicitly mentioned in the text. After these discussions, the entire corpus was re-coded by the two raters, with Rater A shifting to a more conservative, explicit coding style. Although Table 3 and Table 2 indicate persistent disagreements in the Final coding, the final scores improved to indicate "good" or "excellent" agreement for all categories.

The brevity of the narratives contributed to the raters' coding discrepancies. The median word count was 36, with an inter-quartile range of [29, 48] and a total range of [17, 90]. Not all reports were complete with all the data elements (conceptual codes) from Table 1. Table 3 shows the prevalence of each conceptual code across the corpus of reports. For example, a Contributing Factor was able to be coded in 14% of the reports; details about the Environment in 30%; and a Precipitating Mechanism in 58%.

3.2. Thematic Analysis of Hazards

The thematic analysis was only performed for the conceptual categories of Task, Precipitating Mechanism, and Contributing Factor. Excerpts from the other categories did not contain enough information for analysis (e.g. Victim was almost always simply "the employee" with a few exceptions that will be mentioned in Section 4.3.3.

Table 4 details the themes for stationary robots, along with a count of the number of occurrences, and selected examples excerpts. Troubleshooting was the most common theme among Tasks, followed by setups, and maintenance. There is no U.S. regulatory definition of "maintenance", but it is usually defined as keeping equipment in proper condition in a routine, scheduled, or anticipated fashion (OSHA, 2003). Troubleshooting therefore represents unplanned upkeep, when an employee takes action to correct an incipient problem. Sudden motion of the robot while the person was in its working envelope was the most common precipitating mechanism, and the cause of the motion was often unexplained in the report. Excerpts of contributing factors were sparse, but they often mentioned that the equipment was guarded, not guarded, or not locked out.

In contrast to what was observed for stationary robots, regular operation was the most common theme of Task for mobile robots, followed by troubleshooting (Table 5). Entering a robot's path, unbeknownst to the employee, was the most common precipitating mechanism, followed by vehicular collisions.

STATIONARY ROBOTS	N	Example Excerpts
Tasks		
Troubleshooting	N = 14	▪ Entered a robot cell to determine why the robot stopped working ▪ Attempting to clear slag from a welding tip
Setup and Inspection	N = 13	▪ Installing a robotic welder and finishing the cement grouting around the workstation ▪ Trying to change over the robot settings ▪ Loading a weld fixture into a weld robot cell
Maintenance and Cleaning	N = 10	▪ Adjusting the lower pin alignment on a robotic cell stationary welder ▪ Removing lint from a monitor behind a robot ▪ Replacing suction cups on an end-of-arm tool
Regular Operation	N = 6	▪ Reaching to move a paver into a conveyor system ▪ Observing a robot stacking lumber onto pallets for shipment
Trainning	N = 1	▪ Training a new employee on how to operate a robotic welder
Precipitating Mechanisms		
Sudden Unexplained	N = 14	▪ The robot became energized ▪ The machine actuated while his left hand was in it
Troubleshooting Entry	N = 7	▪ An employee entered a robot cell through an opening used to remove sand. As the employee attempted to adjust the casting [...] ▪ A rock fell onto the conveyor. The employee attempted to remove the rock [...]
User Input	N = 3	▪ An employee was trying to change over the robot settings on a pneumatic welding machine when a coworker pressed a button [...] ▪ When an employee turned the control on the robotic extruder machine to auto [...]
Accidental Entry	N = 2	▪ She stepped back into an unguarded robotic material handler ▪ His foot entered the service pit of an adjunct active robotic welder
Sudden Release of Energy	N = 2	▪ When he manually released the clamp, it closed on his left pinky
Trip	N = 2	▪ Tripped and fell over the plug and cord to a Xenex robot
Contributing Factors		
Guarded	N = 4	▪ The active welder was guarded at the time of the incident. ▪ The area was guarded with light curtains at the time of the inciden
Un-Guarded	N = 2	▪ The machine was unguarded at the time.
Not Locked Out	N = 2	▪ The system was not de-energized at the time of the incident ▪ The cell's robot was not locked out during cleaning operations
Malfunction	N = 1	▪ The sensor on the gate malfunctioned and allowed the robot to operate

Table 4: Stationary robots themes. N is the number of unique reports.

MOBILE ROBOTS

Tasks	N	Example Excerpts
Regular Operation	*N* = 6	• The employee put the LGV in manual, got off the machine • Driving a forklift to be parked • Operating a remote-controlled tree trimming robot
Troubleshooting	*N* = 5	• About to move a cart that was blocking an automated guided vehicle from its designated stop • Working on an automatic guided vehicle (AGV) that had stalled • Moving laser guided vehicles (LGV) due to a jam up
Setup	*N* = 3	• Stacking a unit of corrugated sheets • Walking across the floor • Pulling an irregular cart full of heavy bulk packages out of an automated guided vehicle
Maintenance and Cleaning	*N* = 3	• Removing a gearbox from the frame of a laser-guided truck • Cleaning a charging pad for robotic machines<bReplacing a broken clevis and bolt

Precipitating Mechanisms	N	Example Excerpts
Accidental Entry	*N* = 3	• His foot entered the path of an automated material transfer cart • He was sitting on the catwalk with his legs hanging over the edge, when an automated transfer car system traveled beneath the catwalk • As the employee was exiting the charging pad, he placed his right arm and hand outside the charging pad area to push off
Collision	*N* = 3	• Cargo on the second employee's AGV struck a car on the injured employee's AGV train. • The AGV swung around and collided with another AGV
Sudden Release of Energy	*N* = 2	• After removing the last two bolts holding the gearbox to the frame, the gearbox fell • When the employee moved the cylinder to inspect it, the cylinder released in the upward position
Spontaneous Restart	*N* = 1	• The employee kicked the sensor to stop the LGV in auto. The LGV reset after 15 seconds and started up again
Trip	*N* = 1	• Tripped over the hitch of a stationary robot
Sudden Unexplained	*N* = 1	• The cart started to move

Table 5: Mobile robot themes. N is the number of unique reports.

