The risk analysis for the introduction of collaborative robots in the Republic of Korea

by

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The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this thesis. The Graduate College will ensure this thesis is globally accessible and will not permit alterations after a degree is conferred.

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NOMENCLATURE

BBN	Bayesian Belief Network
COBOT	Collaborative Robot
FCRs	Fatalities by Collaborative Robots
FIRs	Fatalities by Industrial Robots
IEC	International Electrotechnical Commission
ISO	International Organization for Standardization
KOSHA	Korea Occupational Safety & Health Agency
OICRs	Occupational Injuries by Collaborative Robots
OIIRs	Occupational Injuries by Industrial Robots
OSHA	Occupational Safety & Health Administration
OSH	Occupational Safety & Health
SMEs	Small Medium-sized Enterprises

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ABSTRACT

Due to an increasing demand for collaborative robots, called “cobots”, in industrial settings, this study aims to predict the chance of accidents occurring due to the introduction of cobots in the Korean manufacturing industry determined by a risk model applied Bayesian belief network. This will suggest effective risk mitigation measures. This study focuses on the types of safety monitored stop, as well as distance and speed control which have a higher collision chance compared to the types of power and force limiting which allow for injury-free contact and that of hand guiding which allows the cobot to move itself only by clear user’s manipulation.

The factors that impact annual accident probability are built on the grounds of the analysis of occupational injuries and fatalities by industrial robots. These factors were then categorized into human, organizational, and technical errors. Each factor’s probability was employed from the result of national statistics. If a probability was not available, notional probability was applied based on extensive literature reviews, and author’s experiences over 10 years in the occupational safety and health fields due to it is scarce elsewhere.

The risk model is constructed with two decision nodes - the employer’s and the policymaker’s view - and twelve uncertainty nodes. The model showed that the estimated annual accident probability was the same as the average accident rate of the entire manufacturing industry of the Republic of Korea in 2018. This could be interpreted as “average-risky”. Additionally, the influential factors were analyzed by a sensitivity analysis. By understanding which factors are highly influential, this study suggests three key measures to mitigate the risk by the introduction of cobots in the stages of design and manufacturing, installation, and usage. Researchers and OSH stakeholders may customize the model to assess the risk by the introduction of cobots.

CHAPTER 1. INTRODUCTION

With the introduction of industrial robots into manufacturing industries, mass production has increased (Long, Chevallereauo, Chablat, & Girin, 2018). Industrial robots take on tasks that are difficult or dangerous tasks for workers to do. However, industrial robots with great power and speed have intrinsic hazards and thus, have been operating in isolation from workers (Villani, Pini, Leali, & Secchi, 2018). Recently, collaborative robots, called “cobots” have been developed in order to work side-by-side with workers without being completely isolated. This means that cobots have an ability to control hazardous conditions and autonomously keep working (Audun, Trygve, Hisashi, & Mihoko, 2015). This ability helps meet the short-run production challenge which is connected to the issue about productivity improvement, faced by various small-medium sized enterprises (SMEs). This lowers the automation barrier tremendously (Zanchettin, Ceriani, Rocco, Ding, & Matthias, 2016).

The world robotics report 2018 by International Federation Robotics (IFR), highlights how compact, efficient, user-friendly, and safe cobots are expected to be, as well as drive the automation market (IFR, 2018). In line with these trends, global robotics companies are launching various kinds of cobots in order to meet this demand, resulting in the decrease of the price of cobots and thus are affordable for SMEs (Friis & Officer, 2016). However, sharing a workplace with robots could allow for the risk of collision between them. Employees especially have a reluctance to work in close proximity with robots when they do not believe it is safe, even if all safety requirements of cobots are satisfied (You, Kim, Lee, Kamat, & Robert, 2018). 45% of workers in the Republic of Korea tend to feel unsafe working around cobots (Youngkook, Jinwoo, 2018). According to the IFR report, there are five leading markets occupying 73% of the world’s sales volume in 2017: China, Japan, the Republic of Korea, the United States, and

Germany. Among those countries, the Republic of Korea has the highest robot densities by far (710 robots per 10,000 employees) in 2017. Given this density, an in-depth study in the Republic of Korea is related to the risk analysis by the introduction of cobots.

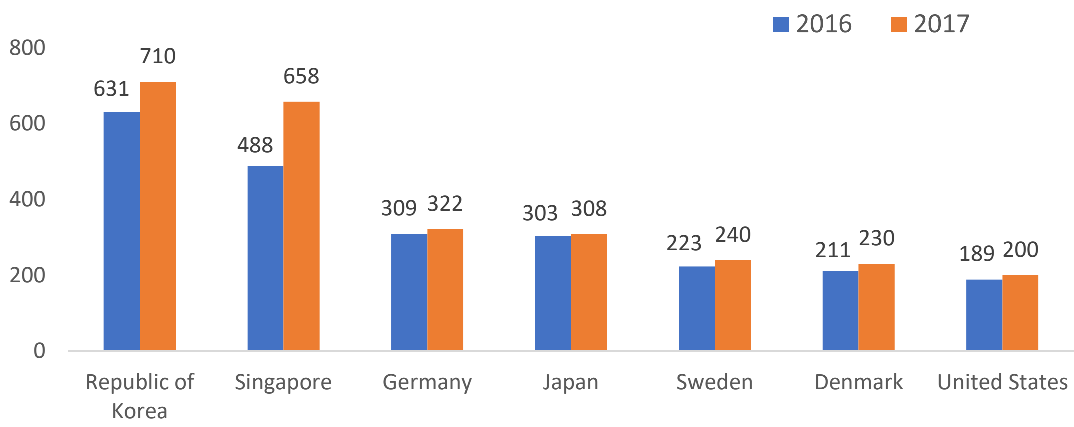

Figure 1.1 Robot density growth: 2016 vs. 2017 (IFR 2018)

In the upcoming years, the introduction of cobots in SMEs is expected to increase the relative vulnerability to occupational accidents compared to large-scale companies due to limited safety budget and manpower. Furthermore, the introduction of cobots may create previously unknown hazards and unexpected accidents (Youngkook, Jinwoo, 2018). Moreover, previous articles investigated that industrial robots have caused many accidents over the past years since their introduction (Vasic & Billard, 2103). At this point, one should ask for quantitative, direct evidence showing the quantity of accidents occurring from cobots or what causes allow for cobot-related accidents. Regrettably, such evidence is not available in the realm of occupational safety and health (OSH) and it is scarce elsewhere. Therefore, the objective of this current research is to predict the chance of cobot-related accidents occurring in the Korean manufacturing industry with a risk model applied Bayesian belief network. Moreover, it will also analyze which factors are the largest contributor to the annual accident probability and finally suggest effective risk mitigation measures.

CHAPTER 2. SCOPE AND METHODS

2.1 Scope

As depicted in Figure 2.1, most of the current risk models for industrial robots do include various aspects: technical, environmental, human, and organizational factors. Moreover, issues about regulations, national characteristics, and stakeholder expectations need to be considered (Thieme & Utne, 2017). However, the scope of this study will not cover all these aspects into one risk model since various international standards such as ISO 10218 part 1, 2 and, 15066 were developed from the technical view for the safety of cobots. The major manufacturers follow these standards in the designing and manufacturing stage of cobots for safety. Moreover, most of the recent literatures with regards to the safety of cobots focus on improving the safety in areas such as control system and algorithm, sensors, and safety device performance which are an in-depth knowledge in the technical side (Long et al., 2018; Michalos et al., 2015; Nikolakis, Maratos, & Makris, 2019; Vemula, Matthias, & Ahmad, 2018; Vogel, Walter, & Elkmann, 2017). Therefore, this study will cover a different part of technical factors such as system reliability.

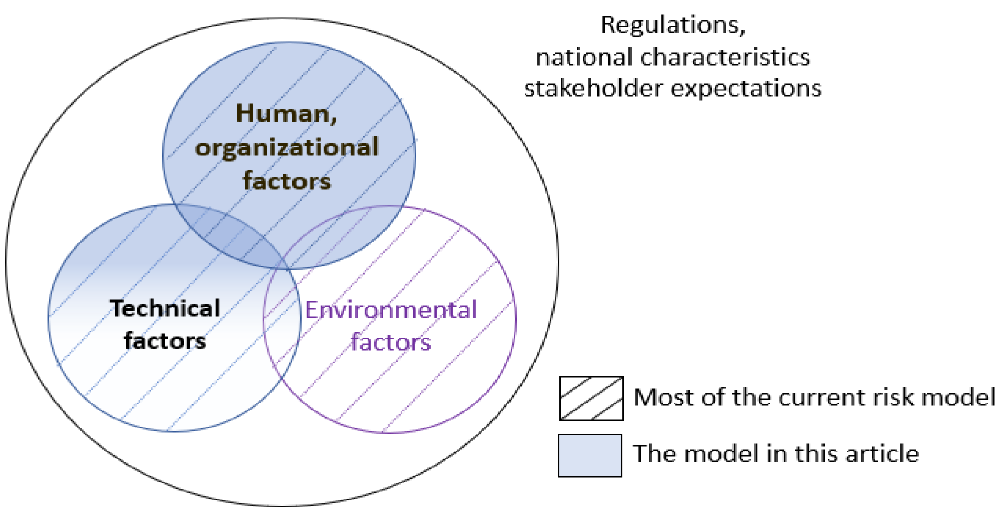

Figure 2.1 The scope of the risk model for this study

In the human and organization side, Thieme & Utne (2017) studied a quantitative risk model based on Bayesian belief network for human-robot collaboration performance on autonomous marine systems. You and Kim (2018) studied cognitive factors for improving the safety in human-robot collaboration, but only for workers in the construction industry. However, there is no previous study about a risk analysis with a quantitative approach by the introduction of cobots, centering on the human and organizational sides. Due to this lack of research, this study will cover the safety of cobots in the stage of usage and installation, considering the characteristics of human errors, organizational errors, and technical errors to some extent.

According to ISO 10218 part 1 and 2, there are four types of cobots. Firstly, Safety monitored stop: the robot stops if it detects a worker intruding into a certain pre-set work area. This type of cobots is often used for minimal collaborative work. Sensors that can detect if a worker enters or remains in a collaborative area are required. Secondly, distance and speed control: the robot can slow down its movements to a safe speed when an operator comes closer. Sensors that can detect the distance and the relative speed between humans and robots are required. Thirdly, hand guiding: the robot moves at limited speed following an explicit request for the operation. Sensors that can detect whether a worker is holding the manipulators or not are required. Fourthly, power and force limiting: the robot is specifically designed to allow for direct interaction with workers without physical safety fences, vision systems, or external scanners. Sensors that can detect contact forces between humans and robots are required. This cobot allows for injury-free contact between a worker and a cobot.

The first three types of cobots are now available for high capacity robots, whereas the fourth type - power and force limiting - is mainly responsible for human and robot collaboration with a special concept. According to ISO 15066, the main idea behind the fourth one is that they shall not result in pain or injury in case of collision. This means that the cobots themselves are not a threat to workers if they work under the legislative regulations or international standards. The values of acting forces are adjusted in a way that makes it impossible to cause permanent injuries under the condition that the cobot does not use any dangerous tools such as cutters, electric burn, or shock (Michal, 2018). In addition, the hand guiding type can move itself only by clear user's manipulation at an extremely limited speed so that the accident resulting in a low probability of accident from this type.

However, in case of the first two types of cobots, it is predictable that there is a high chance of injuries and fatalities occurring like those of industrial robots. This is because the major difference in safety between industrial robots and these types of cobots is that the use of technical safeguards that isolate the robot from the workers and therefore eliminating the hazard is no longer applicable to collaborative human-robot systems (Jansen, A., van der Beek, D., Cremers, A., et al, 2018). To remove physical fences, the technology of reliable and robust virtual safety fences must be applied through safety cameras, proximity sensors, and photoelectronic curtains (IEC 61496-2,3,4) etc. Moreover, Distinguishing area such as worker only, robot only and collaboration or coexistence zone is very important. Research by Jansen, A., van der Beek, D., Cremers, A., et al (2018), shows that installing virtual cages or fences properly is crucial in place of physical cages in new industrial settings. Given this context, this paper will focus on the first two types of cobots: safety monitored stop and distance and speed control.

2.2 Methods

In order to design a risk model and calculate the estimated annual accident probability by the introduction of cobots, we are supposed to use a Software - the Netica version 6.05 developed by Norsys Software Corp. - with the concept of Bayesian Belief Network (BBN). To construct a BBN, the following study used data where applicable, and when this data was not applicable, assumptions were based on the study of cobots and literature review to estimate.

