Quantifying the Effectiveness of IoT Technologies for Accident Prevention

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Abstract: The Internet of Things (IoT) has attracted attention in recent years as a way to prevent construction site accidents. Although various IoT technologies have been tested for the purpose of safety management, few have been implemented in actual projects. One possible reason is that the effectiveness of these technologies has rarely been calculated. In this study, a method for quantitatively evaluating the effectiveness of IoT technologies for accident prevention is presented. Taking the domino theory of accident causation into account, this method has three aspects: the degree of the causes of accidents that an IoT technology prevents, association between accident types and their causes, and frequency of each accident type. To quantify these, two different types of survey were conducted, and statistical records about construction accidents by type were used. To test the applicability of this method, the effectiveness of two IoT technologies was calculated. The method successfully quantified how much each technology contributes to preventing certain types of accident as well as the overall accident-prevention effect. The proposed method can enable practitioners to assess the effectiveness of certain IoT technologies, which will be useful in justifying investments in the technology. The method will lead to deploying more IoT technologies for safety management, which will eventually contribute to decreasing accidents in the construction industry. **DOI:** 10.1061/(ASCE)ME.1943-5479.0000825.

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Introduction

The Internet of Things (IoT) has been widely investigated with the development of sensor technology and wireless internet. For various purposes, it has been applied to many industries such as healthcare (Kulkar and Sathe 2014), production logistics (Qu et al. 2016), manufacturing (Mourtzis et al. 2016), and mining (Wu et al. 2019), as well as the construction industry. Smart homes and smart cities are the main applications of the IoT in the construction industry (Du et al. 2020; Hastak and Koo 2017; Lam and Fu 2019; Zhao et al. 2020). It has been investigated for various purposes, from the control of air conditioning, heating, and lighting, to smart grids for the purpose of monitoring and pattern analysis of electricity use, to smart cities' parking management systems (Arora et al. 2017; Khajenasiri et al. 2017; Park and Rue 2015; Vukicevic et al. 2019).

There have been many studies investigating the IoT for safety management on construction sites because researchers believe that it can contribute to preventing accidents (Kerravala 2014). For example, ensuring personnel safety using wearable instruments, such as helmets equipped with motion sensors and protective vests, has been studied (Cheng and Teizer 2013; Gatti et al. 2014; Yi et al. 2016), as well as providing the necessary safety information in the field (Arslan et al. 2019). Work procedures and safety details in collaboration with augmented-reality technology have been identified (Cheng et al. 2013; Grabowski et al. 2018; Höller et al. 2014).

Although various IoT technologies have been studied for safety management, their applications on construction sites have stagnated. One possible reason for this stagnation is that the effectiveness of the applications has not been considered. For construction companies to adopt these technologies, the effectiveness of the technologies should be investigated as well, because the companies need to invest capital for the application. Most of the studies evaluating IoT technologies to prevent accidents on construction sites have not investigated their effects, and this presumably prevents construction companies from adopting IoT technologies.

The aim of this study is to develop a method to evaluate the effectiveness of IoT-based technologies in preventing accidents on construction sites. Based on Heinrich's (1931) accident-causation theory, this study proposes a method to quantify the effectiveness of an IoT-based technology in preventing different types of accidents occurring on construction sites. The applicability of this method is tested with two different IoT technologies. The main contribution of this study is to help practitioners justify investment in IoT technologies to prevent accidents, which will eventually contribute to a safer construction industry.

This study is organized as follows. After the "Introduction" section, in the Literature Review section, the literature about the IoT technologies in safety management and Heinrich's domino theory, which is the theoretical background of the proposed method, are reviewed. In the next section, a method of quantifying the effectiveness of IoT technologies for accident prevention is proposed. The Case Study section provides case studies based on the application of the proposed method to two different types of IoT technology. This is followed by a discussion and conclusions in the last section.