3.3. Events and Injuries

Table 6 shows the joint distribution of Injury Nature and Body Part. For stationary robots, amputations of the finger are the most frequent specific injury (N=25, 38%) followed by fractures affecting various bones in the arm (N=4, 6%), torso (N=4, 6%), and head (N=3, 5%). Thirty-two injuries (48%) involved the fingers and hands; 19 (29%) involved the head, torso, and pelvis; and 13 (20%) involved the arms, legs, and feet. Amputations are the most frequent type of injury (N=25, 38%), followed by fractures (N=20, 30%), and lacerations (N=8, 12%). Other injury types such as burns, contusions, and electrocutions contribute less frequently with a combined total of 13 cases (20%).

For mobile robots, fractures of the leg are the most common specific injury with 9 cases (33%), followed by soreness of the torso, fractures of the pelvis, and fractures of the foot, each with 3 cases (11% each). Four injuries (15%) involved the fingers and hands; 8 (30%) involved the torso and pelvis; and 15 (56%) involved the arms, legs, and feet. Fractures are the most common injury (N=17, 63%), followed by soreness (N=4, 15%). Less frequent were amputations, avulsions, contusions, crushings, and lacerations, each with 1 or 2 reported instances, totaling 6 cases (22% combined).

Table 6: Joint distribution of injury types and body parts for stationary and mobile robots.

	Arm	Finger	Foot	Hand	Head	Leg	NEI	Pelvis	Torso
Stationary Robots									
Amputation	0	25	0	0	0	0	0	0	0
Avulsion	1	0	0	0	0	0	0	0	0
Burn	1	0	0	0	1	0	0	0	0
Concussion	0	0	0	0	1	0	0	0	0
Contusion	1	0	0	0	1	0	0	0	2
Electrocution	0	0	0	1	0	0	0	0	0
Fracture	4	1	1	2	3	2	1	2	4
Hernia	0	0	0	0	0	0	0	0	1
Laceration	0	3	2	0	1	1	0	0	1
NEI	0	0	0	0	0	0	1	0	0
Puncture	0	0	0	0	0	0	0	0	1
Soreness	0	0	0	0	1	0	0	0	0
Mobile Robots									
Amputation	0	1	0	0	-	0	-	0	0
Avulsion	0	0	0	0	-	1	-	0	0
Contusion	0	0	0	0	-	0	-	1	0
Crushing	0	0	0	0	-	0	-	0	1
Fracture	0	0	3	2	-	9	-	3	0
Laceration	1	0	0	0	-	1	-	0	0
Soreness	0	0	0	1	-	0	-	0	3

Table 7 shows the counts of events and injuries for stationary and mobile robots. The most frequently occurring events for stationary robots were being pinched by an effector or fixture (N=17), pinned against a stationary object (N=15), or struck but not subsequently pinned (N=14). For mobile robots, pinning against a stationary object (including other mobile robots) accounted for the majority of events (N=14), followed by being struck (N=5).

THEMES		Example Excerpts
Stationary Robots		
Pinched	$N = 17$, $I = 18$	• The robotic welder pinched the employee's fingertip • It closed on his left pinky • His left ring finger was caught and amputated in the hydraulic clamp • The machine actuated while his left hand was in it
Pinned	$N = 15$, $I = 19$	• A robotic arm pinned an employee's head to a CNC machine • Got caught between a welding parts machine and a robot • Crushed/pinned the employee's right foot against the barrier guard • The robotic arm struck and pinned the employee • Pinching the employee's right little finger against the tire rim
Struck	$N = 14$, $I = 18$	• Struck in the head by a robotic arm • The handler caught her left leg • The robot swung and hit the employee
Caught in Moving Parts	$N = 3$, $I = 3$	• A drive belt and pulley caught the employee's right index finger • An employee [...] contacted the blades
Explosion	$N = 1$, $I = 2$	• An explosive device fell from the machine to the floor and detonated
Fall Due to Trip	$N = 1$, $I = 2$	• Tripped and fell
Unknown	$N = 1$, $I = 2$	• -
Exposure to Electricity	$N = 1$, $I = 1$	• Received an electrical shock to his left hand while removing a metal cover
Overexertion	$N = 1$, $I = 1$	• After removing the last two bolts holding the gearbox to the frame, the gearbox fell • When the employee moved the cylinder to inspect it, the cylinder released in the upward position
Mobile Robots		
Pinned	$N = 14$, $I = 16$	• The cart ran into him, pinning him against a structural pole • Pinched between the LGV and conveyor • Trapping the employee between the two LGVs • Smashed and broken between the two vehicles
Struck	$N = 5$, $I = 7$	• Struck by an automated guided vehicle • The equipment ran over and fractured his right ankle
Caught in Moving Parts	$N = 1$, $I = 1$	• Caught between the top of the stroke cylinder shaft and the hood base
Fall Due to Trip	$N = 1$, $I = 1$	• Caught between the top of the stroke cylinder shaft and the hood base
Overexertion	$N = 1$, $I = 1$	• Suffered a lower back injury
Struck by Falling Object	$N = 1$, $I = 1$	• The gearbox fell and struck the employees' feet

Table 7: Injury Events for stationary and mobile robots. N is the number of unique reports, and I is the total number of injuries.

Figure 2 shows the distribution of injuries across the body for the most prevalent event types – strikes, pins, and pinches. For stationary robots, strikes are distributed approximately uniformly across the body, whereas pins occur mostly by the fingers, torso, and head, while pinches are predominantly of the fingers. For mobile robots, strikes and pins occur mostly at the legs.