2.2.1 Bayesian belief network

A Bayesian Belief Network or influence diagram visually models the probabilistic relationships among factors that have an impact on a final outcome, uncertainty on the grounds of the Bayes' rule (Corcoran, Tran, & Levine, 2014; Heckerman, 1997). The Bayes' theorem based on the conditional probability is briefly illustrated as the following formula:

$$\mathrm{P(A|B)} = \frac{P(A \cap B)}{P(B)} = \frac{P(B|A) * P(A)}{P(B)}$$

It expresses that P(A|B) is the posterior probability: conditional probability of an event A given an event B. P(B|A) is the likelihood: conditional probability of an event B given an event A. P(A) is prior probability. P(B) is the marginal probability or evidence. With this theorem, BBN helps make it feasible for modeling casual relationships among factors in combination with heterogeneous sources or with insufficient data sets (Uusitalo, 2007). BBN has been widely used for supporting decision-making in the diverse fields such as scientific prognosis and risk analysis (Fan & Yu, 2004; Heckerman, Mamdani, & Wellman, 1995).

BBN is drawn with an acyclic graph called "nodes" that is typical of random variables and arrows that represent their dependencies in Figure 2.2. When two nodes are linked by an arrow, the one with a starting point is called "parent node" and the other one is called "child node". Parent node conditionally has an impact on child node (Leu & Chang, 2013). For example, if technical errors occur (parent node), an accident may occur (child node) as seen in Figure 2.2. This figure also expresses the states [Occur(O), Does not occur (X)] and conditional probability tables for three variables or factors. With this BBN in Figure 2.2, the question of "what is the accident probability, given that technical errors occur?" is answered. By applying the equation (1), the answer can be calculated as follows:

$$\cdot\ P\big(\text{Accident (O)}\big|\text{Technical errors (O)}\big) = \frac{P(T(O)\cap P(A(O)))}{P(T(O))} = \frac{\sum_{H\in\{o,x\}} P(H,T(o),A(o))}{\sum_{H,A\in\{o,x\}} P(T(o))} =$$

$$= \frac{0.4*0.1*0.85+0.6*0.1*0.4}{0.4*0.1*0.85+0.4*0.1*0.15+0.6*0.1*0.4+0.6*0.1*0.6} = 58\%$$

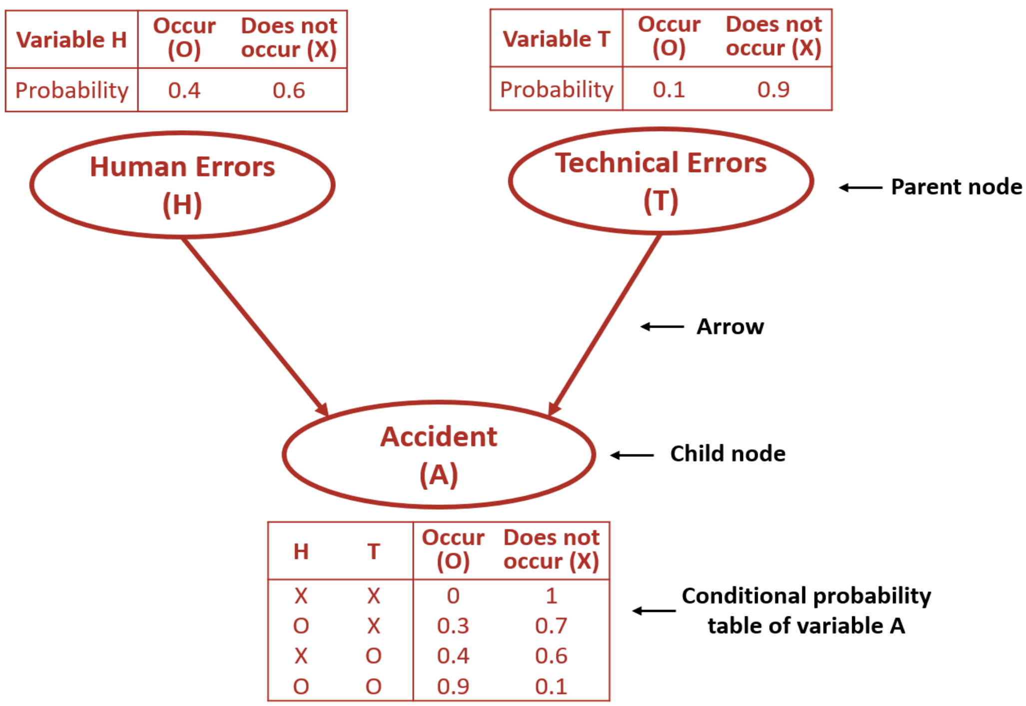

Figure 2.2 Example of Bayesian belief network for risk analysis

As shown in Figure 2.3, however, it is straightforward for Netica software to calculate the final outcome which is P(Accident occurs | Technical errors Occur), by selecting one state.

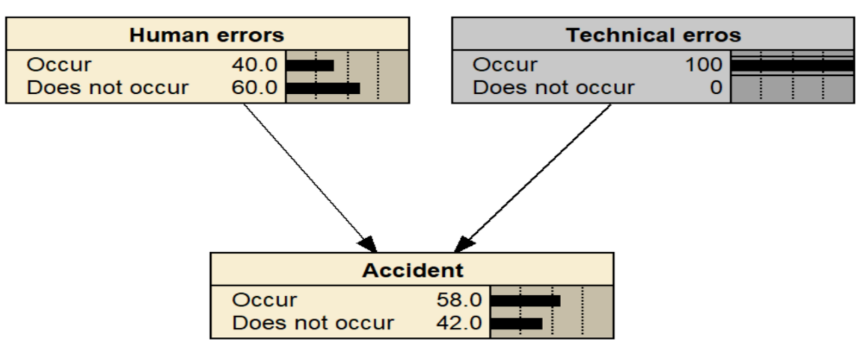

Figure 2.3 Example of Netica for risk analysis, selecting one state.

Furthermore, this powerful and intuitive software helps us to get easily the final outcome given probabilistic relationships between two factors in Figure 2.4.

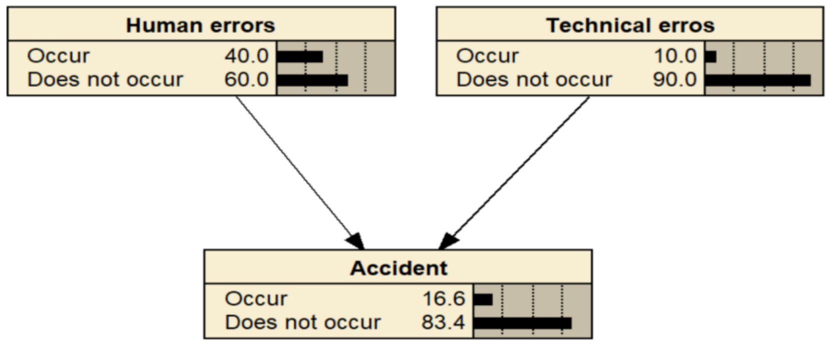

Figure 2.4 Example of Netica for risk analysis with overall probabilistic relationships

2.2.2 Materials

In order to compute the accident probability by the introduction of cobots through BBN, fundamental data needs to be available. However, this data is scarce everywhere due to cobots' growing popularity and accident cases are difficult to find. Given this context, this paper will analyze the occupational injuries and fatalities due to industrial robots in the Republic of Korea. This trend helps to understand the characteristics of the cobot-related accidents because the category of industrial robots includes traditional industrial robots as well as newer collaborative robots. Consequently, this analysis allows for examination of critical factors that impact the occupational injuries by cobots.

Next, the Occupational Safety and Health Company Survey (OSHCS) 2015[1], which is the national statistics of the Republic of Korea, is implemented regularly for other applied researches. This survey is used to provide empirical data that can be utilized to establish mid- to long-term occupational safety and health policy agenda. In this survey, the level of safety

[1] This questionnaire was developed based on EU OSHA's survey of enterprises on new and emerging risks and European company survey by Eurofound.

training, safety management, implementation of risk assessment, and CEO's safety interests in the manufacturing industry in the Republic of Korea have been investigated. This data plays a critical role in providing the probabilities that are considered as parent nodes.

If child nodes are dependent on multiple parent nodes – which means there are multiple conditional probabilities given various conditions – it is reasonable to refer to the data from previous studies and apply a notional probability with assumptions.

Lastly, in order to calculate the outcome that also relies on multiple child nodes, naïve Bayes classifier is adopted to obtain each conditional probability for estimating the likelihood of the accident by cobots, given various conditions. The naïve Bayes method employs Bayes' theorem but assumes that factors are independent of each other. Even if independence is usually an unrealistic assumption, naive Bayes bear remarkably comparison with more elaborate classifiers in the practical point of view (Rish, 2001). The following study has been conducted with the scope, methods, and materials as mentioned above.

CHAPTER 3. INJURIES AND FATALITIES OF INDUSTRIAL ROBOTS

3.1 The status of OIIRs from 2009 from to 2018 in the republic of Korea

The status of occupational injuries by industrial robots (OIIRs in the Republic of Korea has been analyzed with data approved as occupational injuries under the Industry accident Compensation Insurance Act (IACI Act) from 2009 to 2018. In detail, OIIRs were analyzed by dividing them into type of injuries, company size, working period, and work loss day to derive characteristics of OIIRs.

3.1.1 The status of OIIRs by types of occupational injuries

Classification of the types of injuries are crush, fall from the heights, collision, struck by object, cutting/prick etc. Trend of OIIRs by the type of injuries can help derive significant factors about what type of injuries occurred the most. Types of OIIRs are assessed in the following order: crush (50.6%), collision (37.7%), struck by object (3.7%), fall from the height (3.4%), trip/slip (1.4%), and cutting/prick (1.1%). Two types of injuries - crush and collision - occupied roughly 88% of OIIRs. This is due to parts of the workers' body becoming trapped between the moving parts of the robot, or were hit by the robot, resulting in rare fatalities.

Table 3.1 Cases of OIIRs by type of occupational injuries

Type	Crush	Collision	Fall from the height	Struck by object	Trip/slip	Cutting/ prick	Others
Injuries by IRs	177	132	12	13	5	4	7
Injuries in overall manufacturing industries	96,644	23,627	25,592	25,539	29,451	24,477	35,871

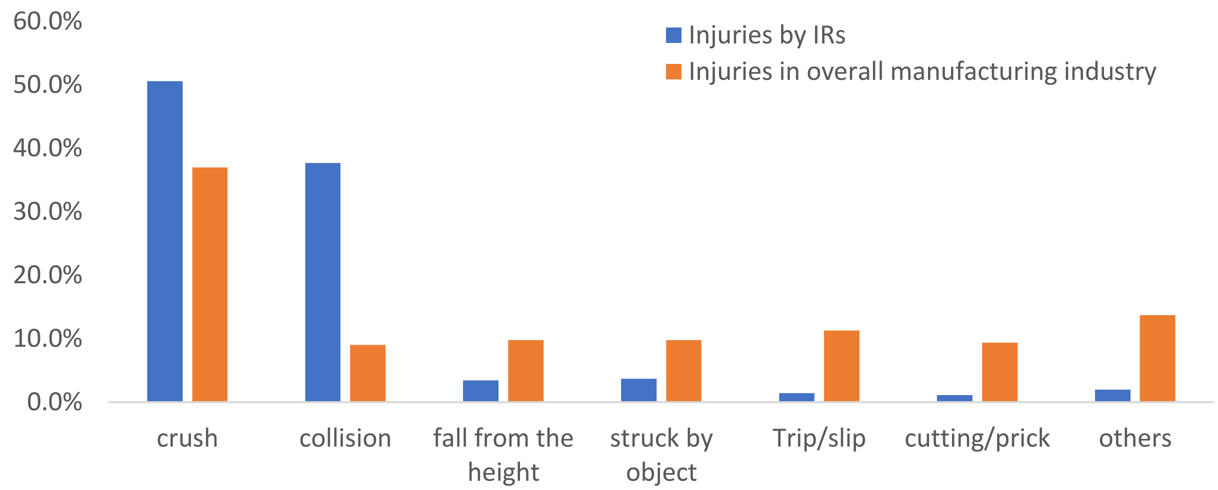

Figure 3.1 Distribution of OIIRs by type of occupational injuries

3.1.2 The status of OIIRs by company size

To analyze the correlation between OIIRs and the size of company, the size of company is divided into 4 categories as seen in Table 3.2. In case of overall injuries in the manufacturing industry, Figure 3.2 shows that the smaller size of the company, the more injuries occur. This trend reflects the injuries by industrial robots in the past 10 years. This could be due to the fact that SMEs have limited safety budget and manpower, thus increasing the probability of injury. As a result, it is recognized that the size of workplace may affect the accident probability with an introduction of cobots.

