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

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3 **Abstract**

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

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

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## 21 1. Introduction

22 One of the principal expressions of the will to automate is the steady in-  
23 crease of robots in the workplace. In 2020, there were approximately 300,000  
24 robots in the United States, a 7% increase from the previous year (Heer,  
25 2020). The International Federation of Robotics has reported a 9% average  
26 annual increase in robot density (robots per worker) in the U.S. since 2014, a  
27 trend driven mostly by the automotive and electronics industry (IFR, 2020).  
28 The U.S. ranks third behind China and Japan in new robot installations per  
29 year (Heer, 2020), and adoption of robots in the workplace is expected to  
30 increase (NIOSH, 2019).

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

45 While these reports and case studies provide insights into fatalities, non-  
46 fatal *severe injuries* are not as well documented (NIOSH, 2019, 2023). How-  
47 ever, some work has been done. For example, Jiang and Gainer (1987)  
48 analyzed 32 reports from Germany, Japan, and Sweden in the late 1970s  
49 through the mid 1980s, finding that most mishaps involved pinch-point in-  
50 juries of front-line workers caused by poor workplace design. Malm et al.  
51 (2010) analyzed 25 robot-related severe injuries which occurred in Finland  
52 during the period spanning 1987 to 2006. They found that most injuries  
53 involved the hands, and more than half occurred during maintenance or re-  
54 pair operations. Gihleb et al. (2022) found that greater robot exposure in  
55 the US and Germany during the period of 2005 - 2011 was associated with  
56 an overall reduction in the rate of work-related injuries – but not the most  
57 severe injuries.

58 These findings notwithstanding, occupational surveillance data on robot-  
59 related injuries in the U.S. has been relatively limited (NIOSH, 2023). Be-  
60 cause of this, the NIOSH Center for Occupational Robotics Research empha-  
61 sizes the need to identify and monitor robot-related injuries and risk factors,  
62 to quantify the burden of occupational injuries using existing data systems,  
63 and to develop new surveillance methods and analytical techniques (NIOSH,  
64 2024). In line with this, more comprehensive data for the US began to be  
65 recorded in 2015 when the Occupational Safety and Health Administration  
66 (OSHA) started requiring employers to report any severe injury that resulted  
67 in a hospitalization (Michaels, 2016).

68 These Severe Injury Reports (SIRs) are a potential boon to understanding  
69 robot-related accidents because they include written narratives in addition  
70 to coded variables. By augmenting the original codes with information from  
71 the narratives, it becomes easier to identify recurring hazard patterns (Drury  
72 and Brill, 1983). Inspired by a scene synopsis in theater or film, a *scenario*  
73 describes a prototypical accident in terms of the actors (victims), the props  
74 (products), the scene (environment), and the action (task) (Drury and Brill,  
75 1983; Lincoln et al., 2004). Lincoln et al. (2004) showed that a thematic  
76 analysis could be used to discover patterns by analyzing the tasks, precipi-  
77 tating mechanisms, and contributing factors from narrative reports. One of  
78 the aims of this paper is to identify hazard patterns via thematic analysis of  
79 the final narratives in the SIRs using the categories of Drury and Brill (1983)  
80 and Lincoln et al. (2004).

81 Accident prediction does not necessarily depend on retrospective analysis  
82 (Grant et al., 2018), and considerable work has already been done to antici-  
83 pate pre-collision scenarios and post-collision injuries in order to develop col-  
84 laborative robots (Vasic and Billard, 2013; Hentout et al., 2019; Villani et al.,  
85 2018; Robelski and Wischniewski, 2016). Collaborative robots, or "cobots",  
86 are a type of robot designed to work alongside humans in a shared workspace.  
87 Unlike traditional industrial robots that operate in guarded areas away from  
88 human workers, cobots are built with features and functionalities that allow  
89 them to (more) safely interact with human operators. The ISO/TS 15066  
90 technical specifications for safety of collaborative robots delineates different  
91 types of collaboration, including speed and separation monitoring (SSM) as  
92 a means to prevent collisions, and power and force limiting (PFL) to miti-  
93 gate the severity of post-collision injuries (Kumar et al., 2021). Due to the  
94 dearth of detailed data on robot-related injuries, controls such as PFL have  
95 turned to domains outside of human-robot interaction, such as automobile

96 crash-testing, for guidance on robot-related injury criteria (Haddadin, 2014).  
97 As a result, the focus has been on injuries to the head, neck, and chest,  
98 with lower extremities excluded due to their assumed reduced relevance for  
99 robotics (Haddadin, 2014). Some researchers contend that automotive in-  
100 jury assessment tools may not be suitable for robotics, because high-speed  
101 collision criteria may not accurately represent lower-speed human-robot in-  
102 teractions (Robla-Gomez et al., 2017). In addition, the focus on the head  
103 and torso to the exclusion of the extremities may not accurately reflect the  
104 empirical distribution of robot-related injuries on the body. More detailed  
105 and differentiated measures of injury severity for human-robot interactions  
106 are needed based on real occupational surveillance data (Haddadin, 2014).