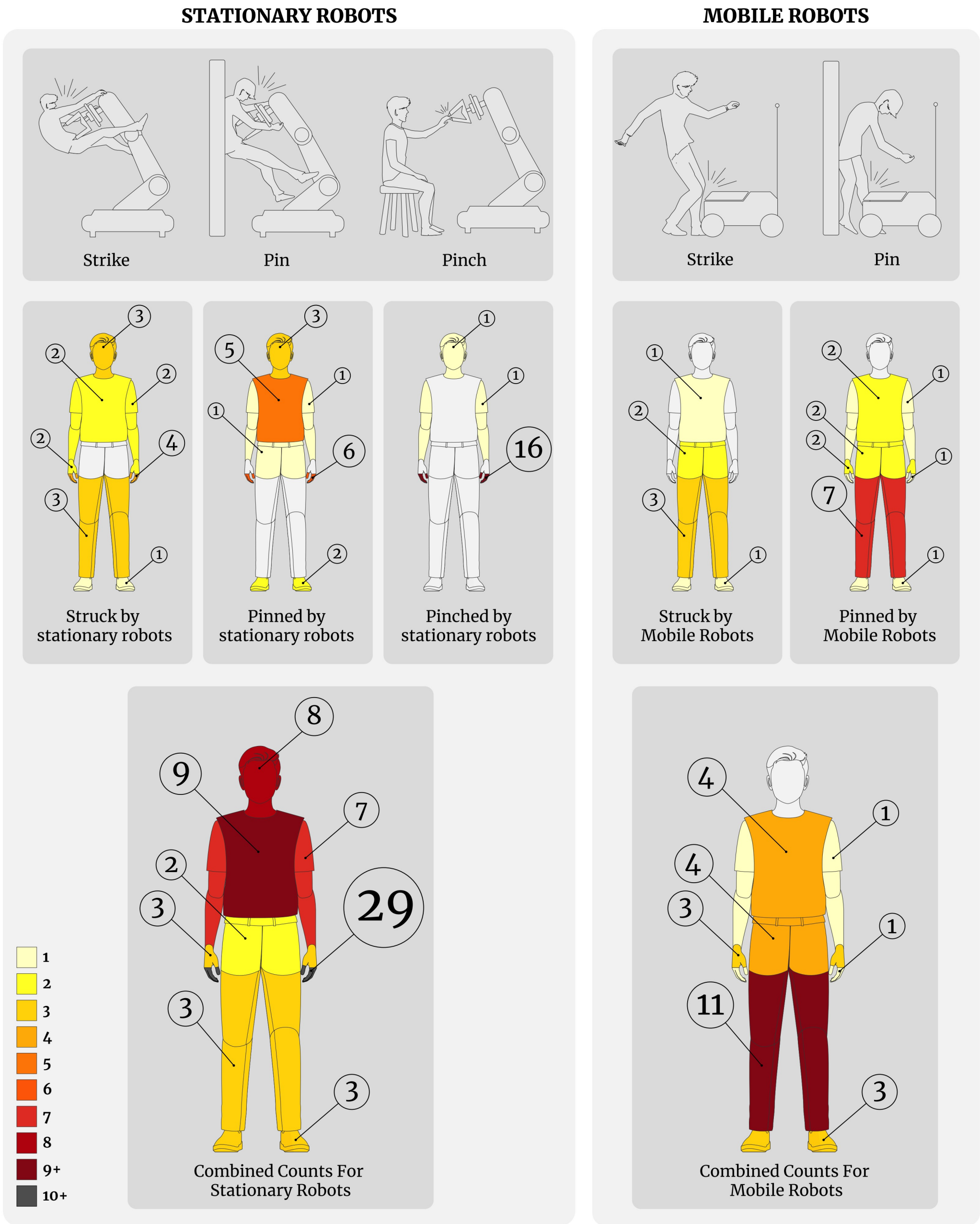

Figure 2: Counts of injuries across the body. The numbers, circle diameter, and colors reflect the raw counts (not normalized by area). The combined counts include all events, not just struck, pinned, and pinched.

4. Discussion

4.1. Narrative reports and robot-specific coding

The final narratives varied significantly in length and content. Excessive brevity or irrelevant details led to missing data elements (Table 3) diminishing the SIRs' value in understanding the causal relationships between robotics technologies and worker injuries. However, these reports did provide valuable context about tasks and (to a lesser extent) precipitating mechanisms.

There was also notable variation in the OIICS codes for Sources and Events. For Sources, the variation reflected different robot applications, with welding machinery being predominant. However, these codes lacked specifics about the robot's make, model, and configuration, and did not even indicate that the source was a robot, thus necessitating the search of final narratives for key words. This omission hinders the identification and categorization of robot-related accidents, potentially widening the surveillance gap for new robotics technologies. For Events, the variation indicated a need for more specific codes for robot-related accidents. For instance, almost all of the reports were able to be re-coded with robot-specific contact events: *struck*, *pinched*, and *pinned*, or what Haddadin et al. (2009) called *unconstrained impacts*, *clamping in the robot structure*, and *constrained impacts*, respectively. Introducing robot-specific event codes would introduce consistent language and enable better comparisons across studies.

4.2. Comparison with Previous Research

The present study and Malm et al. (2010) revealed similar patterns of injury across the body, with partial amputations of the fingers being the most common, followed by fractures to the head and torso. The theme of [sudden] and unexpected actuation (Table 4) and being pinned (Table 7) is also consistent with the findings of Malm et al. (2010) and Jiang and Gainer (1987).However, variations in categorizations between studies make detailed comparisons difficult and speak to the need for standardized definitions in future research as mentioned above.

The results of this study and the work of Malm et al. (2010), Layne (2023), and Kim et al. (2021) highlight troubleshooting and setup as activities during which the majority of accidents occurred. In contrast, Jiang and Gainer (1987) found that most accidents involved "line workers" and very few involved maintenance personnel, suggesting a possible shift in risk over time. This idea is supported by Layne (2023), who found that maintenance was mentioned more often during the period of 2005–2017 compared with the earlier years of 1992–2004, although he does not make a distinction between maintenance and troubleshooting. Taken together, this suggests that hazard controls for non-routine operations are inadequate, and that more effort should be focused there.

4.3. Pre-contact hazard controls

The themes in Tables 4 and 5 suggest several several engineering and administrative controls for both stationary and mobile robots. Some of these are already used in practice, or have already been put forward in the ISO/TS 15066 technical specification for collaborative robots. Nonetheless, this discussion may shed light on the possible prioritization of controls or suggest additional considerations for existing control implementations.