Table 3.2 Cases of OIIRs by company size

Number of workers	**< 50**	**50~299**	**300 ~ 1,999**	**> 2000**	**Total**
Injuries by IRs	169	116	29	36	350
Injuries in overall manufacturing industries	209,475	34,546	6,291	10,889	261,201

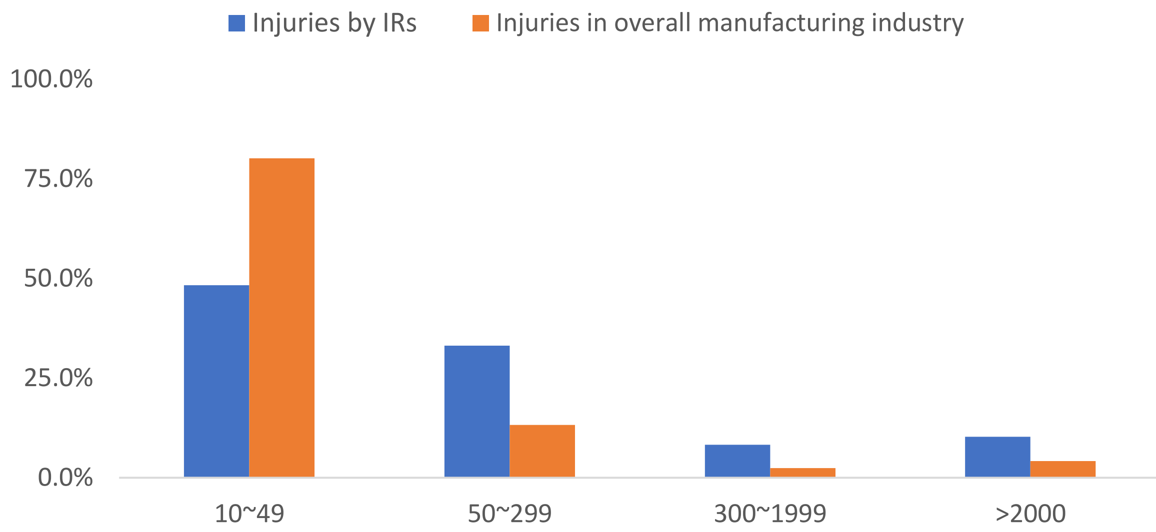

Figure 3.2 Distribution of OIIRs by company size

3.1.3 The status of OIIRs by working period

Workers' proficiency is also one of the major factors that impact the injuries by industrial robots. The correlation between OIIRs and the proficiency of workers injured is analyzed through the analysis of the working period, defined as time spent working, of workers injured. Working period of workers injured by industrial robots has been analyzed in the following order: less than 1 year (48.0%) > 1 year ~ 3 years (17.7%), > 3 years ~ 5 years (6.6%). As can be seen in the two histograms, the occupational injuries of the two conditions dropped at approximately the same rate within 5 years. However, this trend over time varied between the two. Injuries in overall manufacturing industries decreased continuously while OIIRs remained stationary after 5 years. It is important to note that injuries by industrial robots is a problem even for skilled workers.

Table 3.3 Cases of OIIRs by working period

Duration	< 1year	1year ~ 3year	3year ~ 5year	5year ~ 10year	10year ~ 20year	> 20year	Others	Total
Injuries by IRs	168	62	23	32	32	31	2	350
Injuries in overall manufacturing industries	141,066	51,455	20,487	22,171	15,999	8,316	1,707	261,201

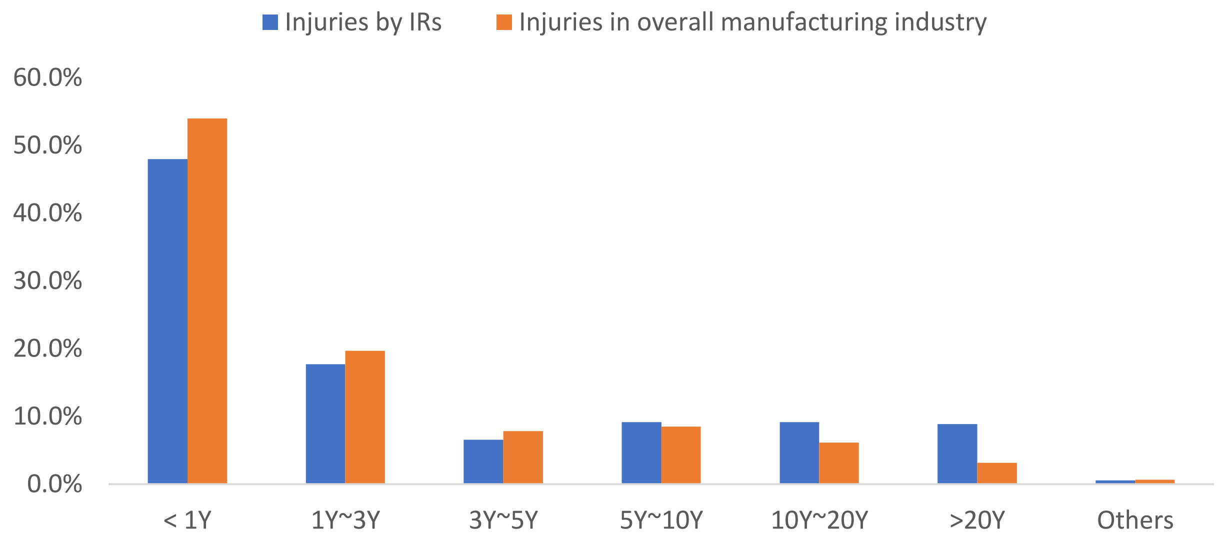

Figure 3.3 Distribution of OIIRs by working period

3.1.4 The status of OIIRs by work loss day

Table 3.4 shows the average work loss day of the two conditions. The average work loss days of all injuries in the manufacturing industry over the past decade totaled 280 days. On the other hand, the average work loss days of OIIRs was 671 days that were 2.4 times higher than that of injuries in overall manufacturing industry. This points out that the severity of injuries caused by an industrial robot is much more severe. In other words, it seems reasonable to say that an injury by industrial robots has a high chance to result in more days missed.

Table 3.4 Cases of OIIRs by work loss day

Year	Ave.	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Injuries by IRs	671.33	724	829	528	995	247	697	994	683	345	721
Injuries in overall manufacturing industries	280.22	243	277	300	305	304	280	280	273	260	270

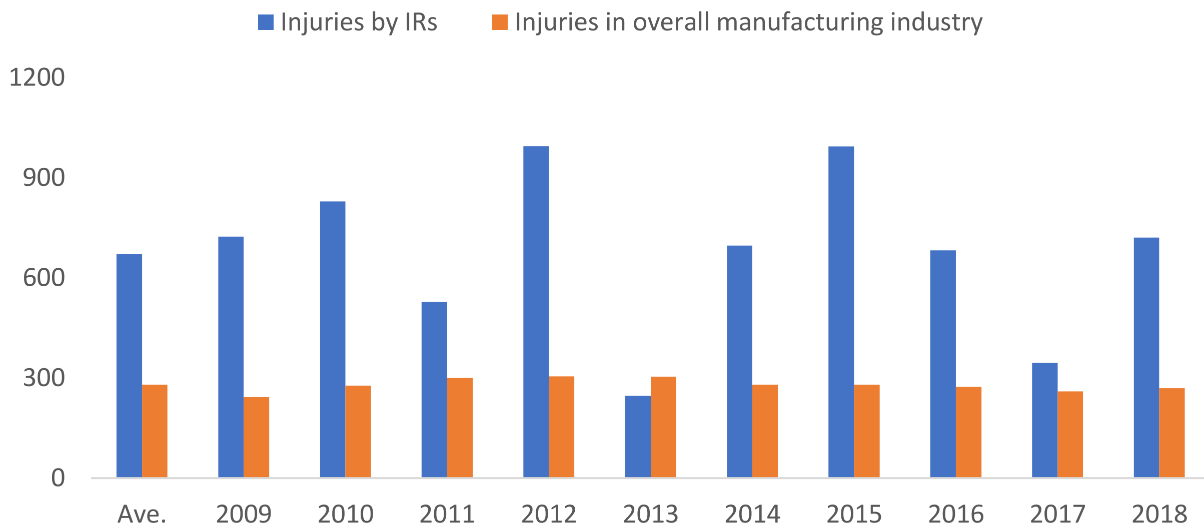

Figure 3.4 Distribution of OIIRs by work loss day

3.1.5 The implications through the analysis of OIIRs

An analysis on OIIRs over the past decade with four categories sheds light on the characteristics for injuries by the introduction of cobots. Firstly, major types of injuries would be crush and collision due to mainly abnormal contact between the driving robot attachments and the workers. Secondly, it is expected that the smaller size of company, the higher the number of injuries by cobots will occur. Next, the more working periods, the lower cobot-related accident probability. This generally means workers who have more working periods, have a higher chance to be well-trained for safety. Therefore, the level of safety training would be one of the major factors to impact on the accident probability by cobots. Lastly, the average work loss days of OIIRs were 2.3 times higher than that of entire injuries in overall manufacturing. This trend predicts the cobots’ case to some extent. However, with the help of sophisticated safety-control functions such as safety monitored stop or distance and speed control, the strength of injuries by cobots would be weaker than that of injuries by industrial robots.

3.2 The status of fatalities by industrial robots

An analysis of 28 fatalities[2] due to industrial robots (FIRs) from 2009 to 2018 was investigated and the major categories for this analysis were the sector in manufacturing industry where the fatality occurred, working period of worker died, installation of safety fence and proper safety measures for an entrance, and type of tasks.

3.2.1 The status of sector of industry involving FIRs

Transport machinery manufacturing industry had the highest frequency of FIRs, which resulted in 12 cases (42.9%) and two cases (7.1%) that took place in the general machinery and metal industry respectively. In the category defined as “other”, the electric device manufacturing and food industry each had one fatality. Among these industries referred, the transportation and general machinery manufacturing industries are related to the automobile industry which generally uses many industrial robots in the Republic of Korea.

Table 3.5 Sector of industry involving FIRs

Industry	Transport machinery	General machinery	Metal	Chemical	Others	Total
Fatalities by IRs	12	2	2	2	10	28
Ratio (%)	42.86	7.14	7.14	7.14	35.71	100

3.2.2 The status of working period involving FIRs

Table 3.6 shows that 10 cases (35.7%) of the fatalities occurred in workers with less than one year of their working period. This indicates that shorter working periods are more likely to result in the high chance to exposure for the fatality. However, one particular thing is that 5 cases occurred over 10 years. This means that FIRs could occur unexpectedly for even skilled workers.

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[2] According to the section 4 of Korean OSH act, fatality is defined as ① an accident in which one or more workers have been killed, ② an accident in which two or more workers are injured simultaneously, requiring three months or more with care, ③ an accident in which more than 10 people were injured or ill at the same time.

Table 3.6 Working periods involving FIRs

Year	< 1 Yr.	1 Yr. ~ 3 Yr.	3 Yr. ~ 5 Yr.	5 Yr. ~ 10 Yr.	> 10 Yr.	Unable to check
Fatalities by IRs	10	8	3	1	5	1
Ratio (%)	35.71	28.57	10.71	3.57	17.86	3.57

3.2.3 The status of installation of safety fence and safety measures for entrances

Table 3.7 shows that 4 FIRs have been caused by the installation of industrial robot cells without safety fence. Out of the 24 cases of installed safety fences, 9 cases were found to install improperly safety interlock for the entrance of safety fences and 1 case was found not to have safety interlock for the entrance installed at all as shown in Table 3.8. This means that workers could access into a robot zone during operation which is directly connected to the high chance of fatality.

Table 3.7 Installation status of physical safety fence

Type	Installed	Not installed
Fatalities by IRs	24	4
Ratio (%)	85.71	14.29

Table 3.8 Installation status of safety interlock for entrance of physical safety fence

Type	Installed properly	Installed improperly	Not installed	Unable to check
Fatalities by IRs	13	9	1	1
Ratio (%)	54.16	37.5	4.17	4.17

With this analysis, we can deduce the probability of human errors, organizational errors, and technical errors to occur given accident. P (human error | accident, H|A) would be derived from the portion of fatality happened although safety fences and interlock for the entrance installed properly. P (organizational error | accident, O|A) would also be derived from the portion of fatality happened when safety fences and interlock for the entrance were not installed. P

(Technical error | accident, T|A) would be derived from the portion of fatality happened when safety fences installed properly but safety interlock was installed improperly and thus it failed to function properly. These probabilities will be applied for the calculation of conditional probabilities.