### 107 *1.1. Research Goals*

108 The first goal of this study (Goal 1) was to assess the Severe Injury  
109 Reports (SIRs) in terms of their utility as a resource for safety research and  
110 surveillance, in line with the NIOSH Strategic Plan (NIOSH, 2023). A mixed-  
111 methods approach was employed to quantify the proportion of narratives  
112 containing the data elements of Drury and Brill (1983) and Lincoln et al.  
113 (2004), as well as the inter-rater reliability of the coding process. Our chosen  
114 methods and their pitfalls are discussed, and we propose enhancements to  
115 the SIRs to increase their value to future researchers.

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

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

## 127 **2. Methods**

### 128 *2.1. Data Source*

129 The U.S. Occupational Safety and Health Administration (OSHA) has  
130 required employers to report severe work-related injuries since January 1,

131 2015 (OSHA, 2023). As defined by OSHA, a *severe injury* is an amputation,  
132 in-patient hospitalization, or loss of an eye (OSHA, 2023). The reports are  
133 freely available for download on the OSHA website (OSHA, 2023). Since the  
134 SIRs only include incidents under federal OSHA jurisdiction, reports from  
135 the 22 states with their own OSH plans covering private sector employees  
136 were not included in the present analysis (OSHA, 2021). The database was  
137 downloaded in November 2022 and included reports from January 1, 2015  
138 through April 30, 2022.

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

## 144 2.2. Record screening procedure

145 Figure 1 depicts the flow of information through the different phases of the  
146 screening procedure, which was based on the Preferred Reporting Items for  
147 Systematic reviews and Meta-Analyses (PRISMA) statement (Page et al.,  
148 2021). When the OSHA SIR database was accessed, it contained 73,254  
149 reports. Because there are no robot-specific OIICS codes, the text of the  
150 final narratives was used to identify robot-related injuries. Forty-eight reg-  
151 ular expressions (regex) patterns were developed to identify mentions of  
152 robots (Table A.10). These targeted key terms and included synonyms,  
153 variations, and misspellings, for example, (?\\i)robo(t|ts|t's|ts')? and  
154 (?\\i)rbt|robt|rbot|robutt|robit. This initial search returned 204 re-  
155 ports.

156 The operational definition of robots is based on ISO 8373: A *robot* is an  
157 automatically controlled, reprogrammable, multipurpose manipulator, pro-  
158 grammable in three or more axes, either fixed in place or mobile for use in  
159 industrial automation applications. A *mobile robot* is defined as a robot able  
160 to travel under its own control, including a mobile platform with or with-  
161 out manipulators. Automated guided vehicles (AGVs), laser guided vehicles  
162 (LGVs) and automated material transfer carts were included in this defini-  
163 tion. Eighty-seven reports remained after non-robots were excluded. False  
164 positives included many instances of all-terrain vehicle (ATV) accidents.

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

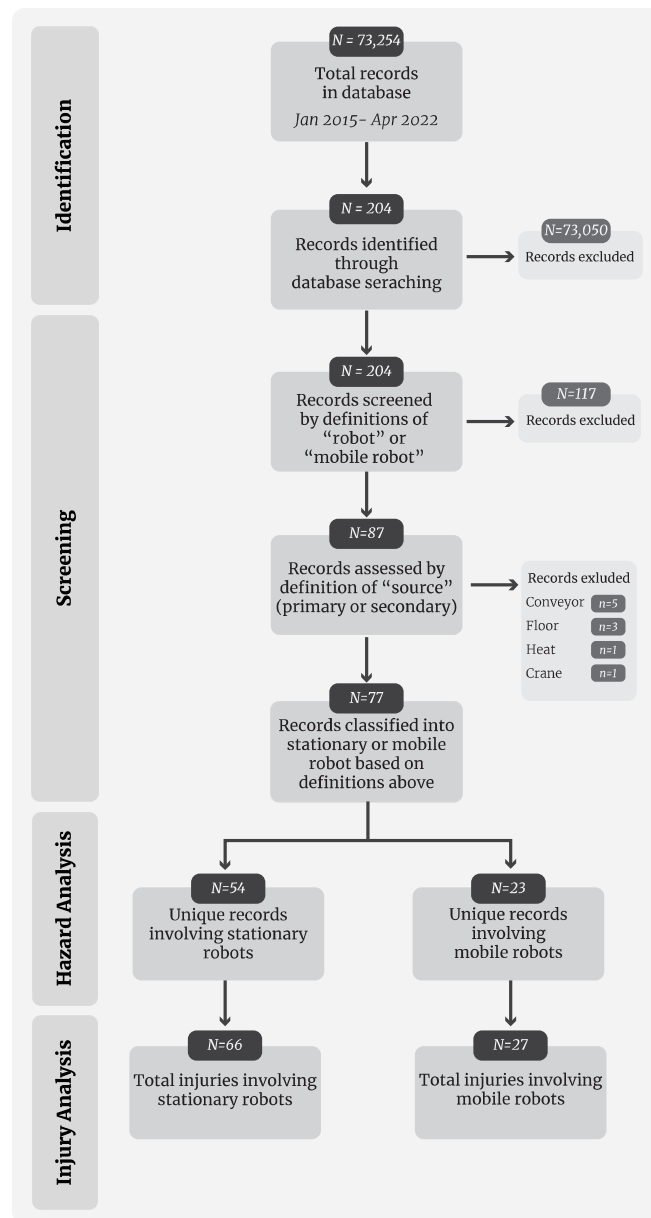


Figure 1: PRISMA flowchart for record screening process

167 records were excluded on these grounds. Ultimately, 54 unique records in-  
 168 volving stationary robots and 23 records for mobile robots were included for  
 169 analysis. False positives involved incidents where a robot was present in the  
 170 environment and mentioned in passing, but was only incidental to the acci-  
 171 dent – it neither directly produced the injury nor generated the source that  
 172 produced the injury.