4.3.1. Design modifications for safety

Contributing factors of "guarded", and precipitating mechanisms of "accidental entry", "user input", and sudden actuation suggest that many accidents might be "prevented through design" (NIOSH, 2014); for example, by *not* requiring a person to enter a robot's working envelope to access its controls, or by designing robot grippers so that they can be installed and adjusted without putting one's fingers or hands inside, or by incorporating locking devices such as electromagnetic brakes to prevent the sudden release of mechanical or pneumatic energy (Plooij et al., 2015). Jiang and Gainer (1987) estimated that about half of accidents were attributable to poor workplace design, but without more detailed narratives we hesitate to make any quantitative estimates.

Machine guards are an element of workplace design that is meant to prevent entry into a work envelope or to detect when entry has occurred (Spellman and Whiting, 1999). In the robotics context, guards include cages with door switches to detect entry; light curtains to detect breaches of un-caged sections of the perimeter; pressure pads to detect a person's presence; and LiDAR and computer-vision to detect human bodies and measure proximity (Kumar et al., 2021).

Themes of accidental entry, troubleshooting entry, guarded, and un-guarded (Table 4) suggest inadequate guarding such that person's entire body or even *just a single body part* was able to enter a robot's working envelope. In some reports the implication was that guards were intentionally circumvented. Inadequate guarding was the tenth most common OSHA violation in 2020

(Grainger, 2021). Jiang and Gainer (1987) found that 45% of their reports involved inadequate guarding, and Malm et al. (2010) found it was 80%. Because of the low code frequency for contributing factor (Table 3) we cannot make any strong quantitative claims about this data.

However, the results underscore that any guard, whether conventional or fenceless, must consider not only a person's entire body *but especially individual body parts* such as hands and feet. This could involve, for example, eliminating gaps in light curtains and cages, even if those gaps seem to be in ostensibly inconsequential places such as along the floor. Sensors such as cameras, pressure plates, LiDAR, etc. should be calibrated to detect not just an entire human body, but merely a single extremity such as an arm or leg.

4.3.2. Collision avoidance systems

Most reports involved a contact event of some kind (Table 7). Speed and separation monitoring (SSM) is a term used in collaborative robotics that refers to stopping or slowing the robot's motion based on a person's proximity (Kumar et al., 2021). The means by which proximity is measured includes computer-vision-based systems (intrinsic or extrinsic), LiDAR scanners, ultrasonic sensors, infrared sensors, pressure mats, and light curtains (Kumar et al., 2021; Rodriguez-Guerra et al., 2021). The results of this study show that collisions can and do occur when only a single body part, such as an arm or a leg, enters a robot's working envelope or path. Therefore, as with machine guards, any SSM or collision-avoidance system should be able to track and recognize not only entire human bodies, but *individual body parts*. For mobile robots especially, engineers implementing any collision avoidance system should consider that hazards may not appear only on the roadway where they "should" appear, but may include workers kneeling on the ground next to the robot, or individual body parts protruding into its path from above or the side, or oversized cargo on another vehicle. The case reports in NIOSH (2019) also involved scenarios of this kind, and Layne (2023) makes a similar call for better collision avoidance systems, writing "Further innovations in sensors and AI are required to increase recognition of objects for collision avoidance". Wearable transponders or remote-controlled emergency stops may also be an effective solution. Advanced driver assistance and crash mitigation systems (Klomp et al., 2019; Austin et al., 2023), such are already in use or under development in the automotive industry, may have prevented some of the collisions in Table 5.

4.3.3. Administrative controls

Failure to lockout/tagout (LOTO) or de-energize contributed to two of the four stationary robot reports that listed contributing factors (Table 4). The themes of maintenance and cleaning (Table 4) also suggest failure to LOTO or adhere to safety protocols, although in most cases this was not explicitly stated. Malm et al. (2010) attributed 60% of accidents to insufficient warnings or instructions, and noted that dangerous working methods due to inadequate training or supervision were common. Jiang and Gainer (1987) also found that "human error" such as not following procedures, accounted for 33% of accidents. Layne (2023) also writes that "Incidents involving traditional industrial robots can be most effectively prevented through ensuring compliance with the guarded areas of the robotic cell or cage, with emphasis on complete power shutdown and lockout tagout during nonroutine operations." Failure to LOTO was the sixth-most common OSHA violation in 2020 (Grainger, 2021), and compliance with the LOTO standard prevents 50,000 severe injuries per year (OSHA, 2002). Failure to LOTO suggests an inadequacy of the employers in developing or enforcing energy control programs, or failure of employees to follow established protocols. In the latter case, the roles of safety culture, leadership, and production pressure on individual safety behaviors should not be underestimated (Griffin and Hu, 2013; Guo et al., 2016).

The temporary status of the victim was mentioned in two final narratives. Non-standard work arrangements accounted for 5% to 40% jobs in the United States in 2015 (Nicholson, 2015). Temporary workers face higher injury risks and poorer illness outcomes than regular employees (Howard, 2017), probably due to their limited job experience and knowledge of hazards (Benavides et al., 2006), and they may hesitate to voice concerns due to their non-standard status (Howard, 2017). Their injuries are often underreported (Picchio and van Ours, 2017). Given this, when it comes to human behavior around robots, engineers should strive to develop engineering controls (rather than administrative controls) that anticipate the inexperience and socio-organizational pressures that might lead to risky behaviors.

4.4. Post-contact hazard controls

Injuries to the upper and lower extremities, although less life-threatening compared to injuries to the head and torso, can have life-long economic, physical, and psychological consequences (Read et al., 2004; Van Eerd et al., 2016). The burden of traumatic hand and finger injuries in particular can be especially severe. People with finger amputations have a resultant disability that diminishes their ability to work and perform daily tasks (Giladi et al., 2014), and they often develop anxiety disorders, major depression, pain syndromes, and adjustment problems (Grob et al., 2008).