Table 3.9 Guidance probabilities of three main errors given accident

Type	P(H|A)	P(O|A)	P(T|A)
Ratio (%)	13 cases /27 cases = 48.15	5 cases / 27 cases = 18.52	9 cases / 27 cases = 33.33

3.2.4 The status of types of tasks involving FIRs

According to the analysis of the type of tasks of FIRs as seen in Table 3.10, 18 cases (64.3%) occurred during repairing of industrial robot systems or related device in industrial robot cells, 8 cases (28.6%) occurred during normal operation and 2 cases (7.1%) occurred during cleaning in industrial robot cells. In the past, many fatalities occurred during inputting programs or teaching robots, but there have been no fatalities during those actions in the last 10 years. It was believed that the fatalities during repairing and cleaning could be prevented by locking the startup switch with the key and managing the key separately or attaching a sign saying "Working” on the startup switch before starting the operation, generally called “Lock out tag out (LOTO)”. In other words, it is recognized that these kinds of risk can be eliminated from the educational and administrative measures such as safety management and training, as well as effective risk assessment.

Table 3.10 Types of tasks involving FIRs

Type	Teaching	Normal operation	Repairing	Cleaning
Fatalities by IR	0	8	18	2
Ratio (%)	0.00	28.57	64.29	7.14

3.2.5 The implication through the analysis of FIRs

An analysis on FIRs over the past decade also sheds light on the characteristics of severe injuries by the introduction of cobots. First of all, it is expected that there will be severe injuries caused by cobots in the automobile and general machinery manufacturing industries, due to many assembly and welding tasks. Secondly, the more working periods, the lower cobot-related fatality, which generally means workers who have more working periods, have a higher chance to be well-trained for safety. However, FIRs occurred unexpectedly even for skilled workers. Therefore, safety training such as refresher courses should be required for skilled workers. Next, proper installation of virtual safety fences is a critical factor to prevent the cobot-related accidents. In addition, the probabilities, which are $P(H|A)$, $P(O|A)$, and $P(T|A)$, reflect the characteristics of the Korean situation. Lastly, it would be meaningful to say that severe accidents are expected to occur in non-routine tasks and thus effective safety training and management, as well as risk assessment should be embedded into the workplace.

3.3 Characteristics factors leading to OIIRs and FIRs

From the analysis of OIIRs, the major types of injuries are crush and collision and the level of safety training based on working period is an important factor to be expected to affect the annual accident probability by the introduction of cobots. Furthermore, it is predicted that company size impacts the probability of accidents due to the different capacity by size to deal with safety issues. OIIRs are three times higher than the rate of the occupational injuries of entire manufacturing industry in case of skilled workers over 20 years of work experience. The analysis of FIRs also shows this tendency. Therefore, training such as refresher courses should be required for skilled workers. From the analysis of FIRs, about 71.4% of FIRs occurred during the non-normal operating condition. OSHA guideline for robotics safety (STD 01-12-002) also points out that many robot accidents usually do not occur during routine tasks but instead, during programming, maintenance, repair, testing, setup, or adjustment. In other words, this kind of risk can be eliminated with educational and administrative measures, such as proper safety management and training, as well as effective risk assessment. According to ISO TS 15066, risk assessment for cobots should include not only cobot itself, but also control systems and safety devices such as virtual fences.

Furthermore, proper installation of safety fences and safety interlock for entrances of safety fences that affect human errors and technical errors should not be overlooked. In case of cobots, it's just that physical safety fences turn into virtual safety ones. Improper installation can lead to serious hazards depending on the amount varied from the original design. Due to this, design, installation requirements, and equipment layout of a robot need to be aligned with the codes and guidelines required by the manufacturer. Therefore, regulatory safety certification at installation is an effective method to prevent accidents, due to the fact that robots are able to adapt to their environmental conditions. In the era of popularization in smart factory, Korean government is preemptively considering whether the safety certification system for cobots will be introduced or not. In addition, OSHA guideline (STD 01-12-002) suggests that the prevention for control errors, mechanical and electronical failures directly impacts the accident probability. In this study, it is collectively called system reliability.

Research by Heinrich’s industrial accident prevention (Heinrich, 1941), suggests that unsafe acts and conditions are major causes for industrial accidents. Most of the unsafe acts result from human errors, and most of the unsafe conditions result from technical errors such as mechanical and physical hazards. This theory is quite an outdated but has suggested simplistic and linear concept about how to approach the accident.

Poor safety management causes the majority of accidents (Johnson, Ashley 2001). Moreover, effective leadership plays a critical role in improving safety performance in high-risk working environments (Flin & Yule, 2004). The starting point of safety leadership is the CEO's safety interest. Lastly, unlike industrial robots, the number of cobots is expected to affect the accident probability due to the high chance of collision between them.

With these significant factors and implications from the analysis and literature review, the characteristic factors leading to the occupational injuries and fatalities is introduced by the collaborative robots in Table 3.11.

Table 3.11 Major characteristics to occur industrial robot accident and cobot accidents

Characteristics of Industrial robots	Characteristics of Collaborative robots
Safety training	Safety training
Type of tasks	Type of tasks
Safety management (Lock out Tag out)	Safety management
CEO's safety interest	CEO's safety interest
Company size	Company size
System reliability	System reliability
Risk assessment	Risk assessment
Proper installation - Physical fences - Fool-proof, fail-safe device	**Proper installation** **- Virtual fences** - Fool-proof, fail-safe device
	Regulatory safety certification at installation
	Number of collaborative robots

CHAPTER 4. RISK MODEL

The risk model by the introduction of cobots can be depicted as a Bayes belief network to aid in conceptualizing the complex interrelationships among factors. Figure 4.1 depicts several interrelated factors affecting the annual accident probability by the introduction of cobots.

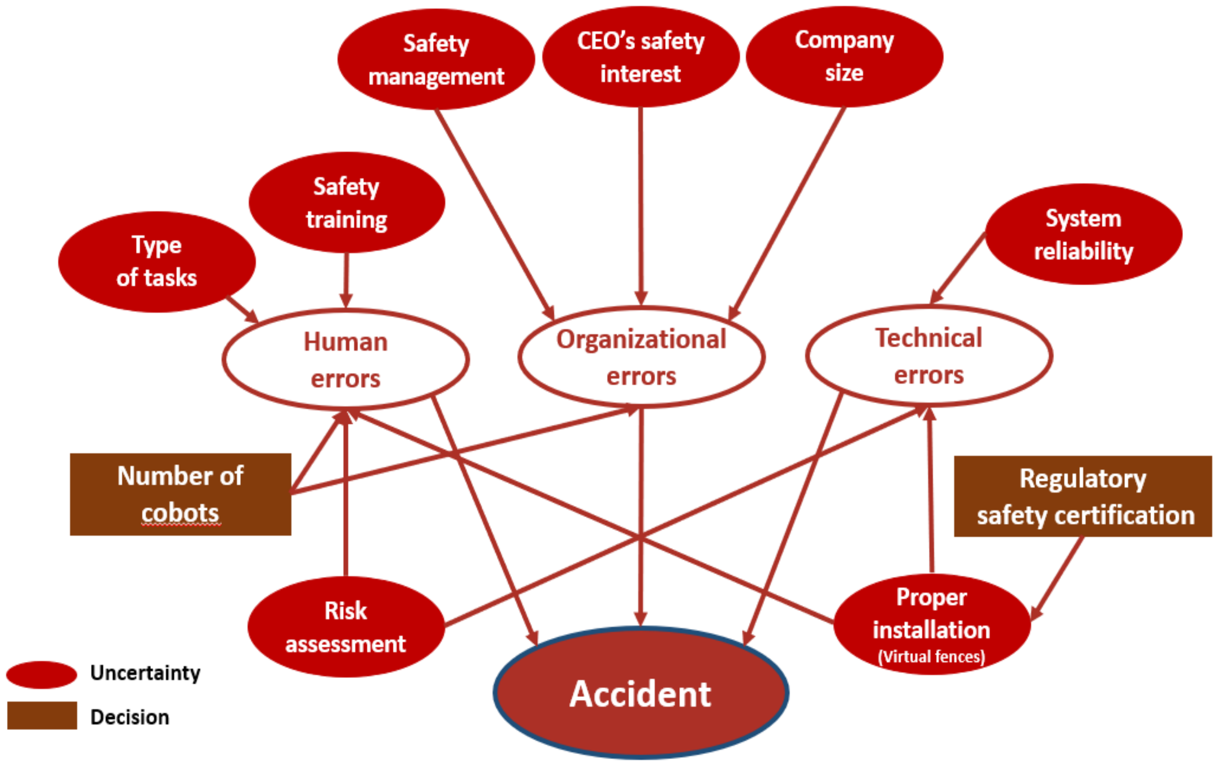

Figure 4.1 Risk (BBN) model of accident prediction by the introduction of cobots

This model includes two decision nodes, twelve uncertainty nodes: three mid-parent nodes (human, organizational and technical errors), eight parent nodes, and one child node (outcome) which is the annual accident probability by the introduction of cobots. It is assumed that the annual accident probability of cobots without any conditions is the average accident rate of the Republic of Korea in 2018. With the prior probability, the model estimates mainly whether the post annual accident probability by the introduction of cobots increases or not under those contributing factors shown in Figure 4.1.

4.1 Decisions

In this paper, the views of two decision makers have been considered. One is an employer who makes the decision about how many cobots invest. The other is a policymaker who takes charge of the occupational safety in the government's body. Therefore, this model contains two decision nodes: 1) number of cobots from the employer's view and, 2) regulatory safety certification at installation from the policymaker's view.

4.1.1 Number of cobots

If cobots become popular in industrial robotics, workers are likely to work with more than one cobot in work cells, in order to maximize productivity. This tendency can affect the frequency of the occupational injuries by collaborative robots (OICRs). This is because workers and cobots are more likely to bump into each other, leading to a higher chance of slips, lapses, and mistakes to occur. This is a result of mainly human and organizational errors, as the number of cobots increases in a shared workplace. In case of technical errors, however, because only products securing system reliability by international standards were distributed, it is assumed that this node does not affect technical errors. In this study, there are three choices for the number of cobots being "one", "two", and "three". Each option refers to the number of cobots per working cell. It is assumed that each cell is designed for one worker.

4.1.2 Regulatory safety certification

The major cause of FIRs is majorly attributed to incomplete installation of industrial robot cells such as physical safety guards or interlock safety devices at every entrance. This allows for a worker to move into robot cell without pausing the robot. This enables workers to violate the safety procedures, being overconfident. Currently, there is no legal system to check the safety performance of industrial robots as well as collaborative robots at the installation stage in the republic of Korea. Therefore, it is believed that a regulatory safety certification system will be necessary to ensure the safety of cobots. This regulatory system can reduce the occurrence of human and technical errors through proper installation. Nowadays, the Korean government is taking a huge consideration of whether the system will be implemented. This node can affect the uncertainty of proper installation. This node has two decisions: “implemented” or “not implemented”. It is assumed that the probability of proper installation is 99.9% when the system is implemented.

4.2. Uncertainties

The eleven uncertainties depicted in the network in Figure 4.1, are sorted into three major categories of human, organizational and technical errors which act as mid-parent nodes. This category was improved to be more appropriate for the complex working environment, based on the concept of Harvey’s 3Es - Education, Enforcement and Engineering - to affect the accident probability of cobots (Julien H. Harvey, 1946). Even though this concept is a little old-fashioned, it is still widely used for occupational safety and health approaches to prevent occupational injuries and illnesses. The remaining eight uncertainties which act as parent nodes affect each mid-parent node.