Literature Review

The construction industry has been recognized as one of the most hazardous industries. According to the Occupational Safety and

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Table 1. Definitions of IoT technology

Organization	Definition	References
International Telecommunications Union-Telecommunication Standardization Sector (ITU-T)	A global infrastructure for the information society, enabling advanced services by interconnecting (physical and virtual) things based on existing and evolving interoperable information and communication technologies.	ITU (2012)
Coordination and Support Action for Global RFID-related Activities and Standardisation (CASAGRAS)	A global network infrastructure linking physical and virtual objects through the exploitation of data capture and communication capabilities	CASAGRAS (2009)
IoT European Research Cluster (IERC), Cluster of European Research Projects (CERP)	A dynamic global network infrastructure with self- configuring capabilities based on standard and interoperable communication protocols where physical and virtual "things" have identities, physical attributes, and virtual personalities, use intelligent interfaces, and are seamlessly integrated into the information network.	CERPIIoT (2010) and IERC (2014)
Internet Engineering Task Force (IETF)	Object connection around us (electronic, electrical, and nonelectrical) to provide seamless communication and contextual services.	IETF (2010)
Institute of Electrical and Electronics Engineers (IEEE)	A network of items—each embedded with sensors—which are connected to the internet.	IEEE (2015)

Health Administration (OSHA), 21.1% of workplace fatalities occurred in the construction industry in 2016 (OSHA 2017). In addition to the fatalities, the industry has the third-highest number of nonfatal injuries, resulting in many days away from work among the major industries in 2015 (CPWR 2018). Reducing the number of accidents should be one of the most urgent tasks for the construction industry.

In this section, how IoT technologies have been investigated for safety management is examined. The Heinrich theory, which is the theoretical background of the method proposed in this study, is reviewed.

IoT Technologies for Safety Management

There have been various definitions of IoT technologies. Table 1 summarizes the definitions from various institutes. Even though the meanings of those definitions are slightly different from each other, they generally indicate that IoT technology is a network infrastructure connecting virtual and physical objects in an interoperable manner to provide seamless communication. Based on the definitions in Table 1, IoT technologies for safety management in construction can be described as technologies collecting various kinds of information about workers, equipment, and site circumstances and delivering such information to computers or virtual spaces, such as building information modeling (BIM), to create useful information for safety management and transferring such useful information to related subjects to prevent accidents (Kim et al. 2016b).

IoT technologies have been widely studied as a way to improve safety performance in the construction industry. Those technologies can be classified into three categories, as indicated in Table 2. For the IoT technologies checking physiological conditions, the workers' mental workloads (Chen et al. 2016), body temperature (Yi et al. 2016), heart rate (Faust et al. 2019; Gatti et al. 2014; Hwang et al. 2016; Lee et al. 2020), and breathing rate (Gatti et al. 2014) were measured to evaluate the feasibility of such measures from IoT technologies to prevent accidents.

For physical condition checking, IoT technologies have been studied to check the physical condition of workers, equipment, and construction sites. Kelm et al. (2013) used a mobile passive radio frequency identification (RFID) portal to check the use of personal protective equipment (PPE). The technologies have been tested to identify hazardous areas (Kim et al. 2016a) and slip and trip (Lim et al. 2016), check the safety of concrete formworks using ubiquitous sensor networks (USNs) (Moon et al. 2012, 2015), check the oxygen and temperature that make confined spaces hazardous (Riaz et al. 2014), and monitor the ergonomically safe and unsafe behaviors of construction workers (Cheng and Teizer 2013).

IoT technologies identifying location have been studied to identify the location of workers and equipment. RFID, chirp-spread-spectrum (CSS), ultra-wideband (UWB), global positioning system (GPS), and Bluetooth technologies are being tested for better safety management (Lee et al. 2012; Li et al. 2015; Martinez et al. 2020; Park et al. 2017; Pradhananga and Teizer 2013; Yang et al. 2012). These location-identification technologies can be used to prevent collisions between laborers and between laborers and equipment (Cheng and Teizer 2014; Dzeng et al. 2014; Fang et al. 2016; Golovina et al. 2016; Hwang 2012; Hwang et al. 2016; Park et al. 2016; Ren and Wu 2015; Teizer and Cheng 2015; Vahdatikhaki and Hammad 2015; Wang and Razavi 2016; Zhang et al. 2015). The accuracy of such technologies is critically important to prevent safety accidents (Maalek and Sadeghpour 2016).