Automotive-based injury indices such as the Abbreviated Injury Scale (AIS) and Head Injury Criterion (HIC) have provided guidance for robotic power-and-force-limiting (PFL) based on injury tolerances for the head and torso (Robla-Gomez et al., 2017; Haddadin, 2014). These indices diminish the significance of injuries to the extremities because they were designed for the prediction of survival and not subsequent quality of life (Read et al., 2004). Given that head and torso injuries accounted for only 1/3 of the total, new robot-specific injury indices that focus on the extremities, *especially the fingers and hands*, may be beneficial. Cadaver studies may be helpful in developing robot-specific injury indices that focus on the extremities, especially the fingers and hands. One example is Carpanen et al. (2019) which provides empirical injury tolerances for the metacarpophalangeal (MCP) and proximal interphalangeal (PIP) joints of the hand.

4.5. Limitations and future work

There are three main limitations of this study. First, the dataset is completely U.S.-centric. it is quite possible that systematic legal, cultural, and socio-organizational differences in countries such as Germany, Japan, and China may have an effect on the quantity, nature, and categorization of robot-related accidents and their causes.

Second, the number of incidents reported here are almost certainly a lower-bound for three reasons. First, the data does not account for several categories of workers and workplaces that fall outside of federal OSHA's jurisdiction, including self-employed workers, immediate family members of farm employers, and workplaces covered by other federal agencies such as the Mine Safety and Health Administration, the Federal Aviation Administration, the Federal Railroad Administration, and states with their OSHA-approved plan. Second, injuries are probably under-reported by 50% even within the states that were included (Michaels, 2016). Third, the lack of specific robot-related OIICS codes meant that the narrative reports had to be relied on to identify robot-related events. It is possible that many more robot-related accidents occurred where the robot was described as a "machine" or "welder" in the report, and thus eluded identification. The introduction of robot-specific source and event OIICS codes would facilitate more precise identification and categorization of reports (see Section 4.1).

Third, the present analysis can only be as good as the data on which it is based. The missing data elements (see Section 4.1) did not enable a detailed reconstruction of all incidents. Therefore, the themes presented in this study should be considered hypothetical (in the scientific sense) and subject to testing and re-evaluation should better data become available. Future work might cross reference the scenarios here with past case studies. Chi et al. (2009) and Chi and Lin (2018) could be used for methodological inspiration, as they also analyzed narrative reports to identify hazard scenarios and used more sophisticated safety engineering techniques such as fault-tree analysis. Variability in the narrative reports of the SIRs highlights the potential benefit of a semi-structured reporting format, ensuring consistent and comprehensive capture of incident details. Additionally, integrating multimedia data into SIRs, such as images or videos, might provide a clearer context of the incident scene, aiding in analysis.

An area warranting further exploration is human factors studies, with a focus on situation awareness (Endsley, 2015) and individuals' mental models of robot actions. Some reports hinted at a potential lack of situation awareness or perhaps a misunderstanding of robot's ”intentions” and capabilities. Examining the mental models that individuals form about robot behavior could shed light on their decisions and actions around robots. Enhancing these mental models, alongside improving situation awareness, might offer avenues for refining safety protocols and training. Finally, machine learning techniques such as natural language processing might be employed to search for and code the narrative reports, decreasing the workload of the researchers and enabling inferential statistical analysis rather than the descriptive approach provided here.

4.6. Funding Sources

This work was supported by [omitted for blind review]

4.7. Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the first author used ChatGPT 4 to help brainstorm alternative terms and spellings for robots, to generate the regex expressions to search for those terms, to generate LaTeX code for tables, to correct transcription errors in dictated notes, and to help shape those notes into early outlines and drafts. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

Appendix A. Appendix

Appendix A.1. Coding

Table A.8: Original OIICS codes for Event with researchers' re-coding shown in bold

Event	Description
-	**Pinched**
6412	Caught in running equipment or machinery during regular operation
6410	Caught in running equipment or machinery, unspecified
6411	Caught in running equipment or machinery during maintenance, cleaning
6419	Caught in running equipment or machinery, n.e.c.
533	Contact with hot objects or substances
6233	Struck by object falling from vehicle or machinery-other than vehicle part
642	Compressed or pinched by shifting objects or equipment
-	**Pinned**
6411	Caught in running equipment or machinery during maintenance, cleaning
640	Caught in or compressed by equipment or objects, unspecified
6412	Caught in running equipment or machinery during regular operation
6419	Caught in running equipment or machinery, n.e.c.
-	**Pinned by mobile robot**
642	Compressed or pinched by shifting objects or equipment
2441	Pedestrian struck by vehicle propelled by another vehicle in nonroadway area
2721	Part of occupant's body caught between vehicle and other object in nonroadway transport incident
2734	Fall or jump from and struck by same vehicle in normal operation, nonroadway
6211	Caught between rolling powered vehicle and other object
6229	Struck by rolling object or equipment-other than powered vehicle, n.e.c.
640	Caught in or compressed by equipment or objects, unspecified
6412	Caught in running equipment or machinery during regular operation
-	**Struck**
6412	Caught in running equipment or machinery during regular operation
9999	Nonclassifiable
620	Struck by object or equipment, unspecified
6411	Caught in running equipment or machinery during maintenance, cleaning
6419	Caught in running equipment or machinery, n.e.c.
-	**Struck by mobile robot**
6219	Struck by powered vehicle-nontransport, n.e.c.
629	Struck by object or equipment, n.e.c.
-	**Other**
6411	Caught in running equipment or machinery during maintenance, cleaning
640	Caught in or compressed by equipment or objects, unspecified
511	Direct exposure to electricity

Table A.9: Original OIICS codes for Source with researchers' re-coding shown in bold

Code	Description
-	**Robot**
3594	Welding machinery
30	Machinery, unspecified
392	Product assembly machinery, n.e.c.
9999	Nonclassifiable
3799	Special process machinery, n.e.c.
3499	Material and personnel handling machinery, n.e.c.
4211	Clamps, couplings
3796	Painting, priming, metal coating machinery
3732	Packaging, wrapping, bundling machinery
3730	Packaging, bottling, wrapping machinery, unspecified
3532	Extruding machinery
3530	Extruding, injecting, forming, molding machinery, unspecified
3493	Stacking machinery
799	Tools, instruments, and equipment, n.e.c.
350	Metal, woodworking, and special material machinery, unspecified
340	Material and personnel handling machinery, unspecified
40	Parts and materials, unspecified
-	**Mobile robot**
3499	Material and personnel handling machinery, n.e.c.
8629	Industrial vehicle, material hauling and transport-powered, n.e.c
8621	Forklift, order picker, platform truck-powered
3325	Kilns
3199	Agricultural and garden machinery, n.e.c.
340	Material and personnel handling machinery, unspecified
30	Machinery, unspecified

Table A.10: Search Terms for Identifying Robots. Likely misspellings were included in the regex patterns but are not shown here.