CONCEPTUAL CODES AND DEFINITIONS	
<b>Activity</b>	The type of broad activity the injured person was engaged in when the injury occurred
<b>Task</b>	The specific activity engaged in when the injury occurred providing additional detail
<b>Contributing Factor</b>	The key element that increased the risk such that what is normally completed without incident resulted in injury
<b>Precipitating Mechanism</b>	The cause that initiated the chain of events leading to the injury; those mechanisms involved at the start of the injury event
<b>Primary Source</b>	The object, substance, bodily motion, or exposure that directly produced or inflicted the previously identified injury or illness
<b>Secondary Source</b>	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
<b>Injury Event</b>	The principal characteristic of the injury or illness
<b>Injury Nature</b>	The part of the body directly affected by the nature of injury
<b>Body Part</b>	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

173 *2.3. Application of Trustworthiness Criteria for Thematic Analysis*

174 The qualitative analysis was performed by the first two authors. Trust-  
175 worthiness was established via the criteria defined by Guba and Lincoln  
176 (1982), Tobin and Begley (2004), and Nowell et al. (2017). Trustworthiness  
177 is composed of four elements:

178 *Credibility.* Credibility is analogous to internal validity (Tobin and Begley,  
179 2004). It addresses the fit between the actual events and the OSHA inves-  
180 tigators' written accounts, versus the researchers' interpretations of those  
181 accounts. Credibility is typically established via member checks, where the  
182 researchers confirm their findings by following up with the respondents. In  
183 this case, the authors did not have access to either the investigators or the  
184 victims – only the text itself. Therefore, the authors established credibil-  
185 ity by comparing their interpretations via inter-rater reliability calculations  
186 (described in Section 2.4.1).

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

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

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

205 *2.4. Thematic Analysis*

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

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

221 *2.4.1. First-Stage Deductive Coding Procedure*

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

232 This was done by calculating inter-rater reliability (IRR) via Cohen's  
233 Kappa (Cohen, 1960; De Vries et al., 2008). Cohen's Kappa applies to a  
234 situation where two or more judges independently assign mutually exclusive  
235 nominal categories to a set of independent items. It indexes the proportion  
236 of agreement after chance agreement is removed from consideration (Cohen,  
237 1960). In our case, the judges were Raters A and B, and the mutually ex-  
238 clusive nominal categories were the conceptual codes in Table 1. A straight-  
239 forward IRR calculation was thwarted because the items (excerpts) were not  
240 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.

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

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

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

253 "Good" agreement ultimately depends on the context and judgement of  
254 the researchers, and there are a variety of standards proposed by different  
255 authors. Fleiss (1971) suggests that .60 to .74 is "good", and .75 to 1.0 is  
256 "excellent". Landis and Koch (1977) propose that values between 0.61 to  
257 0.80 represent "substantial agreement" and 0.81 to 1.0 is "almost perfect"  
258 agreement. Cicchetti (1994) suggest that values below .70 are unacceptable,  
259 between [.70 and .79] are fair; between [.80 and .89] are good, and greater  
260 than .90 are excellent. We therefore established a cutoff of 0.70 for this  
261 analysis.

#### 262 2.4.2. Second-Stage Inductive Coding Procedure

263 Thematic analysis can be used for a wide range of epistemologies (Now-  
264 ell et al., 2017). Developed for constructivist paradigms in the social sci-  
265 ences, theme discovery and mixed-methods can be applied to both post-  
266 positivist and interpretivist epistemologies (Ryan and Bernard, 2003). A  
267 post-positivist stance was taken here, where it was assumed that the haz-  
268 ard patterns which preceded the accidents did indeed constitute an objective  
269 truth "out there", although the authors recognized that only successive ap-  
270 proximations of that truth could be made (Blandford et al., 2016).

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

- 274 1. Generating initial codes: Each rater independently reviewed the ex-  
275 cerpts in each category from the from the previous stage, parsing them  
276 one at a time, and abstracting from each specific excerpt one or more  
277 tentative codes.

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

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

#### 294 *2.5. Re-Coding OIICS Codes for Injury Analysis*

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

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

309 **3. Results**

310 *3.1. Inter-Rater Reliability and the Utility of Narrative Reports*

311 The initial inter-rater reliability test revealed low agreement for Environ-  
 312 ment, Contributing Factors, and Precipitating Mechanisms. Close inspection  
 313 of the test results showed that what Rater B labeled as "environment," Rater  
 314 A often categorized as a "contributing factor." Similarly, classifications by  
 315 Rater A as "contributing factor" were frequently coded by Rater B as "task,"  
 316 "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.