One drawback of communication-based technologies is that the strength of the signals received varies depending on time and position; thus, the accuracy can be low because no direct relationship exists between sensing range and signal strength. To reduce this drawback, studies have been performed on the combined use of RFID and GPS (Cai et al. 2014), or RFID, real-time kinematic (RTK), and GPS (Su et al. 2014) technologies. Other purposes of using location-identification IoT technologies for safety management include falling-accident prevention (Jebelli et al. 2016) and construction site monitoring (Ding et al. 2013; Naticchia et al. 2013; Soltanmohammadlou et al. 2019; Yi et al. 2016).

The performance of the technologies in Table 2 was mainly evaluated by two approaches: (1) by constructing an experimental environment where the performance could be reviewed and assessed with actual field applications (AlBahnassi and Hammada 2012; Cai et al. 2014; Chen et al. 2016; Cheng et al. 2013; Cheng and Teizer 2014; Dzeng et al. 2014; Fang et al. 2016; Gatti et al. 2014; Hwang 2012; Hwang et al. 2016; Jebelli et al. 2016; Kelm et al. 2013; Kim et al. 2016a; Lee et al. 2012; Li et al. 2015; Lim et al. 2016; Luo et al. 2014; Maalek and Sadeghpour 2016; Moon et al. 2012, 2015; Naticchia et al. 2013; Park et al. 2016; Pradhananga and Teizer 2013; Ren and Wu 2015; Riaz et al. 2014; Su et al. 2014; Teizer and Cheng 2015; Vahdatikhaki and Hammad 2015; Wang and Cho 2015; Wang and Razavi 2016; Yang et al. 2012; Yi et al. 2016; Zhang et al. 2015; Zhang and Hammad 2012); and (2) by interviewing workers and practitioners to check the effectiveness of such technologies (Ding et al. 2013; Golovina et al. 2016). However, there has been