4.2.1 Human errors

Heinrich (1941) suggested that most of industrial accidents came from unsafe act that result from human errors. Research by Senders and Moray (1991) defined that human error means something has been done that was "not intended by the actor; not desired by a set of rules or an external observer; or that led the task or system outside its acceptable limits”. According to Health and Safety Executive (HSE), there are three types of human error: slips, lapses, and mistakes. Both slips (generally called “commission error”) and lapses (generally called "omission error") occur in very familiar tasks which can occur without much conscious attention, whereas mistakes are attributable to decision-making failures. There should be many causes leading to human errors in the worksites such as poor design, distraction, time pressure, workload, and communication systems. Although detailed considerations along these causes are meaningful for an entire body of research, it is beyond the scope of this paper. Therefore, we intend to apply four factors found from the analysis of OIIRs and FIRs will be applied. There are four uncertainties to be concerned: safety training, risk assessment, proper installation, and type of tasks. The probability of human error assumes 0.003 in case of "P (safety training: high, risk assessment: implemented, type of task: routine, proper installation: proper)" which is general human error rate for an act performed incorrectly (Kirwan. B., 1994). When it comes to each conditional probability[3], Table 4.1 was applied.

Table 4.1 Impact on human errors of four uncertainties and one decision node

Safety training	**Risk Assessment**	**Type of tasks**	**Proper installation**	**Number of cobots**
High (0)	Implemented (0)	Routine (0)	Proper (0)	1 (0)
Medium (+0.025)	Not implemented (+0.05)	Non-routine (+0.05)	Improper (+0.05)	2 (+0.025)
Low (+0.05)				3 (+0.05)

4.2.1.1 Safety training

OSHA argues that education and training plays a critical role in informing workers and managers about worksite hazards and controls so they can work safely and productively. In addition, the more years of working periods, the lower accident probability found from the

[3] Book (Robot system reliability and safety, 2015) by Dhillon stated that that roughly 20% of industrial accidents with robots resulted from human error. Therefore, the sum of four uncertainty factors' probability is 20% with the same level of contribution. In regards to the number of cobots, the same amount of contribution is applied for the objective research.

analysis on OIIRs. It generally means that workers who have more working periods, have a higher chance to be well-trained for safety. This is attributed to the fact that employers regularly provide a safety education – over 6 hours per quarter - for the employee according to Article 31 of the Korean OSH act. Furthermore, the introduction of cobots will make the integrated system more complicated. Therefore, safety education can increase the awareness surrounding risks such as collision and trapping from cobots and in turn reduce the chance of human errors. The outcomes of this uncertainty are “high, medium and low”. From the previous study of KOSHA (Junseok, 2012), the level of safety training in the workplace where industrial robots are investigated as shown in Table 4.2. High means “safety training regularly”. Medium means “safety training if necessary”. Low means “no training”. The same distribution in case of cobots was assumed.

Table 4.2 The ratio of the level of safety training

Low	**Medium**	**High**
0.077	0.224	0.699

4.2.1.2 Type of tasks

As being similar to the FIRs cases, most of the accidents by cobots are expected to be non-routine tasks. From the analysis of FIRs, it shows that 71.4% of FIRs occurred during the non-normal operating condition. Research by Brazendale (1988), non-routine tasks give a high chance of human errors occurring because of unfamiliarity and unpredictability. The outcomes of this uncertainty are “routine” and “non-routine”. The portion of routine and non-routine task was assumed in Table 4.3.

Table 4.3 The ratio of routine and non-routine tasks

Routine	Non-routine
0.93	0.07

4.2.1.3 Risk assessment

According to ISO TS 15066, risk assessment for cobots should include not only the cobot itself, but also control systems and safety devices such as virtual fences. However, ISO 15066 refers to ISO 10218-2 based on the ISO 12100 for risk assessment and mitigation of safety machinery for designers. This means that this standard does not completely cover hazards at the installation and usage stage. In order to implement an effective risk assessment for users, a high Safety Integrity Level (SIL; IEC 62061) and/or Performance Level (PL; ISO 13849-1) for functional safety need to be applied. Unlike other parent nodes, this node affects two mid-parents' node which are human and technical errors. The outcomes of this uncertainty are "implemented" or "not implemented". From the OSHCS 2015 in Korea, 83.3% of workplaces in the manufacturing industry implemented risk assessment systems under the article 4.1 of Korean OSH act as shown in Table 4.4. The same distribution was assumed with cobots.

Table 4.4 The ratio of the implementation of risk assessment

Implemented	Not implemented
0.833	0.167

4.2.1.4 Proper installation

Cobots and coordinate systems should be installed according to the law or international safety standards because the design, requirements, and layout of equipment, utilities, and facilities can lead to hazards if they are not correctly installed. For instance, although there is no function of safety monitored stop in co-existence or collaboration zone, a worker might make a wrong judgment to try and enter a cell without caution. Therefore, proper installation is one of the major factors that affects human error. This study also considers proper installation as the factor of technical errors because if not, the virtual cage for safety has a chance to fail to function properly. Therefore, this node can affect two errors - human and technical errors – like the case of the node for risk assessment. The outcomes of this uncertainty are proper and improper. From the OSHCS 2015, 90.3% of the interviewees replied that preventative measures under the article 25 of Korean occupational safety and health act were completely applied at workplaces where hazardous machinery equipment, such as industrial robots, were installed. It is applied that the ratio of the cobots' case also has the same distribution.

Table 4.5 The ratio of proper and improper installation of cobots

Proper	**Improper**
0.903	0.097

4.2.2 Organizational errors

Under the article 5 of Korean OSH act, employers have a responsibility to provide a safe work environment and improve working conditions so as to prevent occupational injuries and illnesses. Therefore, the CEO's safety interest based on employers' responsibility is crucial to implement an effective safety management system of occupational safety and health program that is encouraged by Korea occupational safety and health agency (KOSHA). Moreover, the degree of organizational ability to manage OSH issues generally depends on the size of the company because of safety budget and manpower. In this category, there are three uncertainties: safety management, CEO's safety interest, and the size of the company. The probability of organizational errors assumes 0.003 in case of "P (safety management: high, CEO's interest: high, company size: greater than 300)" which is the same probability of human error. When it comes to each conditional probability[4], the probability following Table 4.6 was applied.

Table 4.6 Impact on organizational errors of three uncertainties and one decision node

Safety management		CEO's safety interest		Company size		Number of Cobots	
High	(0)	High	(0)	Greater than 300	(0)	1	(0)
Medium	(+0.033)	Medium	(+0.033)	50 ~ 299	(+0.033)	2	(+0.033)
Low	(+0.066)	Low	(+0.066)	1~49	(+0.066)	3	(+0.066)

4.2.2.1 Safety management

On the basis of the accident analysis of FIRs, 27 workplaces where fatality occurred had a proper safety procedure such as Lock Out/Tag Out (LOTO) [5]. However, these tragic fatalities happened because the safety procedure was superficial, which implies safety management was insufficient and did not work with a chemical bond. Therefore, safety management works to reduce accidents caused by cobots. The outcomes of this uncertainty are high, medium, low. High means "well built-in". Medium means "somehow built-in". Low means "rarely built-in or needed". From the OSHCS 2015, the level of safety management was below Table 4.7. The same distribution like the case of cobots was assumed.

Table 4.7 The ratio of the level of safety management

High	Medium	Low
0.153	0.81	0.037

[4] The sum of three uncertainties' probability is 20% with the same level of contribution as the case of human error. Generally speaking, human and organizational error is a result of interaction by two major factors. Environmental factors are not considered in the scope section of this study - and thus affect the occurrence of accident together. For clarity, the probability of organizational error is assumed the same as that of human error. In case of number of cobots, the same amount of contribution is applied for the objective research.

[5] OSHA Standard 29 CFR 1910.147 for control of hazardous energy, or lockout/tagout (LOTO), is used to prevent unexpected startup of equipment, and thus decrease the amount of injuries from harm during maintenance.

4.2.2.2 CEO's safety interest

In manufacturing environments, effective leadership is used in order to increase the safety performance of workers in high-risk situations. (Flin & Yule, 2004). Safety leadership is projected at the level of the CEO's safety's interest. This is essential to show leadership and enable employees to energize their safety performance in a positive way. The outcomes of this uncertainty are high, medium, low. High means "strong interest for safety from CEO". Medium means "Moderate interest for safety from CEO". Low means "Rarely or no CEO's safety interest". From the OSHCS 2015, the level of CEO's safety interest was below Table 4.8.

Table 4.8 The ratio of the level of CEO's safety interest

High	**Medium**	**Low**
0.367	0.601	0.032

4.2.2.3 Company size

Larger-size companies have usually lower rates of fatal injuries compared to smaller-size companies (Mendeloff, Ewing Marion Kauffman, & Kauffman, 2006). Recently, in the republic of Korea, this trend is becoming rigid because of the increase in outsourcing hazardous work from a contractor to a sub-contractor for cost reduction (Ministry of Employment and Labor, 2015). Moreover, it is expected that cobots in SMEs will have higher relative vulnerability to occupational accidents compared to large-scale companies due to limited safety budget and manpower. In this node, the outcomes of this uncertainty are small, medium and large. From the national statistics (2018) from the Ministry of Employment and Labor in the Republic of Korea, the proportion of company size in the manufacturing industry is shown in Table 4.9.

Table 4.9 The ratio of company size in the manufacturing industry

Small (1 ~ 49)	**Medium** (50 ~ 299)	**Large** (greater than 300)
0.9606	0.0370	0.0024

4.2.3 Technical errors

The innovative technological advancements from physical cages to virtual cages with laser curtains, cameras and sensors for preventing collision and trapping, paved the way to make it possible for robots to share workplace with workers. Unlike the accident case of industrial robots, with the help of the state-of-art intrinsic safety system, the injuries and fatalities from cobots are expected to decrease. However, system reliability is still an important factor that affects the occurrence of occupational injuries by cobots. Effective implementation of the risk assessment and proper installation by the international standards has a significant impact on technical errors. Therefore, three factors can affect technical errors. In this category, there are three uncertainties: system reliability, risk assessment, proper installation. The probability of technical errors 0.001 in case of "P (system reliability: acceptable, risk assessment: implemented, proper installation: proper)" which is the required reliability of cobots system by the international standard (IEC 62061). When it comes to each conditional probability[6], the probability following Table 4.10 was applied.

Table 4.10 Three uncertainties and their impact on technical errors

System reliability		**Risk assessment**		**Proper installation** (Virtual fences)	
Acceptable	(0)	Implemented	(0)	Proper	(0)
Unacceptable	(+0.8)	Not implemented	(+0.05)	Improper	(+0.05)

4.2.3.1 System reliability

Cobots are designed for real-time interactions with humans in a shared place. This technical advancement requires complicated logics and hardware reliability compared to

[6] It is applied that the most contributable factor was system reliability in technical errors which is directly connected to occur the accident in the workplace, if it happens. As a result, the probability occurrence of technical errors increases up to 80% in case of unacceptable system reliability. The rest of two, risk assessment and proper installation were considered as the same level of contributors like the case of human errors.

industrial robots (Maurtua, Ibarguren, Kildal, Susperregi, & Sierra, 2017). According to the research on Perrow (1994), more complex logics has a chance to increase dysfunctional interactions among system components which is called “system accidents”. In addition, faults of safety devices, sensors, and control panels of cobot system (electrical and mechanical failures) is directly associated with the occurrence of the accident by cobots.

However, these failures should not be improved in the stage of usage or installation but in the stage of design and manufacturing. It was assumed that all of cobot manufacturers follow international standards such as ISO 15066, 10218-1,2 and IEC 62061 etc. According to IEC 62061, cobot manufacturers should satisfy all requirements over Safety integrity level (SIL) 2 for selling their products. The probability of failure on demand (PFD), corresponding to SIL 2 is 10^{-3}< x <10^{-2} of low demand mode. Therefore, the probability of hardware failure is 0.001 as shown in Table 4.11.

Table 4.11 The reliability of cobots and cobot system

Acceptable	**Not acceptable**
0.999	0.001

4.3. Outcome

The estimated annual accident probability by the introduction of cobots is affected by three major categories: human, organizational, and technical errors. Table 4.12 shows the eight conditional probabilities for that are inputted into the Netica Software in order to be computed. Naïve Bayes classifier based on Bayes’ theorem is applied to calculate eight values as shown in Table 4.12.