Code	Prevalence	Rater A B		Rater B A	
		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

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

331 The brevity of the narratives contributed to the raters' coding discrep-  
 332 ancies. The median word count was 36, with an inter-quartile range of [29,

333 48] and a total range of [17, 90]. Not all reports were complete with all the  
334 data elements (conceptual codes) from Table 1. Table 3 shows the prevalence  
335 of each conceptual code across the corpus of reports. For example, a Con-  
336 tributing Factor was able to be coded in 14% of the reports; details about  
337 the Environment in 30%; and a Precipitating Mechanism in 58%.

### 338 *3.2. Thematic Analysis of Hazards*

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

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

356 In contrast to what was observed for stationary robots, regular opera-  
357 tion was the most common theme of Task for mobile robots, followed by  
358 troubleshooting (Table 5). Entering a robot's path, unbeknownst to the em-  
359 ployee, was the most common precipitating mechanism, followed by vehicular  
360 collisions.

## STATIONARY ROBOTS

### Tasks

Task	N	Example Excerpts
<b>Troubleshooting</b>	N = 14	<ul style="list-style-type: none"> <li>Entered a robot cell to determine why the robot stopped working</li> <li>Attempting to clear slag from a welding tip</li> </ul>
<b>Setup and Inspection</b>	N = 13	<ul style="list-style-type: none"> <li>Installing a robotic welder and finishing the cement grouting around the workstation</li> <li>Trying to change over the robot settings</li> <li>Loading a weld fixture into a weld robot cell</li> </ul>
<b>Maintenance and Cleaning</b>	N = 10	<ul style="list-style-type: none"> <li>Adjusting the lower pin alignment on a robotic cell stationary welder</li> <li>Removing lint from a monitor behind a robot</li> <li>Replacing suction cups on an end-of-arm tool</li> </ul>
<b>Regular Operation</b>	N = 6	<ul style="list-style-type: none"> <li>Reaching to move a paver into a conveyor system</li> <li>Observing a robot stacking lumber onto pallets for shipment</li> </ul>
<b>Training</b>	N = 1	<ul style="list-style-type: none"> <li>Training a new employee on how to operate a robotic welder</li> </ul>

### Example Excerpts

### Precipitating Mechanisms

Mechanism	N	Example Excerpts
<b>Sudden Unexplained</b>	N = 14	<ul style="list-style-type: none"> <li>The robot became energized</li> <li>The machine actuated while his left hand was in it</li> </ul>
<b>Troubleshooting Entry</b>	N = 7	<ul style="list-style-type: none"> <li>An employee entered a robot cell through an opening used to remove sand. As the employee attempted to adjust the casting [...]</li> <li>A rock fell onto the conveyor. The employee attempted to remove the rock [...]</li> </ul>
<b>User Input</b>	N = 3	<ul style="list-style-type: none"> <li>An employee was trying to change over the robot settings on a pneumatic welding machine when a coworker pressed a button [...]</li> <li>When an employee turned the control on the robotic extruder machine to auto [...]</li> </ul>
<b>Accidental Entry</b>	N = 2	<ul style="list-style-type: none"> <li>She stepped back into an unguarded robotic material handler</li> <li>His foot entered the service pit of an adjunct active robotic welder</li> </ul>
<b>Sudden Release of Energy</b>	N = 2	<ul style="list-style-type: none"> <li>When he manually released the clamp, it closed on his left pinky</li> </ul>
<b>Trip</b>	N = 2	<ul style="list-style-type: none"> <li>Tripped and fell over the plug and cord to a Xenex robot</li> </ul>

### Contributing Factors

Factor	N	Example Excerpts
<b>Guarded</b>	N = 4	<ul style="list-style-type: none"> <li>The active welder was guarded at the time of the incident.</li> <li>The area was guarded with light curtains at the time of the incident</li> </ul>
<b>Un-Guarded</b>	N = 2	<ul style="list-style-type: none"> <li>The machine was unguarded at the time.</li> </ul>
<b>Not Locked Out</b>	N = 2	<ul style="list-style-type: none"> <li>The system was not de-energized at the time of the incident</li> <li>The cell's robot was not locked out during cleaning operations</li> </ul>
<b>Malfunction</b>	N = 1	<ul style="list-style-type: none"> <li>The sensor on the gate malfunctioned and allowed the robot to operate</li> </ul>