Table 2. IoT-based safety management technologies

Information type	References	Technology	Research goal	Verification
Checking physiological condition	Chen et al. (2016)	Electroencephalography (EEG) safety helmet	Detection of a person's mental state	Evaluation of usability of technology
	Gatti et al. (2014)	Physiological status monitors	Monitoring of workers' physical conditions	Evaluation of usability of technology
	Hwang et al. (2016)	Photoplethysmography (PPG) sensor	Monitoring of construction worker heart rate	Experimental performance review
	Yi et al. (2016)	Global system for mobile communication (GSM)-based environmental sensor, smart bracelet, and smartphone application	Prevention of accidents in hot and humid environments	Experimental performance review
Checking physical condition (person, equipment, and structure, among others)	Kelm et al. (2013)	Mobile passive RFID portal	Reviewing of worker's personal protective equipment	Experimental performance review
	Kim et al. (2016b)	Real-time location system (RTLS), building information modeling (BIM)	Hazardous-area identification	Experimental performance review
	Lim et al. (2016)	Triaxial accelerometer, smart artificial neural network (ANN)-based slip-trip classification method	Falling and slipping prevention	Experimental performance review
	Moon et al. (2012)	Ubiquitous sensor network (USN)	Safety monitoring of formwork	Experimental performance review
	Riaz et al. (2014)	BIM, wireless sensor	Checking status of enclosed space	Experimental performance review
	Cheng et al. (2013)	Nonintrusive real-time worker location sensing (RTLS) and physiological status monitoring (PSM) technology	Monitoring of unsafe behavior	Experimental performance review
	Ding et al. (2013)	Fiber Bragg grating (FBG) sensor system and RFID-based labor-tracking system	Prevention through real-time field monitoring and worker tracking	Qualitative evaluation of technical effects through interviews
Location identification (RFID and GPS, among others)	Kim et al. (2016b)	RTLS, BIM	Hazardous area identification	Experimental performance review
	Naticchia et al. (2013)	Real-time monitoring system based ZigBee	Health and safety monitoring	Experimental performance review
	Dzeng et al. (2014)	Smartphone (built-in accelerometers)	Collision prevention	Experimental performance review
	Cai et al. (2014)	Location-tracking system (GPS and RFID)	Improved location accuracy	Experimental performance review
	Zhang and Hammad (2012)	RTLS based ultra-wideband (UWB)	Collision prevention	Experimental performance review
	Fang et al. (2016)	Crane motion capturing	Collision prevention	Experimental performance review
	Golovina et al. (2016)	Building information modeling, GPS, heat maps	Collision prevention	Experimental performance review and evaluation of usability of technology
	AlBahnassi and Hammada (2012)	Real-time motion planning system	Collision prevention	Experimental performance review
	Jebelli et al. (2016)	Inertial measurement unit (IMU) sensors	Falling prevention	Experimental performance review
	Park et al. (2016)	Proximity detection and alert system using Bluetooth sensing technology	Collision prevention	Experimental performance review
	Hwang (2012)	Location tracking system (UWB)	Collision prevention	Experimental performance review
	Wang and Razavi (2016)	Condition tracking using GPS and inertial navigation system sensor	Collision prevention	Experimental performance review
	Lee et al. (2012)	RFID-based RTLS	Location tracking	Experimental performance review
	Li et al. (2015)	Chirp-spread-spectrum-based RTLS	Location tracking	Evaluation of usability of technology
	Luo et al. (2014)	RTLS	Improved location accuracy	Experimental performance review
	Maalek and Sadeghpour (2016)	UWB-based RTLS	Improved location accuracy	Experimental performance review
	Pradhananga and Teizer (2013)	GPS	Location tracking	Experimental performance review
	Teizer and Cheng (2015)	Real-time resource location tracking	Collision prevention	Experimental performance review
	Vahdatikhaki and Hammad (2015)	Real-time tracking technologies (pose and location)	Collision prevention	Experimental performance review
	Wang and Cho (2015)	Real-time three-dimensional (3D) scanning	Collision prevention	Experimental performance review
	Ren and Wu (2015)	Locating system that integrates RFID and real-time kinematic (RTK) GPS	Collision prevention	Performance review through field application
	Su et al. (2014)	BIM and GPS	Improved location accuracy	Experimental performance review
	Zhang et al. (2015)	Laser scanner and RTLS	Collision prevention	Experimental performance review
	Cheng and Teizer (2014)	Environment monitoring and location tracking using WSN, RFID, and ZigBee RFID sensor	Collision prevention	Experimental performance review
	Yang et al. (2012)	FBG sensor system and RFID-based labor-tracking system	Location tracking	Experimental performance review

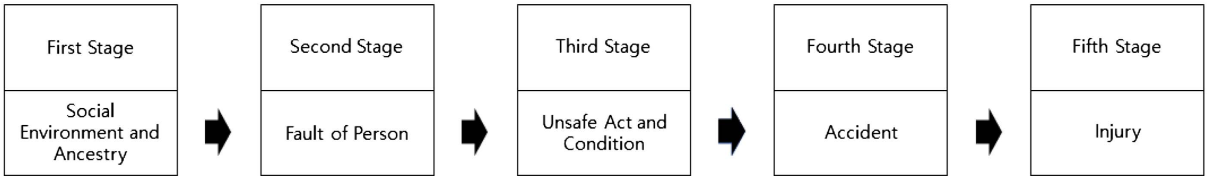

Fig. 1. Five stages in Heinrich's assessment of the occurrence of accidents.

no study quantitatively evaluating the effectiveness of IoT technologies employed for accident prevention.