Table 4.12 Eight accident probabilities given each condition for outcome node

① P (accident | human error (**o**) ∩ organizational error (x) ∩ technical error (x))	= 0.13747
② P (accident | human error (x) ∩ organizational error (**o**) ∩ technical error (x))	= 0.00353
③ P (accident | human error (x) ∩ organizational error (x) ∩ technical error (**o**))	= 0.07902
④ P (accident | human error (**o**) ∩ organizational error (**o**) ∩ technical error (x))	= 0.24588
⑤ P (accident | human error (**o**) ∩ organizational error (x) ∩ technical error (**o**))	= 0.88749
⑥ P (accident | human error (x) ∩ organizational error (**o**) ∩ technical error (**o**))	= 0.14931
⑦ P (accident | human error (**o**) ∩ organizational error (**o**) ∩ technical error (**o**))	= 0.94164
⑧ P (accident | human error (x) ∩ organizational error (x) ∩ technical error (x))	= 0.6E-8

4.3.1 Computation of conditional probabilities with naïve Bayes

Naïve Bayes assumes that factors are independent each other and thus evidence or marginal probability can be divided into independent parts. For example, the annual accident probability given that all of three errors occur can be expressed as the following equation.

$$= \frac{P(accident\ given\ that\ three\ errors\ occurs)}{P(accident\ given\ that\ three\ errors\ occurs) + P(no\ accident\ given\ three\ errors)}$$

$$= \frac{P(accident) * P(human\ errors|accident) * P(organizational\ errors|accident) * P(technical\ errors|accident)}{\begin{array}{c}\{\, P(accident) * P(human\ errors|accident) * P(organizational\ errors|accident) * P(technical\ errors|accident) + \\ P(no\ Accident) * P(human\ errors|no\ accident) * P(organizational\ errors|no\ accident) * P(technical\ errors|no\ accident)\,\}\end{array}}$$

Therefore, this equation requires a P(A) which is the marginal probability. Accident probability “P(A)” is assumed that it would occur as much as the average occupational accident rate of the republic of Korea. In 2018, the average occupational accident rate of the republic of Korea was 0.54%. In case of likelihood such as P(human errors | accident), P(organizational errors | accident) and P(technical errors | accident), calculated from the status of installation of safety fence and safety measures for entrances, in the analysis on FIRs are applied. There are six likelihoods depicted in Table 4.13.

Table 4.13 Six probabilities given that accident occurs

P(human error | accident, H|A)	= 0.4815	P(no human error | accident, ~H|A)	= 0.5185
P(organization error | accident, O|A)	= 0.1852	P(no organization error | accident, ~O|A)	= 0.8148
P(technical error | accident, T|A)	= 0.3333	P(no technical error | accident), ~T|A)	= 0.6667

In addition, P (human errors | no accident) is assigned 0.01 which is "human error in a routine operation where care is required" from the book that is "A guide practical human reliability assessment" written by Barry Kirwan. P (organizational error | no accident) is applied 0.1 that "supervisor does not recognize the operator's error" from the book that is "A guide practical human reliability assessment" written by Barry Kirwan. In case of P (technical error | no accident), the probability of safety integrity level (SIL) 2 from the IEC 62061 is 0.01 as shown in Table 4.14.

Table 4.14 Six probabilities given that accident does not occurs

P(human error | no accident, H|~A)	= 0.01	P(no human error | no accident, ~H|~A)	= 0.99
P(organization error | no accident, O|~A)	= 0.1	P(no organization error | no accident, ~O|~A)	= 0.9
P(technical error | no accident, T|~A)	= 0.01	P(no technical error | no accident, ~T|~A)	= 0.99

With these values, eight posterior probabilities have been computed below:

① P(accident | human error(o) ∩ organizational error(x) ∩ technical error(x))

$$= \mathrm{P}(\mathrm{A} \mid \mathrm{H} \cap \sim \mathrm{O} \cap \sim \mathrm{T}) \doteqdot \frac{P(H|A)*P(\sim O|A)*P(\sim T|A)*P(A)}{P(H|A)*P(\sim O|A)*P(\sim T|A)*P(A) + P(H|\sim A)*P(\sim O|\sim A)*P(\sim T|\sim A)*P(\sim A)}$$

$$= \frac{0.4815*0.8148*0.6667*0.0054}{0.4815*0.8148*0.6667*0.0054+0.01*0.9*0.99*0.9946}$$

$$= 0.13747 = 13.747\%$$

② P(accident | human error(x) ∩ organizational error(o) ∩ technical error(x))

$$= P(A \mid \sim H \cap O \cap \sim T) \doteqdot \frac{P(\sim H|A)*P(O|A)*P(\sim T|A)*P(A)}{P(\sim H|A)*P(O|A)*P(\sim T|A)*P(A) + P(\sim H|\sim A)*P(O|\sim A)*P(\sim T|\sim A)*P(\sim A)}$$

$$= \frac{0.5185*0.1852*0.6667*0.0054}{0.5185*0.1852*0.6667*0.0054+0.99*0.6*0.99*0.9946}$$

$$= 0.00353 = 0.353\%$$

③ P(accident | human error(x) ∩ organizational error(x) ∩ technical error(o))

$$= P(A \mid \sim H \cap \sim O \cap T) \doteqdot \frac{P(\sim H|A)*P(\sim O|A)*P(T|A)*P(A)}{P(\sim H|A)*P(\sim O|A)*P(T|A)*P(A) + P(\sim H|\sim A)*P(\sim O|\sim A)*P(T|\sim A)*P(\sim A)}$$

$$= \frac{0.5185*0.8148*0.3333*0.0054}{0.5185*0.8148*0.3333*0.0054+0.99*0.9*0.01*0.9946}$$

$$= 0.07902 = 7.902\%$$

④ P(accident | human error(o)∩ organizational error(o) ∩ technical error(x))

$$= P(A \mid H \cap O \cap \sim T) \doteqdot \frac{P(H|A)*P(O|A)*P(\sim T|A)*P(A)}{P(H|A)*P(O|A)*P(\sim T|A)*P(A) + P(H|\sim A)*P(O|\sim A)*P(\sim T|\sim A)*P(\sim A)}$$

$$= \frac{0.4815*0.1852*0.6667*0.054}{0.4815*0.4*0.1852*0.6667*0.0054+0.01*0.1*0.99*0.9946}$$

$$= 0.24588 = 24.588\%$$

⑤ P(accident | human error(o) ∩ organizational error(x) ∩ technical error(o))

$$= P(A \mid H \cap \sim O \cap T) \doteqdot \frac{P(H|A)*P(\sim O|A)*P(T|A)*P(A)}{P(H|A)*P(\sim O|A)*P(T|A)*P(A) + P(H|\sim A)*P(\sim O|\sim A)*P(T|\sim A)*P(\sim A)}$$

$$= \frac{0.4815*0.8148*0.3333*0.0054}{0.4815*0.8148*0.3333*0.0054+0.01*0.9*0.01*0.9946}$$

$$= 0.88749 = 88.749\%$$

⑥ P(accident | human error(x) ∩ organizational error(o) ∩ technical error(o))

$$= P(A \mid \sim H \cap O \cap T) \doteqdot \frac{P(\sim H|A)*P(O|A)*P(T|A)*P(A)}{P(\sim H|A)*P(O|A)*P(T|A)*P(A) + P(\sim H|\sim A)*P(O|\sim A)*P(T|\sim A)*P(\sim A)}$$

$$= \frac{0.5185*0.1852*0.3333*0.0054}{0.5185*0.1852*0.3333*0.0054+0.99*0.1*0.01*0.9946}$$

$$= 0.14932 = 14.932\%$$

⑦ P(accident | human error(o) ∩ organizational error(o) ∩ technical error(o))

$$= P(A \mid H \cap O \cap T) \doteqdot \frac{P(H|A)*P(O|A)*P(T|A)*P(A)}{P(H|A)*P(O|A)*P(T|A)*P(A) + P(H|\sim A)*P(O|\sim A)*P(T|\sim A)*P(\sim A)}$$

$$= \frac{0.4815*0.1852*0.3333*0.0054}{0.4815*0.1852*0.3333*0.0054+0.01*0.1*0.01*0.9946}$$

$$= 0.94165 = 94.165\%$$

⑧ P(accident | human error(x) ∩ organizational error(x) ∩ technical error(x))

$$= P(A \mid \sim H \cap \sim O \cap \sim T) \doteqdot \frac{P(\sim H|A)*P(\sim O|A)*P(\sim T|A)*P(A)}{P(\sim H|A)*P(\sim O|A)*P(\sim T|A)*P(A) + P(\sim H|\sim A)*P(\sim O|\sim A)*P(\sim T|\sim A)*P(\sim A)} =$$

$$= \frac{0.5185*0.8148*0.6667*0.0054}{0.5185*0.8148*0.6667*0.0054+ 0.99*0.9*0.99*0.9946}$$

$$= 0.00000006{=}0.000006\%$$

CHAPTER 5. RESULTS

As a result of Netica software with the decision “one cobot” and “No implementation of regulatory safety certification”, the chance of accident occurrence by introduction of cobots is 0.66 as shown below in Figure 5.1.

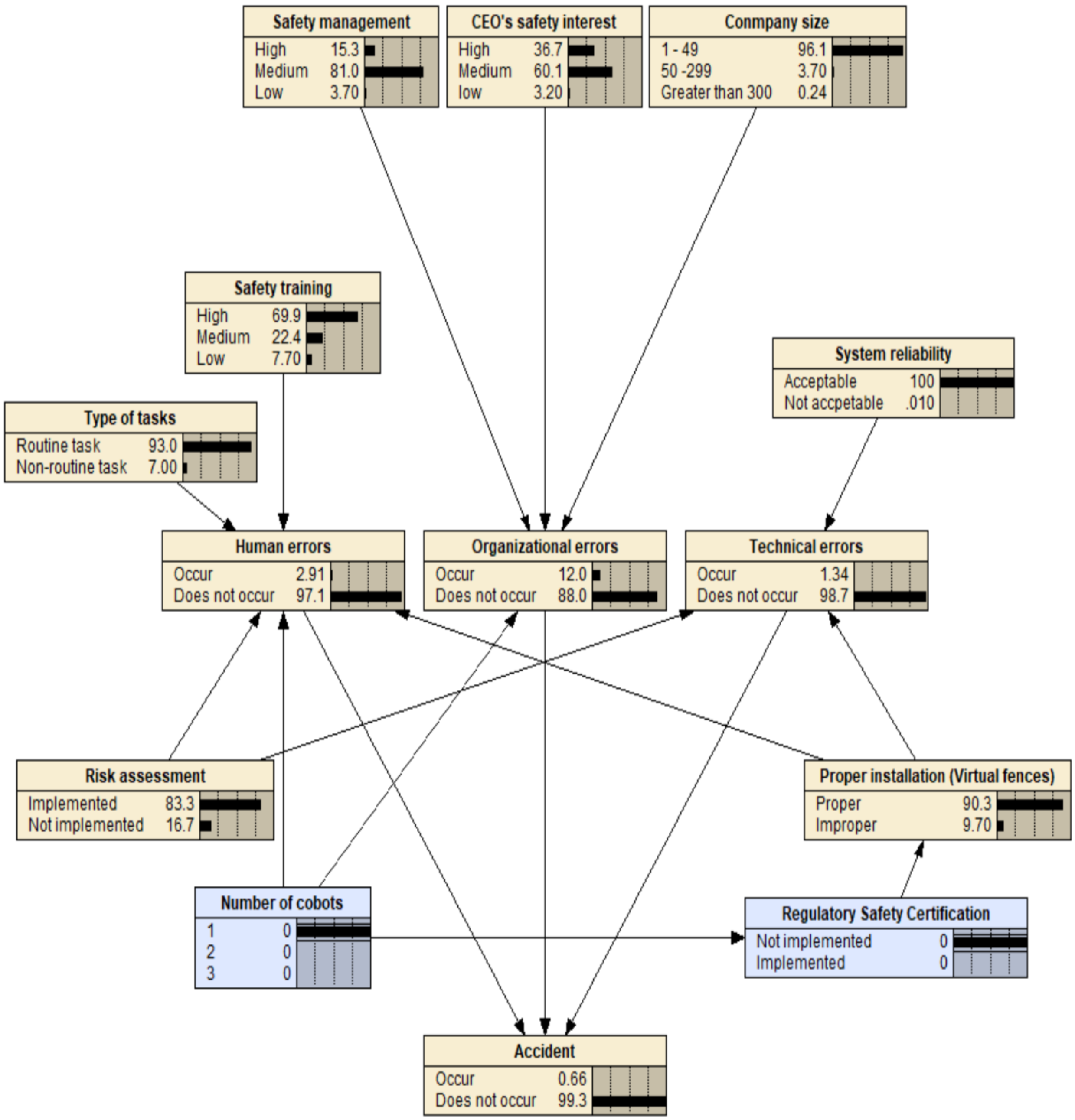

Figure 5.1 Bayesian belief network of the annual accident probability by cobots using Netica

Regarding other decision nodes, Netica software shows the results in each state below Table 5.1.