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

## MOBILE ROBOTS

Tasks		Example Excerpts
<b>Regular Operation</b>	N = 6	<ul style="list-style-type: none"> <li>• The employee put the LGV in manual, got off the machine</li> <li>• Driving a forklift to be parked</li> <li>• Operating a remote-controlled tree trimming robot</li> </ul>
<b>Troubleshooting</b>	N = 5	<ul style="list-style-type: none"> <li>• About to move a cart that was blocking an automated guided vehicle from its designated stop</li> <li>• Working on an automatic guided vehicle (AGV) that had stalled</li> <li>• Moving laser guided vehicles (LGV) due to a jam up</li> </ul>
<b>Setup</b>	N = 3	<ul style="list-style-type: none"> <li>• Stacking a unit of corrugated sheets</li> <li>• Walking across the floor</li> <li>• Pulling an irregular cart full of heavy bulk packages out of an automated guided vehicle</li> </ul>
<b>Maintenance and Cleaning</b>	N = 3	<ul style="list-style-type: none"> <li>• Removing a gearbox from the frame of a laser-guided truck</li> <li>• Cleaning a charging pad for robotic machines</li> <li>• Replacing a broken clevis and bolt</li> </ul>
Precipitating Mechanisms		
<b>Accidental Entry</b>	N = 3	<ul style="list-style-type: none"> <li>• His foot entered the path of an automated material transfer cart</li> <li>• He was sitting on the catwalk with his legs hanging over the edge, when an automated transfer car system traveled beneath the catwalk</li> <li>• As the employee was exiting the charging pad, he placed his right arm and hand outside the charging pad area to push off</li> </ul>
<b>Collision</b>	N = 3	<ul style="list-style-type: none"> <li>• Cargo on the second employee's AGV struck a car on the injured employee's AGV train.</li> <li>• The AGV swung around and collided with another AGV</li> </ul>
<b>Sudden Release of Energy</b>	N = 2	<ul style="list-style-type: none"> <li>• After removing the last two bolts holding the gearbox to the frame, the gearbox fell</li> <li>• When the employee moved the cylinder to inspect it, the cylinder released in the upward position</li> </ul>
<b>Spontaneous Restart</b>	N = 1	<ul style="list-style-type: none"> <li>• The employee kicked the sensor to stop the LGV in auto. The LGV reset after 15 seconds and started up again</li> </ul>
<b>Trip</b>	N = 1	<ul style="list-style-type: none"> <li>• Tripped over the hitch of a stationary robot</li> </ul>
<b>Sudden Unexplained</b>	N = 1	<ul style="list-style-type: none"> <li>• The cart started to move</li> </ul>

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

361 *3.3. Events and Injuries*

362 Table 6 shows the joint distribution of Injury Nature and Body Part. For  
363 stationary robots, amputations of the finger are the most frequent specific  
364 injury (N=25, 38%) followed by fractures affecting various bones in the arm  
365 (N=4, 6%), torso (N=4, 6%), and head (N=3, 5%). Thirty-two injuries  
366 (48%) involved the fingers and hands; 19 (29%) involved the head, torso,  
367 and pelvis; and 13 (20%) involved the arms, legs, and feet. Amputations  
368 are the most frequent type of injury (N=25, 38%), followed by fractures  
369 (N=20, 30%), and lacerations (N=8, 12%). Other injury types such as burns,  
370 contusions, and electrocutions contribute less frequently with a combined  
371 total of 13 cases (20%).

372 For mobile robots, fractures of the leg are the most common specific injury  
373 with 9 cases (33%), followed by soreness of the torso, fractures of the pelvis,  
374 and fractures of the foot, each with 3 cases (11% each). Four injuries (15%)  
375 involved the fingers and hands; 8 (30%) involved the torso and pelvis; and  
376 15 (56%) involved the arms, legs, and feet. Fractures are the most common  
377 injury (N=17, 63%), followed by soreness (N=4, 15%). Less frequent were  
378 amputations, avulsions, contusions, crushings, and lacerations, each with 1  
379 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
<b>Stationary Robots</b>									
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
<b>Mobile Robots</b>									
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

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

THEMES		Example Excerpts
<b>Stationary Robots</b>		
<b>Pinched</b>	$N = 17$ $I = 18$	<ul style="list-style-type: none"> <li>▪ The robotic welder pinched the employee's fingertip</li> <li>▪ It closed on his left pinky</li> <li>▪ His left ring finger was caught and amputated in the hydraulic clamp</li> <li>▪ The machine actuated while his left hand was in it</li> </ul>
<b>Pinned</b>	$N = 15$ $I = 19$	<ul style="list-style-type: none"> <li>▪ A robotic arm pinned an employee's head to a CNC machine</li> <li>▪ Got caught between a welding parts machine and a robot</li> <li>▪ Crushed/pinned the employee's right foot against the barrier guard</li> <li>▪ The robotic arm struck and pinned the employee</li> <li>▪ Pinching the employee's right little finger against the tire rim</li> </ul>
<b>Struck</b>	$N = 14$ $I = 18$	<ul style="list-style-type: none"> <li>▪ Struck in the head by a robotic arm</li> <li>▪ The handler caught her left leg</li> <li>▪ The robot swung and hit the employee</li> </ul>
<b>Caught in Moving Parts</b>	$N = 3$ $I = 3$	<ul style="list-style-type: none"> <li>▪ A drive belt and pulley caught the employee's right index finger</li> <li>▪ An employee [...] contacted the blades</li> </ul>
<b>Explosion</b>	$N = 1$ $I = 2$	<ul style="list-style-type: none"> <li>▪ An explosive device fell from the machine to the floor and detonated</li> </ul>
<b>Fall Due to Trip</b>	$N = 1$ $I = 2$	<ul style="list-style-type: none"> <li>▪ Tripped and fell</li> </ul>
<b>Unknown</b>	$N = 1$ $I = 2$	<ul style="list-style-type: none"> <li>▪ -</li> </ul>
<b>Exposure to Electricity</b>	$N = 1$ $I = 1$	<ul style="list-style-type: none"> <li>▪ Received an electrical shock to his left hand while removing a metal cover</li> </ul>
<b>Overexertion</b>	$N = 1$ $I = 1$	<ul style="list-style-type: none"> <li>▪ After removing the last two bolts holding the gearbox to the frame, the gearbox fell</li> <li>▪ When the employee moved the cylinder to inspect it, the cylinder released in the upward position</li> </ul>
<b>Mobile Robots</b>		
<b>Pinned</b>	$N = 14$ $I = 16$	<ul style="list-style-type: none"> <li>▪ The cart ran into him, pinning him against a structural pole</li> <li>▪ Pinched between the LGV and conveyor</li> <li>▪ Trapping the employee between the two LGVs</li> <li>▪ Smashed and broken between the two vehicles</li> </ul>
<b>Struck</b>	$N = 5$ $I = 7$	<ul style="list-style-type: none"> <li>▪ Struck by an automated guided vehicle</li> <li>▪ The equipment ran over and fractured his right ankle</li> </ul>
<b>Caught in Moving Parts</b>	$N = 1$ $I = 1$	<ul style="list-style-type: none"> <li>▪ Caught between the top of the stroke cylinder shaft and the hood base</li> </ul>
<b>Fall Due to Trip</b>	$N = 1$ $I = 1$	<ul style="list-style-type: none"> <li>▪ Caught between the top of the stroke cylinder shaft and the hood base</li> </ul>
<b>Overexertion</b>	$N = 1$ $I = 1$	<ul style="list-style-type: none"> <li>▪ Suffered a lower back injury</li> </ul>
<b>Struck by Falling Object</b>	$N = 1$ $I = 1$	<ul style="list-style-type: none"> <li>▪ The gearbox fell and struck the employees' feet</li> </ul>