Terms for Stationary Robots	**Terms for Mobile Robots**
Automated Industrial Equipment	AGV (Autonomous Guided Vehicle)
Automated System	AMR (Automated Mobile Robot)
Automatically Controlled Manipulator	ATV (Automated Transport Vehicle)
Industrial Automaton	Automated Forklift
Mechatronic System	Automated Guided Vehicle
Mobile Manipulator	Automated Material Transfer Cart
Multi-Axis Manipulator	Automated Track
Multi-Purpose Automated Machinery	Automated Transfer Car
Programmable Automation Device	Automated Vehicle
Programmable Mechanical Device	Automatic Guided
Reprogrammable Machine	Autonomous Vehicle
Robot	Driverless
Robotesque	Intelligent Mobile
Robotic	Laser Guided Truck
Roboticism	LGV (Laser Guided Vehicle)
Roboticist	Mobile Manipulator
Roboticization	Mobile Robot
Roboticize	Programmable Mobile
Robotic-like	Remote Controlled
Robotization	Robotic Cart
Robotize	Robotic Vehicle
Self-Moving Automaton	Self Driving
Self-Propelled Machine	Self Navigating
	Track-Based
	UGV (Unmanned Ground Vehicle)

References

Austin, T., Grimes, W., Cheek, T., Plant, D., Steiner, J., Higgins, B., Lombardi, K., DiSogra, M., Wilcoxson, G., 2023. Testing of Heavy Truck Advanced Driver Assistance Systems and Crash Mitigation Systems, in: WCX SAE World Congress Experience, SAE International. doi:10.4271/2023-01-0010.

Benavides, F.G., Benach, J., Muntaner, C., Delclos, G.L., Catot, N., Amable, M., 2006. Associations between temporary employment and occupational injury: What are the mechanisms? Occupational and Environmental Medicine 63, 416–421. doi:10.1136/oem.2005.022301.

Blandford, A., Furniss, D., Makri, S., 2016. Qualitative HCI Research. Synthesis Lectures on Human-Centered Informatics, Springer International Publishing, Cham. doi:10.1007/978-3-031-02217-3.

Braun, V., Clarke, V., 2006. Using thematic analysis in psychology. Qualitative Research in Psychology 3, 77–101. doi:10.1191/1478088706qp063oa, arXiv:504.

Carpanen, D., Kedgley, A.E., Shah, D.S., Edwards, D.S., Plant, D.J., Masouros, S.D., 2019. Injury risk of interphalangeal and metacarpophalangeal joints under impact loading. Journal of the Mechanical Behavior of Biomedical Materials 97, 306–311. doi:10.1016/j.jmbbm.2019.05.037.

Chi, C.F., Lin, S.Z., 2018. Classification scheme and prevention measures for caught-in-between occupational fatalities. Applied Ergonomics 68, 338–348. doi:10.1016/j.apergo.2017.12.007.

Chi, C.F., Yang, C.C., Chen, Z.L., 2009. In-depth accident analysis of electrical fatalities in the construction industry. International Journal of Industrial Ergonomics 39, 635–644. doi:10.1016/j.ergon.2007.12.003.

Cicchetti, D.V., 1994. Guidelines, criteria, and rules of thumb for evaluating normed and standardized assessment instruments in psychology. Psychological Assessment 6, 284–290. doi:10.1037/1040-3590.6.4.284.

Cohen, J., 1960. A Coefficient of Agreement for Nominal Scales. Educational and Psychological Measurement 20, 37–46. doi:10.1177/001316446002000104.

De Vries, H., Elliott, M.N., Kanouse, D.E., Teleki, S.S., 2008. Using Pooled Kappa to Summarize Interrater Agreement across Many Items. Field Methods 20, 272–282. doi:10.1177/1525822X08317166.

Drury, C.G., Brill, M., 1983. Human Factors in Consumer Product Accident Investigation. Human Factors 25, 329–342. doi:10.1177/001872088302500310.

Endsley, M.R., 2015. Situation Awareness Misconceptions and Misunderstandings. Journal of Cognitive Engineering and Decision Making 9, 4–32. doi:10.1177/1555343415572631.

Fereday, J., Muir-Cochrane, E., 2006. Demonstrating Rigor Using Thematic Analysis: A Hybrid Approach of Inductive and Deductive Coding and Theme Development. International Journal of Qualitative Methods 5, 80–92. doi:10.1177/160940690600500107.

Fleiss, J.L., 1971. Measuring nominal scale agreement among many raters. Psychological Bulletin 76, 378–382. doi:10.1037/h0031619.

Gihleb, R., Giuntella, O., Stella, L., Wang, T., 2022. Industrial robots, Workers' safety, and health. Labour Economics 78, 102205. doi:10.1016/j.labeco.2022.102205.

Giladi, A.M., McGlinn, E.P., Shauver, M.J., Voice, T.P., Chung, K.C., 2014. Measuring outcomes and determining long-term disability after revision amputation for treatment of traumatic finger and thumb amputation injuries. Plastic and Reconstructive Surgery 134, 746e–755e. doi:10.1097/PRS.0000000000000591.

Grainger, 2021. Top 10 OSHA Violations: 2020. URL: https://web.archive.org/web/20240223202033/https://www.grainger.com/know-how/safety-health/management/kh-top-10-osha-violations-2020.