Table 5.1 The annual accident probability by the introduction of cobots

Number of Cobots	safety certification implements	Safety certification does not implement
1	0.52%	0.66%
2	0.94%	1.09%
3	1.37%	1.54%

It shows that the estimated annual accident probability increases as the number of cobots increases, specifically, from one (0.66%) to three (1.54%), given that safety certification is not implemented. The introduction of the safety certification system has a positive effect on decreasing the annual accident probability from 0.66% (if not implemented) to 0.52% (if implemented) with one cobot by directly affecting the ratio of proper installation from 90.3% to 99.9% in Figure 5.1.

Regarding the three main errors, organizational errors have the most frequent probability (12.0%) as shown in Figure 5.1. In terms of impact, however, human errors have the largest impact on annual accident probability as shown in Table 5.2 due to large fluctuation between the lowest outcome: 0% occurs selected and the highest outcome: 100% occurs selected.

Table 5.2 The impact level of three main errors for the annual accident probability

Three categories	Estimated annual accident probability		
	The lowest[7]	The highest[8]	Variance
Human errors	0.15%	17.5%	17.35
Organizational errors	0.57%	1.31%	0.74
Technical errors	0.47%	14.5%	14.03

[7] The probability when selected that the outcome has not fully occurred in the category
[8] The probability when selected that the outcome has fully occurred in the category

CHAPTER 6. SENSITIVITY ANALYSIS

Assumptions on how different factors interact with one another allow for probabilities to be based on these assumptions. Sensitivity analysis allows researchers to see how these factors interact with one another, and relies on these assumptions and measure the impacts of fluctuations by changing the inputs of each factor (Stallard, Mackenzie, & Peters, 2018). The Bayesian belief network diagram is able to extrapolate to what extent changing inputs will have on target value. Figure 6.1 shows that the variance of accident probability as each factor moves from the best condition to the worst condition while the other factors are fixed. The outcome is based on one cobot installed with no safety certification system. For instance, if safety training is fully high, the annual accident probability is 0.51%, if fully low, it is 1.30% as seen in Figure 6.1.

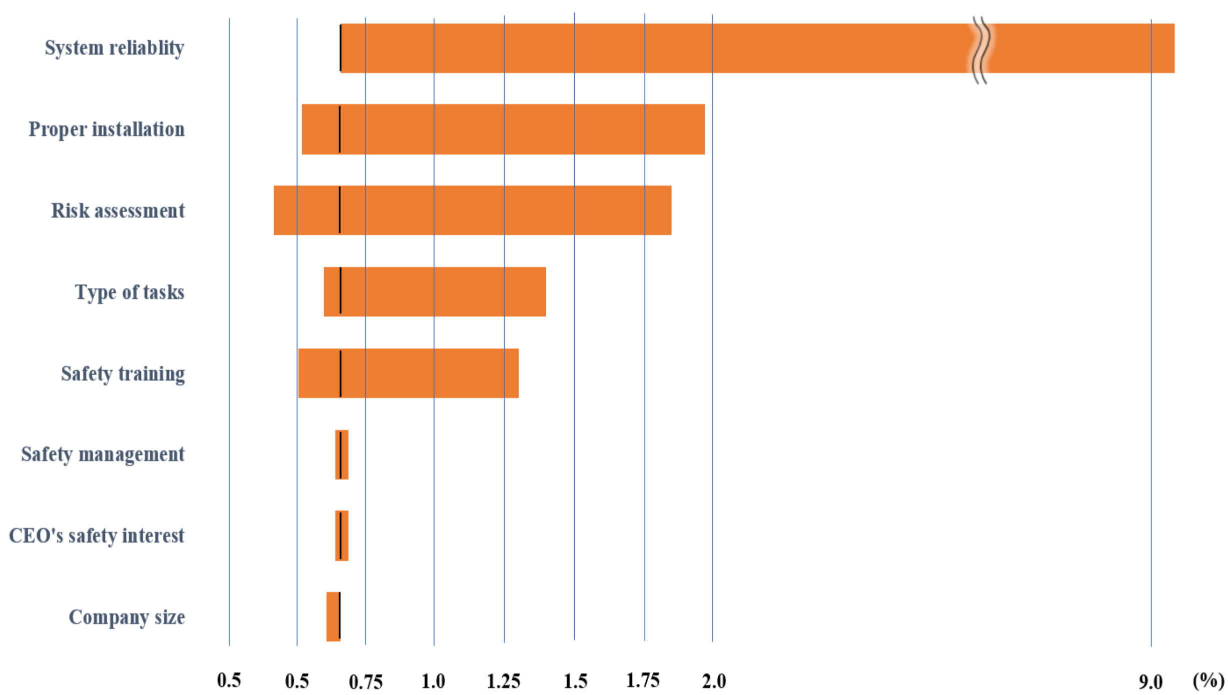

Figure 6.1 Sensitivity analysis for the annual accident probability with one cobot installed and regulatory safety certification system implemented

As shown in Figure 6.1, the factor that has the largest fluctuation on the outcome is system reliability. If system reliability is unacceptable, the probability of accident occurrence increases up to 9.15%. However, the level of system reliability has the limitations for improvement in usage or installation stages, but not as many in the stages of design and manufacturing. It was assumed in this paper that cobots were distributed only if they met international standards such as ISO 15066, 10218-1,2 and IEC 62061 for system reliability. Due to this, this paper is inconclusive to say that safety reliability has the greatest impact on the accident probability.

The next largest variable factors are proper installation and risk assessment. If installation is improper, the probability of accident occurrence increases up to 1.97% and the impacts of fluctuations from the best state and the worst state is 1.45%. If risk assessment is not fully implemented, the outcome increases up to 1.85% and the impacts of fluctuations from the best state to worst state is 1.43%.

On the other hand, three factors belonging to organizational errors are measured with relatively small variability. It is estimated that the portion of $P(O|A)$ is correspondingly small compared to $P(H|A)$, $P(T|A)$ and also $P(O|\sim A)$ is correspondingly big compared to $P(H|\sim A)$, $P(T|\sim A)$. This is explained by organizational errors affecting accident probability, but they may have indirect effects on the chance of accident occurrence which means that human and technical errors can cause occupational injuries to occur while organizational errors may play a role in a multiplier for the increase of both errors.

CHAPTER 7. DISCUSSION

The model suggested illustrates how a Bayes belief network is applied to predict an annual accident probability by the introduction of cobots. In order to validate the model, the question posed should be: “Are they safe or not?”. When using the comparative indicator of actual accident rate by industrial robots in Korea, the number of accidents by industrial robots can be shown, but the number of workers who work with industrial robots is not able to be determined. Therefore, researchers compared with the average accident rate of the entire manufacturing industry of Korea in 2018, at a percentage of 0.66%. This percentage is the same annual accident probability, when using one cobot and no safety certification system. This is classified as “average-risky”. However, with the help of technological advancement such as virtual safety fences using light curtains with vision camera and potential collision sensor, the accident intensity of cobots is expected to be lower than that of industrial robots. This is due to the decrease of speed and power before collision even if there is a collision with unexpected human behavior. From this point of view, cobots enable to decrease the work loss days, and thus conclude that cobots are safer than industrial robots, even though the number of accidents of cobots and industrial robots are very similar.

Both the analysis on FIRs and the sensitivity analysis on the risk model indicate that proper installation is the most influential factor on the chance of accident occurrence. From the analysis of FIRs, the cause of 14 out of 28 cases was improper installation of safety fences and interlock for the entrance designed to keep the robot inaccessible to workers. This unsafe condition can allow workers to enter into a high-risk collision zone with no regard for safety. However, the primary risk mitigation strategy of industrial robots that is to separate the robot from workers is no longer applicable to cobots. The physical cage needs to be replaced with a reliable, robust virtual cage to guarantee the safety of their human colleagues (Anne Jansen, 2018). To install this cage safely including the total cobots system, the introduction of the safety certification would be an effective regulatory system at the government level. To realize this measure at the application level, the government needs to consider introducing qualifications or licenses related to the installation of cobots. This will raise the technological level for integrators installing cobots’ cells. Furthermore, only safety devices and equipment such as light curtain, vision camera and pressure sensors that have passed the safety certification system should be distributed to the industry.

Another effective risk mitigation strategy derived from the risk model is to implement an effective risk assessment. The reduction of annual accident probability was significant between “implemented” and “not implemented”. However, it is believed that the concept of implementation for risk assessment should be changed as human-robot collaboration become more popular. While isolation from humans has been the best way to prevent accidents, from now on, it is necessary to control and cooperate with robots which are the main hazards to mitigate risk. One of the practical approaches is that risk assessment for cobots is not volume or static-based, but rather sequence or process-based that will change over time with the method recommended by ISO 15066.

Next, the model points out the importance of safety measures during non-routine tasks such as programming, relocating and repairing. Due to the usability and versatility of cobots, cobots have a chance to conduct themselves of their various tasks in the workplaces and due to this, they will be frequently relocated and reprogrammed. Therefore, sophisticated safety training and procedure should be required.

Promoting safety awareness through a high-level of safety training for workers is important. From the model, the difference in the annual accident probability between high safety training and low safety training is 0.79%. From the analysis of OIIRs, it was recognized that there has been a number of accidents for skilled workers who have worked for over 20 years. Therefore, training is required for new employees as well as refresher courses need to be for programmers, operators, and maintenance workers.

Another implication is that cannot be overlooked is the CEO's safety interest as well as the safety management system although their level of impact on the annual accident probability is relatively lower than other factors. This is attributed to the fact that leadership affects the formation of safety culture in the workplace. According to the KOSHA, the safety management system refers to a management system that combines the safety management priority based on CEO's safety interest. Declaring safety management as a priority by the CEO is the foundation for this system. This functions through a plan-do-check-action cycle in a systematic and autonomous manner. High-level of the safety management system combined with the CEO's high-level of safety interest prevents accident by the introduction of collaborative robots.

It should not be overlooked if the annual accident probability will increase as the number of cobots increase per cell. In this study, it was assumed that the risk will simply increase linearly with each condition. However, there would be many factors to affect risk in real environments, such as unintended movements due to the communication errors between multiple cobots.

CHAPTER 8. CONCLUSION

The demand for collaborative robots is increasing rapidly in the era of 4th industrial revolution (Badri, Boudreau-Trudel, & Souissi, 2018). In the line with this trend, the occupational injuries by cobots also is regrettably expected to increase. In this respect, it is believed that this article is one to initially attempt to suggest a BBN for the risk analysis for the introduction of cobots. This study has strived to obtain trustworthy probabilities through the analysis on OIIRs, FIRs and national statistics in the Republic of Korea. In addition to this data, notional data with renowned literature reviews, as well as the author's experiences over the 10 years of occupational safety and health field.

With the timely attempt, the risk (BBN) model was developed based on the factors for the annual accident probability by cobots. This gave outcome of 0.66%, given one cobot and no regulatory safety certification. As the validating process, the outcome was compared with the average accident rate of entire manufacturing industry of Korea in 2018. Both were the same. It can be interpreted "average-risky" in terms of accident frequency, but in terms of the accident intensity, that of cobots is expected to be lower than that of industrial robots. This is due to well-rounded and sophisticated safety system components and devices such as speed and force limit with virtual fence. Nonetheless, accident rate and intensity should never be ignorable.

Through the risk analysis with BBN and sensitivity analysis, these outcomes demonstrated how important it is to identify the optimal strategies for mitigating accident by cobots. As the saying goes "An ounce of prevention is worth a pound of cure", all measures mentioned in the discussion are vital to accident prevention. However, this paper focuses on three key measures to mitigate the risk by the introduction of cobots based on what is realistic and effective.

The first measure is cobots that have secured safety reliability are designed, produced, and distributed at the design and manufacturing stage. Not only should it be based on the result of the sensitivity analysis, but it should be done in accordance with the international standards such as ISO 15066, 10218-1,2 and IEC 62061. Even though this is out of the scope, this should be carried in a big picture view.

The second measure is that regulatory safety certification system at installation is an urgent need in the government level. It has the greatest sensitivity of all of the measures, besides the system reliability, and its effect for the accident reduction is magnificent.

Last but not least, implementing an effectual risk assessment following the international standards or regulations at the usage stage as enforced by the law and ISO 15066. This proactive measure helps workers alongside cobots to recognize and control hazards in various conditions, promote safety awareness, and finally reduce the cobot-related annual accident probability as well as costs. Consequently, this paper suggests an effectual concept for preventing the cobot-related accident in the Republic of Korea as seen in Figure 8.1.