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

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

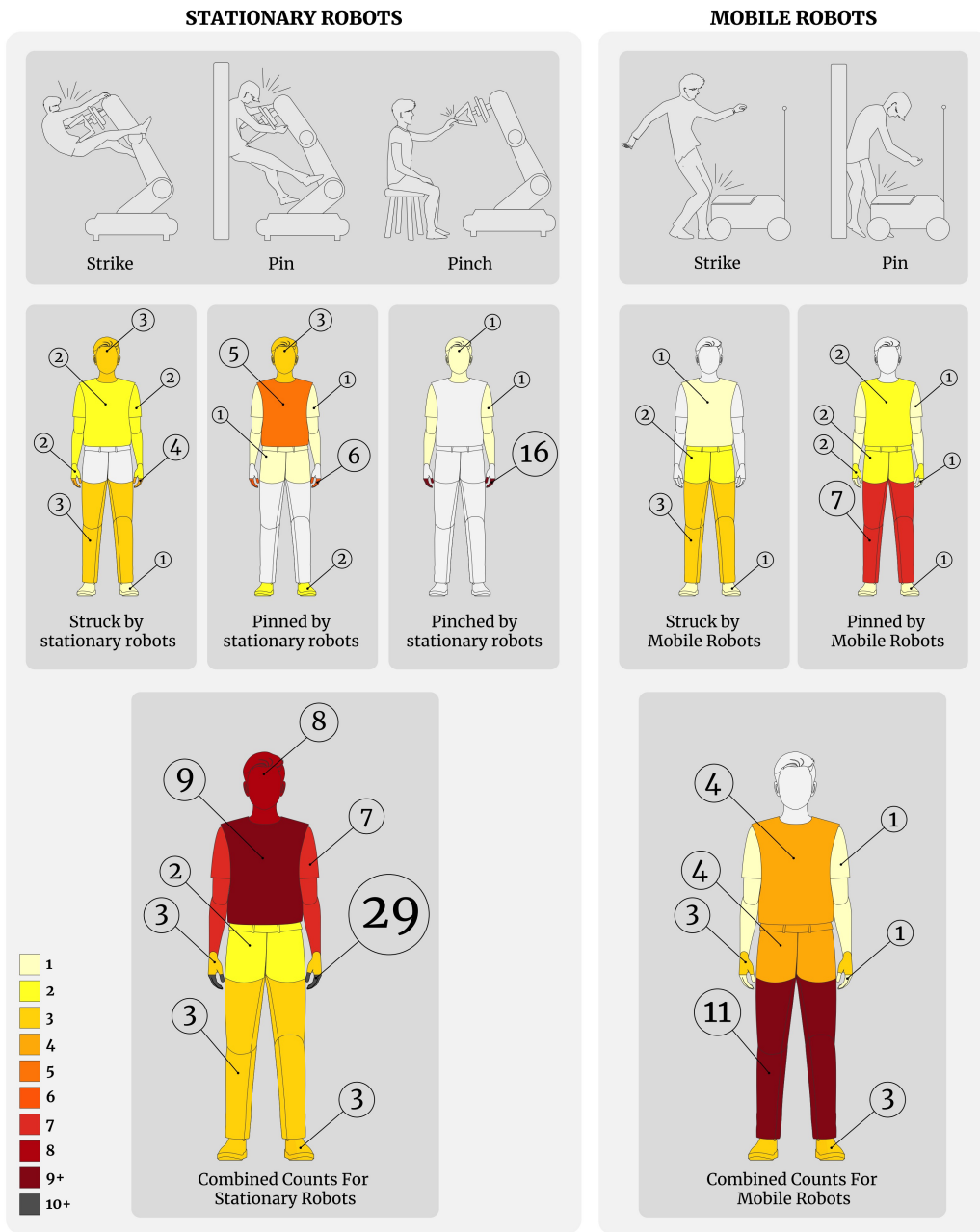


Figure 2: Counts of injuries across the body. The numbers, circle diameter, and colors reflect the raw counts (not normalized by area). The combined counts include all events, not just struck, pinned, and pinched.