Grant, E., Salmon, P.M., Stevens, N.J., Goode, N., Read, G.J., 2018. Back to the future: What do accident causation models tell us about accident prediction? Safety Science 104, 99–109. doi:10.1016/j.ssci.2017.12.018.

Griffin, M.A., Hu, X., 2013. How leaders differentially motivate safety compliance and safety participation: The role of monitoring, inspiring, and learning. Safety Science 60, 196–202. doi:10.1016/j.ssci.2013.07.019.

Grob, M., Papadopulos, N.A., Zimmermann, A., Biemer, E., Kovacs, L., 2008. The psychological impact of severe hand injury. Journal of Hand Surgery: European Volume 33, 358–362. doi:10.1177/1753193407087026.

Guba, E.G., Lincoln, Y.S., 1982. Epistemological and methodological bases of naturalistic inquiry. ECTJ 30, 233–252. doi:10.1007/BF02765185.

Guest, G., MacQueen, K., Namey, E., 2012. Applied Thematic Analysis. SAGE Publications, Inc., Thousand Oaks. doi:10.4135/9781483384436.

Guo, B.H., Yiu, T.W., González, V.A., 2016. Predicting safety behavior in the construction industry: Development and test of an integrative model. Safety Science 84, 1–11. doi:10.1016/j.ssci.2015.11.020.

Haddadin, S., 2014. Crash-Testing in Robotics, in: Towards Safe Robots. Springer Berlin Heidelberg, Berlin, Heidelberg. volume 90 of *Springer Tracts in Advanced Robotics*. chapter 5, pp. 11–26. doi:10.1007/978-3-642-40308-8.

Haddadin, S., Albu-Schäfferffer, Hirzinger, G., 2009. Requirements for safe robots: Measurements, analysis and new insights. International Journal of Robotics Research 28, 1507–1527. doi:10.1177/0278364909343970.

Heer, C., 2020. Record 293,000 Robots In United States' Factories. International Federation of Robotics URL: https://web.archive.org/web/20220402132842/https://ifr.org/downloads/press2018/2020-09-24__Record_293%2C000_Robots_In_United_States'_Factories__IFR_press_release_WR.pdf.

Hentout, A., Aouache, M., Maoudj, A., Akli, I., 2019. Human–robot interaction in industrial collaborative robotics: a literature review of the decade 2008–2017. Advanced Robotics 33, 764–799. doi:10.1080/01691864.2019.1636714.

Howard, J., 2017. Nonstandard work arrangements and worker health and safety. American Journal of Industrial Medicine 60, 1–10. doi:10.1002/ajim.22669.

IFR, 2020. Executive Summary World Robotics 2020 Industrial Robots. International Federation of Robotics URL: https://web.archive.org/web/20240308215458/https://ifr.org/img/worldrobotics/Executive_Summary_WR_2020_Industrial_Robots_1.pdf.

Jiang, B.C., Gainer, C.A., 1987. A cause-and-effect analysis of robot accidents. Journal of Occupational Accidents 9, 27–45. doi:10.1016/0376-6349(87)90023-X.

Kim, S., Lee, J., Kang, C., 2021. Analysis of industrial accidents causing through jamming or crushing accidental deaths in the manufacturing industry in South Korea: Focus on non-routine work on machinery. Safety Science 133. doi:10.1016/j.ssci.2020.104998.

Klomp, M., Jonasson, M., Laine, L., Henderson, L., Regolin, E., Schumi, S., 2019. Trends in vehicle motion control for automated driving on public roads. Vehicle System Dynamics 57, 1028–1061. doi:10.1080/00423114.2019.1610182.

Kumar, S., Savur, C., Sahin, F., 2021. Survey of Human-Robot Collaboration in Industrial Settings: Awareness, Intelligence, and Compliance. IEEE Transactions on Systems, Man, and Cybernetics: Systems 51, 280–297. doi:10.1109/TSMC.2020.3041231.

Landis, J.R., Koch, G.G., 1977. The Measurement of Observer Agreement for Categorical Data. Biometrics 33, 159. doi:10.2307/2529310.

Layne, L.A., 2023. Robot-related fatalities at work in the United States, 1992–2017. American Journal of Industrial Medicine , 454–461doi:10.1002/ajim.23470.

Lincoln, A.E., Sorock, G.S., Courtney, T.K., Wellman, H.M., Smith, G.S., Amoroso, P.J., 2004. Using narrative text and coded data to develop hazard scenarios for occupational injury interventions. Injury Prevention 10, 249–254. doi:10.1136/ip.2004.005181.

Malm, T., Viitaniemi, J., Latokartano, J., Lind, S., Venho-Ahonen, O., Schabel, J., 2010. Safety of interactive robotics-learning from accidents. International Journal of Social Robotics 2, 221–227. doi:10.1007/s12369-010-0057-8.

Michaels, D., 2016. Year One of OSHA's Severe Injury Reporting Program: An Impact Evaluation. Occupational Safety and Health Administration URL: https://web.archive.org/web/20240103035754/https://www.osha.gov/sites/default/files/severe-injury-2015.pdf.

Nicholson, J.R., 2015. Temporary Help Workers in the U.S. Labor Market. U.S. Department of Commerce, Economics and Statistics Administration URL: https://web.archive.org/web/20240118063544/https://www.commerce.gov/sites/default/files/migrated/reports/temporary-help-workers-in-the-us-labor-market.pdf.

NIOSH, 2014. The State of the National Initiative on Prevention through Design. Technical Report. DHHS (NIOSH). URL: https://web.archive.org/web/20240516213511/https://www.cdc.gov/niosh/docs/2014-123/pdfs/2014-123_v2.pdf?id=10.26616/NIOSHPUB2014123.

NIOSH, 2019. FACE Investigations Make Recommendations to Improve the Safety of New Types of Robots. The National Institute for Occupational Safety and Health (NIOSH) Science Blog URL: https://web.archive.org/web/20240516220117/https://www.proquest.com/docview/2297110169.