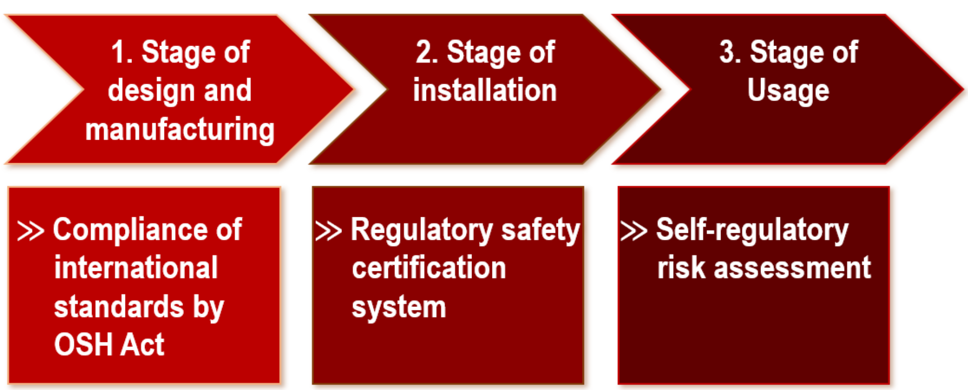

Figure 8.1 A step-by-step approach for preventing the cobot-related accident

CHAPTER 9. FUTURE STUDY

This study is one of the first attempts that suggest a BBN for the risk analysis by the introduction of cobots, this model should be reinforced further to include more factors and a complete set of decisions, mirroring actual situations in the future and take more consideration to use subjective probabilities through more robust data from expert group surveys or empirical experiments.

These limitations also pointed toward a very powerful and useful approach using Bayesian belief network, based on subjective assessments with notional data. Further study needs to reflect and consolidate it with present limitations and other important considerations: cyber security risks, environmental risks (e.g. electromagnetic interference), cognitive factors, regulations, and stakeholder requirements. Moreover, automated guided vehicles called “mobile robots” which move on autonomous platforms are the next challenge for safety in the workplace. Therefore, the future study should consider the limitations mentioned above to construct more a reliable model.

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APPENDIX. PROBABILITY IN NETICA SOFTWARE

The probability of occurrence for human errors in Netica

Type of tasks	Risk assessment	Proper installation (Virtual fenc...	Safety training	Number of cobots	Occur	Does not occur
Routine task	Implemented	Proper	High	1	0.3	99.7
Routine task	Implemented	Proper	High	2	2.8	97.2
Routine task	Implemented	Proper	High	3	5.3	94.7
Routine task	Implemented	Proper	Medium	1	2.8	97.2
Routine task	Implemented	Proper	Medium	2	5.3	94.7
Routine task	Implemented	Proper	Medium	3	7.8	92.2
Routine task	Implemented	Proper	Low	1	5.3	94.7
Routine task	Implemented	Proper	Low	2	7.8	92.2
Routine task	Implemented	Proper	Low	3	10.3	89.7
Routine task	Implemented	Improper	High	1	5.3	94.7
Routine task	Implemented	Improper	High	2	7.8	92.2
Routine task	Implemented	Improper	High	3	10.3	89.7
Routine task	Implemented	Improper	Medium	1	7.8	92.2
Routine task	Implemented	Improper	Medium	2	10.3	89.7
Routine task	Implemented	Improper	Medium	3	12.8	87.2
Routine task	Implemented	Improper	Low	1	10.3	89.7
Routine task	Implemented	Improper	Low	2	12.8	87.2
Routine task	Implemented	Improper	Low	3	15.3	84.7
Routine task	Not implemented	Proper	High	1	5.3	94.7
Routine task	Not implemented	Proper	High	2	7.8	92.2
Routine task	Not implemented	Proper	High	3	10.3	89.7
Routine task	Not implemented	Proper	Medium	1	7.8	92.2
Routine task	Not implemented	Proper	Medium	2	10.3	89.7
Routine task	Not implemented	Proper	Medium	3	12.8	87.2
Routine task	Not implemented	Proper	Low	1	10.3	89.7
Routine task	Not implemented	Proper	Low	2	12.8	87.2
Routine task	Not implemented	Proper	Low	3	15.3	84.7
Routine task	Not implemented	Improper	High	1	10.3	89.7
Routine task	Not implemented	Improper	High	2	12.8	87.2
Routine task	Not implemented	Improper	High	3	15.3	84.7
Routine task	Not implemented	Improper	Medium	1	12.8	87.2
Routine task	Not implemented	Improper	Medium	2	15.3	84.7
Routine task	Not implemented	Improper	Medium	3	17.8	82.2
Routine task	Not implemented	Improper	Low	1	15.3	84.7
Routine task	Not implemented	Improper	Low	2	17.8	82.2
Routine task	Not implemented	Improper	Low	3	20.3	79.7
Non-routine task	Implemented	Proper	High	1	5.3	94.7
Non-routine task	Implemented	Proper	High	2	7.8	92.2
Non-routine task	Implemented	Proper	High	3	10.3	89.7
Non-routine task	Implemented	Proper	Medium	1	7.8	92.2
Non-routine task	Implemented	Proper	Medium	2	10.3	89.7
Non-routine task	Implemented	Proper	Medium	3	12.8	87.2
Non-routine task	Implemented	Proper	Low	1	10.3	89.7
Non-routine task	Implemented	Proper	Low	2	12.8	87.2
Non-routine task	Implemented	Proper	Low	3	15.3	84.7
Non-routine task	Implemented	Improper	High	1	10.3	89.7
Non-routine task	Implemented	Improper	High	2	12.8	87.2
Non-routine task	Implemented	Improper	High	3	15.3	84.7
Non-routine task	Implemented	Improper	Medium	1	12.8	87.2
Non-routine task	Implemented	Improper	Medium	2	15.3	84.7
Non-routine task	Implemented	Improper	Medium	3	17.8	82.2
Non-routine task	Implemented	Improper	Low	1	15.3	84.7
Non-routine task	Implemented	Improper	Low	2	17.8	82.2
Non-routine task	Implemented	Improper	Low	3	20.3	79.7

Non-routine task	Not implemented	Proper	High	1	10.3	89.7
Non-routine task	Not implemented	Proper	High	2	12.8	87.2
Non-routine task	Not implemented	Proper	High	3	15.3	84.7
Non-routine task	Not implemented	Proper	Medium	1	12.8	87.2
Non-routine task	Not implemented	Proper	Medium	2	15.3	84.7
Non-routine task	Not implemented	Proper	Medium	3	17.8	82.2
Non-routine task	Not implemented	Proper	Low	1	15.3	84.7
Non-routine task	Not implemented	Proper	Low	2	17.8	82.2
Non-routine task	Not implemented	Proper	Low	3	20.3	79.7
Non-routine task	Not implemented	Improper	High	1	15.3	84.7
Non-routine task	Not implemented	Improper	High	2	17.8	82.2
Non-routine task	Not implemented	Improper	High	3	20.3	79.7
Non-routine task	Not implemented	Improper	Medium	1	17.8	82.2
Non-routine task	Not implemented	Improper	Medium	2	20.3	79.7
Non-routine task	Not implemented	Improper	Medium	3	22.8	77.2
Non-routine task	Not implemented	Improper	Low	1	20.3	79.7
Non-routine task	Not implemented	Improper	Low	2	22.8	77.2
Non-routine task	Not implemented	Improper	Low	3	25.3	74.7

The probability of occurrence for organizational errors in Netica

Safety management	CEO's safety interest	Conmpany size	Number of cobots	Occur	Does not occur
High	High	1 - 49	1	6.96	93.04
High	High	1 - 49	2	10.29	89.71
High	High	1 - 49	3	13.62	86.38
High	High	50 -299	1	3.63	96.37
High	High	50 -299	2	6.96	93.04
High	High	50 -299	3	10.29	89.71
High	High	Greater than 300	1	0.3	99.7
High	High	Greater than 300	2	3.63	96.37
High	High	Greater than 300	3	6.96	93.04
High	Medium	1 - 49	1	10.29	89.71
High	Medium	1 - 49	2	13.62	86.38
High	Medium	1 - 49	3	16.95	83.05
High	Medium	50 -299	1	6.96	93.04
High	Medium	50 -299	2	10.29	89.71
High	Medium	50 -299	3	13.62	86.38
High	Medium	Greater than 300	1	3.63	96.37
High	Medium	Greater than 300	2	6.96	93.04
High	Medium	Greater than 300	3	10.29	89.71
High	low	1 - 49	1	13.62	86.38
High	low	1 - 49	2	16.95	83.05
High	low	1 - 49	3	20.28	79.72
High	low	50 -299	1	10.29	89.71
High	low	50 -299	2	13.62	86.38
High	low	50 -299	3	16.95	83.05
High	low	Greater than 300	1	6.96	93.04
High	low	Greater than 300	2	10.29	89.71
High	low	Greater than 300	3	13.62	86.38
Medium	High	1 - 49	1	10.29	89.71
Medium	High	1 - 49	2	13.62	86.38
Medium	High	1 - 49	3	16.95	83.05
Medium	High	50 -299	1	6.96	93.04
Medium	High	50 -299	2	10.29	89.71
Medium	High	50 -299	3	13.62	86.38
Medium	High	Greater than 300	1	3.63	96.37
Medium	High	Greater than 300	2	6.96	93.04
Medium	High	Greater than 300	3	10.29	89.71
Medium	Medium	1 - 49	1	13.62	86.38
Medium	Medium	1 - 49	2	16.95	83.05
Medium	Medium	1 - 49	3	20.28	79.72

Safety management	CEO's safety interest	Conmpany size	Number of cobots	Occur	Does not occur
Medium	Medium	50 -299	1	10.29	89.71
Medium	Medium	50 -299	2	13.62	86.38
Medium	Medium	50 -299	3	16.95	83.05
Medium	Medium	Greater than 300	1	6.96	93.04
Medium	Medium	Greater than 300	2	10.29	89.71
Medium	Medium	Greater than 300	3	13.62	86.38
Medium	low	1 - 49	1	16.95	83.05
Medium	low	1 - 49	2	20.28	79.72
Medium	low	1 - 49	3	23.61	76.39
Medium	low	50 -299	1	13.62	86.38
Medium	low	50 -299	2	16.95	83.05
Medium	low	50 -299	3	20.28	79.72
Medium	low	Greater than 300	1	10.29	89.71
Medium	low	Greater than 300	2	13.62	86.38
Medium	low	Greater than 300	3	16.95	83.05
Low	High	1 - 49	1	13.62	86.38
Low	High	1 - 49	2	16.95	83.05
Low	High	1 - 49	3	20.28	79.72
Low	High	50 -299	1	10.29	89.71
Low	High	50 -299	2	13.62	86.38
Low	High	50 -299	3	16.95	83.05
Low	High	Greater than 300	1	6.96	93.04
Low	High	Greater than 300	2	10.29	89.71
Low	High	Greater than 300	3	13.62	86.38
Low	Medium	1 - 49	1	16.95	83.05
Low	Medium	1 - 49	2	20.28	79.72
Low	Medium	1 - 49	3	23.61	76.39
Low	Medium	50 -299	1	13.62	86.38
Low	Medium	50 -299	2	16.95	83.05
Low	Medium	50 -299	3	20.28	79.72
Low	Medium	Greater than 300	1	10.29	89.71
Low	Medium	Greater than 300	2	13.62	86.38
Low	Medium	Greater than 300	3	16.95	83.05
Low	low	1 - 49	1	20.28	79.72
Low	low	1 - 49	2	23.61	76.39
Low	low	1 - 49	3	26.94	73.06
Low	low	50 -299	1	16.95	83.05
Low	low	50 -299	2	20.28	79.72
Low	low	50 -299	3	23.61	76.39
Low	low	Greater than 300	1	13.62	86.38
Low	low	Greater than 300	2	16.95	83.05
Low	low	Greater than 300	3	20.28	79.72

The probability of occurrence for technical errors

System reliability	Proper installation (Virtual fenc...	Risk assessment	Occur	Does not occur
Acceptable	Proper	Implemented	1.00e-2	99.99
Acceptable	Proper	Not implemented	5.01	94.99
Acceptable	Improper	Implemented	5.01	94.99
Acceptable	Improper	Not implemented	10.01	89.99
Not accpetable	Proper	Implemented	80.01	19.99
Not accpetable	Proper	Not implemented	85.01	14.99
Not accpetable	Improper	Implemented	85.01	14.99
Not accpetable	Improper	Not implemented	90.01	9.99