## 391 4. Discussion

### 392 4.1. Narrative reports and robot-specific coding

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

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

### 412 4.2. Comparison with Previous Research

413 The present study and Malm et al. (2010) revealed similar patterns of  
414 injury across the body, with partial amputations of the fingers being the  
415 most common, followed by fractures to the head and torso. The theme of  
416 [sudden] and unexpected actuation (Table 4) and being pinned (Table 7) is  
417 also consistent with the findings of Malm et al. (2010) and Jiang and Gainer  
418 (1987). However, variations in categorizations between studies make detailed  
419 comparisons difficult and speak to the need for standardized definitions in  
420 future research as mentioned above.

421 The results of this study and the work of Malm et al. (2010), Layne  
422 (2023), and Kim et al. (2021) highlight troubleshooting and setup as activi-  
423 ties during which the majority of accidents occurred. In contrast, Jiang and  
424 Gainer (1987) found that most accidents involved "line workers" and very  
425 few involved maintenance personnel, suggesting a possible shift in risk over  
426 time. This idea is supported by Layne (2023), who found that maintenance

427 was mentioned more often during the period of 2005–2017 compared with the  
428 earlier years of 1992–2004, although he does not make a distinction between  
429 maintenance and troubleshooting. Taken together, this suggests that haz-  
430 ard controls for non-routine operations are inadequate, and that more effort  
431 should be focused there.

#### 432 4.3. *Pre-contact hazard controls*

433 The themes in Tables 4 and 5 suggest several several engineering and ad-  
434 ministrative controls for both stationary and mobile robots. Some of these  
435 are already used in practice, or have already been put forward in the ISO/TS  
436 15066 technical specification for collaborative robots. Nonetheless, this dis-  
437 cussion may shed light on the possible prioritization of controls or suggest  
438 additional considerations for existing control implementations.

##### 439 4.3.1. *Design modifications for safety*

440 Contributing factors of "guarded", and precipitating mechanisms of "ac-  
441 cidental entry", "user input", and sudden actuation suggest that many ac-  
442 cidents might be "prevented through design" (NIOSH, 2014); for example,  
443 by *not* requiring a person to enter a robot's working envelope to access its  
444 controls, or by designing robot grippers so that they can be installed and  
445 adjusted without putting one's fingers or hands inside, or by incorporating  
446 locking devices such as electromagnetic brakes to prevent the sudden release  
447 of mechanical or pneumatic energy (Plooij et al., 2015). Jiang and Gainer  
448 (1987) estimated that about half of accidents were attributable to poor work-  
449 place design, but without more detailed narratives we hesitate to make any  
450 quantitative estimates.

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

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

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

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

#### 474 4.3.2. Collision avoidance systems

475 Most reports involved a contact event of some kind (Table 7). Speed and  
476 separation monitoring (SSM) is a term used in collaborative robotics that  
477 refers to stopping or slowing the robot’s motion based on a person’s proxim-  
478 ity (Kumar et al., 2021). The means by which proximity is measured includes  
479 computer-vision-based systems (intrinsic or extrinsic), LiDAR scanners, ul-  
480 trasonic sensors, infrared sensors, pressure mats, and light curtains (Kumar  
481 et al., 2021; Rodriguez-Guerra et al., 2021). The results of this study show  
482 that collisions can and do occur when only a single body part, such as an arm  
483 or a leg, enters a robot’s working envelope or path. Therefore, as with ma-  
484 chine guards, any SSM or collision-avoidance system should be able to track  
485 and recognize not only entire human bodies, but *individual body parts*. For  
486 mobile robots especially, engineers implementing any collision avoidance sys-  
487 tem should consider that hazards may not appear only on the roadway where  
488 they ”should” appear, but may include workers kneeling on the ground next  
489 to the robot, or individual body parts protruding into its path from above or  
490 the side, or oversized cargo on another vehicle. The case reports in NIOSH  
491 (2019) also involved scenarios of this kind, and Layne (2023) makes a similar  
492 call for better collision avoidance systems, writing ”Further innovations in  
493 sensors and AI are required to increase recognition of objects for collision  
494 avoidance”. Wearable transponders or remote-controlled emergency stops  
495 may also be an effective solution. Advanced driver assistance and crash mit-  
496 igation systems (Klomp et al., 2019; Austin et al., 2023), such are already in  
497 use or under development in the automotive industry, may have prevented  
498 some of the collisions in Table 5.