NIOSH, 2023. Intermediate Goal 6.3 (Injuries related to emerging technologies). Technical Report. DHHS (NIOSH). URL: https://web.archive.org/web/20240516211349/https://www.cdc.gov/niosh/media/pdfs/2024/05/V8-NIOSH-Strategic-Plan_V8_August-2023_FINAL.pdf.

NIOSH, 2024. Center for Occupational Robotics Research. URL: https://web.archive.org/web/20240516215424/https://www.cdc.gov/niosh/centers/robotics.html.

Nowell, L.S., Norris, J.M., White, D.E., Moules, N.J., 2017. Thematic Analysis: Striving to Meet the Trustworthiness Criteria. International Journal of Qualitative Methods 16, 1–13. doi:10.1177/1609406917733847.

OSHA, 2002. Lockout/Tagout: OSHA Fact Sheet. Occupational Safety and Health Administration URL: https://web.archive.org/web/20210306082103/https://www.osha.gov/sites/default/files/publications/factsheet-lockout-tagout.pdf.

OSHA, 2003. OSHA Standard Interpretation. Occupational Safety and Health Administration URL: https://web.archive.org/web/20240224090238/https://www.osha.gov/laws-regs/standardinterpretations/2003-11-18.

OSHA, 2021. State Plans. Occupational Safety and Health Administration URL: https://web.archive.org/web/20240403170930/https://www.osha.gov/stateplans.

OSHA, 2023. Severe Injury Reports. Occupational Safety and Health Administration URL: https://web.archive.org/web/20240515180425/https://www.osha.gov/severeinjury.

Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D., Shamseer, L., Tetzlaff, J.M., Akl, E.A., Brennan, S.E., Chou, R., Glanville, J., Grimshaw, J.M., Hróbjartsson, A., Lalu, M.M., Li, T., Loder, E.W., Mayo-Wilson, E., McDonald, S., McGuinness, L.A., Stewart, L.A., Thomas, J., Tricco, A.C., Welch, V.A., Whiting, P., Moher, D., 2021. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 372. doi:10.1136/bmj.n71.

Picchio, M., van Ours, J.C., 2017. Temporary jobs and the severity of workplace accidents. Journal of Safety Research 61, 41–51. doi:10.1016/j.jsr.2017.02.004.

Plooij, M., Mathijssen, G., Cherelle, P., Lefeber, D., Vanderborght, B., 2015. Lock Your Robot: A Review of Locking Devices in Robotics. IEEE Robotics & Automation Magazine 22, 106–117. doi:10.1109/MRA.2014.2381368.

Read, K.M., Kufera, J.A., Dischinger, P.C., Kerns, T.J., Ho, S.M., Burgess, A.R., Burch, C.A., 2004. Life-Altering Outcomes after Lower Extremity Injury Sustained in Motor Vehicle Crashes. The Journal of Trauma: Injury, Infection, and Critical Care 57, 815–823. doi:10.1097/01.TA.0000136289.15303.44.

Robelski, S., Wischniewski, S., 2016. Scoping Review on Human-Machine Interaction and Health and Safety at Work, in: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and

Lecture Notes in Bioinformatics). Toronto, ON, Canada. volume 9752, pp. 337–347. doi:10.1007/978-3-319-39399-5_32.

Robla-Gomez, S., Becerra, V.M., Llata, J.R., Gonzalez-Sarabia, E., Torre-Ferrero, C., Perez-Oria, J., 2017. Working Together: A Review on Safe Human-Robot Collaboration in Industrial Environments. IEEE Access 5, 26754–26773. doi:10.1109/ACCESS.2017.2773127.

Rodriguez-Guerra, D., Sorrosal, G., Cabanes, I., Calleja, C., 2021. Human-Robot Interaction Review: Challenges and Solutions for Modern Industrial Environments. IEEE Access 9, 108557–108578. doi:10.1109/ACCESS.2021.3099287.

Ryan, G.W., Bernard, H.R., 2003. Techniques to Identify Themes. Field Methods 15, 85–109. doi:10.1177/1525822X02239569.

Sanderson, L.M., Collins, J.W., McGlothlin, J.D., 1986. Robot-related fatality involving a U.S. manufacturing plant employee: Case report and recommendations. Journal of Occupational Accidents 8, 13–23. doi:10.1016/0376-6349(86)90027-1.

Spellman, F., Whiting, N., 1999. Machine Guarding Handbook: A Practical Guide to OSHA Compliance and Injury Prevention. Government Institutes, Lanham, MD.

Stowers, K., Leyva, K., Hancock, G.M., Hancock, P.A., 2016. Life or Death by Robot? Ergonomics in Design 24, 17–22. doi:10.1177/1064804616635811.

Tobin, G.A., Begley, C.M., 2004. Methodological rigour within a qualitative framework. Journal of Advanced Nursing 48, 388–396. doi:10.1111/j.1365-2648.2004.03207.x.

U.S. Department of Labor, 2012. Occupational Injury and Illness Classification Manual. U.S. Department of Labor URL: https://web.archive.org/web/20230105182544/https://www.bls.gov/iif/definitions/oiics-manual-2010.pdf.

Van Eerd, D., Munhall, C., Irvin, E., Rempel, D., Brewer, S., van der Beek, A.J., Dennerlein, J.T., Tullar, J., Skivington, K., Pinion, C., Amick, B., 2016. Effectiveness of workplace interventions in the prevention of upper extremity musculoskeletal disorders and symptoms: an update of the evidence. Occupational and Environmental Medicine 73, 62–70. doi:10.1136/oemed-2015-102992.

Vasic, M., Billard, A., 2013. Safety issues in human-robot interactions, in: 2013 IEEE International Conference on Robotics and Automation, IEEE. pp. 197–204. doi:10.1109/ICRA.2013.6630576.

Villani, V., Pini, F., Leali, F., Secchi, C., 2018. Survey on human–robot collaboration in industrial settings: Safety, intuitive interfaces and applications. Mechatronics 55, 248–266. doi:10.1016/j.mechatronics.2018.02.009.