499 *4.3.3. Administrative controls*

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

520 The temporary status of the victim was mentioned in two final narra-  
521 tives. Non-standard work arrangements accounted for 5% to 40% jobs in  
522 the United States in 2015 (Nicholson, 2015). Temporary workers face higher  
523 injury risks and poorer illness outcomes than regular employees (Howard,  
524 2017), probably due to their limited job experience and knowledge of haz-  
525 ards (Benavides et al., 2006), and they may hesitate to voice concerns due  
526 to their non-standard status (Howard, 2017). Their injuries are often under-  
527 reported (Picchio and van Ours, 2017). Given this, when it comes to human  
528 behavior around robots, engineers should strive to develop engineering con-  
529 trols (rather than administrative controls) that anticipate the inexperience  
530 and socio-organizational pressures that might lead to risky behaviors.

531 *4.4. Post-contact hazard controls*

532 Injuries to the upper and lower extremities, although less life-threatening  
533 compared to injuries to the head and torso, can have life-long economic,  
534 physical, and psychological consequences (Read et al., 2004; Van Eerd et al.,  
535 2016). The burden of traumatic hand and finger injuries in particular can

536 be especially severe. People with finger amputations have a resultant dis-  
537 ability that diminishes their ability to work and perform daily tasks (Giladi  
538 et al., 2014), and they often develop anxiety disorders, major depression,  
539 pain syndromes, and adjustment problems (Grob et al., 2008).

540 Automotive-based injury indices such as the Abbreviated Injury Scale  
541 (AIS) and Head Injury Criterion (HIC) have provided guidance for robotic  
542 power-and-force-limiting (PFL) based on injury tolerances for the head and  
543 torso (Robla-Gomez et al., 2017; Haddadin, 2014). These indices diminish  
544 the significance of injuries to the extremities because they were designed for  
545 the prediction of survival and not subsequent quality of life (Read et al.,  
546 2004). Given that head and torso injuries accounted for only 1/3 of the to-  
547 tal, new robot-specific injury indices that focus on the extremities, *especially*  
548 *the fingers and hands*, may be beneficial. Cadaver studies may be helpful in  
549 developing robot-specific injury indices that focus on the extremities, espe-  
550 cially the fingers and hands. One example is Carpanen et al. (2019) which  
551 provides empirical injury tolerances for the metacarpophalangeal (MCP) and  
552 proximal interphalangeal (PIP) joints of the hand.

#### 553 4.5. Limitations and future work

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

559 Second, the number of incidents reported here are almost certainly a  
560 lower-bound for three reasons. First, the data does not account for several  
561 categories of workers and workplaces that fall outside of federal OSHA’s juris-  
562 diction, including self-employed workers, immediate family members of farm  
563 employers, and workplaces covered by other federal agencies such as the Mine  
564 Safety and Health Administration, the Federal Aviation Administration, the  
565 Federal Railroad Administration, and states with their OSHA-approved plan.  
566 Second, injuries are probably under-reported by 50% even within the states  
567 that were included (Michaels, 2016). Third, the lack of specific robot-related  
568 OIICS codes meant that the narrative reports had to be relied on to identify  
569 robot-related events. It is possible that many more robot-related accidents  
570 occurred where the robot was described as a “machine” or “welder” in the  
571 report, and thus eluded identification. The introduction of robot-specific

572 source and event OIICS codes would facilitate more precise identification  
573 and categorization of reports (see Section 4.1).

574 Third, the present analysis can only be as good as the data on which it is  
575 based. The missing data elements (see Section 4.1) did not enable a detailed  
576 reconstruction of all incidents. Therefore, the themes presented in this study  
577 should be considered hypothetical (in the scientific sense) and subject to  
578 testing and re-evaluation should better data become available. Future work  
579 might cross reference the scenarios here with past case studies. Chi et al.  
580 (2009) and Chi and Lin (2018) could be used for methodological inspiration,  
581 as they also analyzed narrative reports to identify hazard scenarios and used  
582 more sophisticated safety engineering techniques such as fault-tree analysis.  
583 Variability in the narrative reports of the SIRs highlights the potential benefit  
584 of a semi-structured reporting format, ensuring consistent and comprehensive  
585 capture of incident details. Additionally, integrating multimedia data into  
586 SIRs, such as images or videos, might provide a clearer context of the incident  
587 scene, aiding in analysis.

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

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#### 602 *4.7. Declaration of Generative AI and AI-assisted technologies in the writing* 603 *process*

604 During the preparation of this work the first author used ChatGPT 4  
605 to help brainstorm alternative terms and spellings for robots, to generate  
606 the regex expressions to search for those terms, to generate LaTeX code for  
607 tables, to correct transcription errors in dictated notes, and to help shape

608 those notes into early outlines and drafts. After using this tool/service, the  
609 author reviewed and edited the content as needed and takes full responsibility  
610 for the content of the publication.

611 **Appendix A. Appendix**

612 *Appendix A.1. Coding*

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

Event	Description
-	<b>Pinched</b>
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
-	<b>Pinned</b>
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.
-	<b>Pinned by mobile robot</b>
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
-	<b>Struck</b>
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.
-	<b>Struck by mobile robot</b>
6219	Struck by powered vehicle-nontransport, n.e.c.
629	Struck by object or equipment, n.e.c.
-	<b>Other</b>
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

<b>Code</b>	<b>Description</b>
-	<b>Robot</b>
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
-	<b>Mobile robot</b>
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.

<b>Terms for Stationary Robots</b>	<b>Terms for Mobile Robots</b>
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
Robotique	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)

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