The lack of an approach to quantifying the impact of IoT technologies has been a main reason why people hesitate to use such technologies. Without quantifying the effects, it is difficult to conduct economic analyses, such as benefit/cost (B/C) ratio or return on investment (ROI). Indeed, econometric analyses assessing the impact of information technology have suffered (Kelley 1994) because the benefits of IT investment are intangible and disproportionately difficult to measure (Brynjolfsson et al. 2002). In the construction industry, most construction companies have not performed formal evaluations of the benefits of IT investments (Churcher et al. 1996; Kang et al. 2015; Karlsson et al. 2008; Kim et al. 2017), which has hindered the adoption of technology as well as restricted the range of application and usefulness (Back and Moreau 2001; Hosseini et al. 2018; Mitropoulos and Tatum 1999). To diffuse more IoT technologies for more-effective project delivery in the construction industry, it is necessary to have methods for quantifying the impact of such technologies.

Heinrich's Domino Theory

Safety means a status without danger. This concept may be supported directly or indirectly because businesses that do not protect lives of their employees are not likely to survive. In a cooperative sense, safety is the protection from accidents in industry, and occupational safety reflects the safety of workers and that of the consumers who buy and/or use the products of various businesses (Lee et al. 2009).

Heinrich (1931) proposed sources of accidents in his domino theory, which pointed toward social climate or personal genetic characteristics. In his book *Industrial Accident Prevention*, Heinrich indicated that accidents occur owing to a chain reaction of the five factors presented in Fig. 1.

Heinrich identified unstable acts and conditions as the factors that function as accident sources and stated that eliminating these should be the objective of safety programs. Also, he demonstrated that the combination of human error and material failure accounts for 98% of all accidental injuries, whereas unavoidable calamities account for only 2%. This indicates that most accidents can be prevented and that risks should be removed as a preliminary measure instead of a countermeasure.

Table 3 provides the detailed factors associated with unsafe behaviors and conditions, as proposed based on Heinrich. In this study, these detailed factors were used as accident causes to evaluate the effectiveness of IoT technologies for accident prevention.

Table 3. Summary of accident causes in the workplace

Category	Causes
Unsafe conditions	Inadequate supports or guardrails
	Defective tools, equipment, or supplies
	Workplace congestion
	Inadequate warning systems
	Fire and explosion hazards
	Poor housekeeping
	Hazardous atmospheric conditions (gases, dust, fumes, and vapors)
	Excessive noise
	Poor illumination
	Poor ventilation
	Radiation exposure
	Operating equipment at improper speeds
	Operating equipment without authority
	Using equipment improperly
Unsafe acts	Using defective equipment
	Disabling safety devices
	Failure to warn coworkers or to secure equipment
	Failure to use PPE
	Improper loading or placement of equipment or supplies
	Taking improper working position
	Improper lifting
	Servicing operating equipment
	Horseplay
	Use of alcoholic beverages and drugs
	Lax safety assurance
	Failure to conduct work procedures properly
	Approaching dangerous locations
	Improper positions for performing work

Quantifying the Effectiveness of IoT Technologies for Accident Prevention

In this section, the step-by-step process for quantifying the effectiveness of IoT technologies for accident prevention is presented. Fig. 2 summarizes the process. First, it is assumed that IoT technologies used for safety management should contribute to removing the accident causes, which should lead to lowering the number of accidents according to Heinrich's theory. The prevention effect was quantified by considering two aspects: (1) quantifying the association between accident causes and accident types by expert survey, and (2) quantifying the impact of each accident type by considering the accident statistics. In this section, more details about each step are presented.

The first step is to quantify the degree that a certain IoT technology reduces accident causes. Heinrich's theory claimed that accidents can be prevented by removing the causes of accidents owing to unstable behavior and conditions as they are caused by unstable ones (Heinrich 1931). This concept can be used to represent the characteristics of a construction site. According to Heinrich's logic, the effects of accident prevention can be assessed by removing accident causes. That is, the effects of the IoT technology on accident prevention can be evaluated based on the portion of accident causes to be reduced because of the use of IoT technology. A survey was developed to evaluate the degree that a certain IoT technology reduces certain types of accident causes. More details about the survey are presented in the next section.

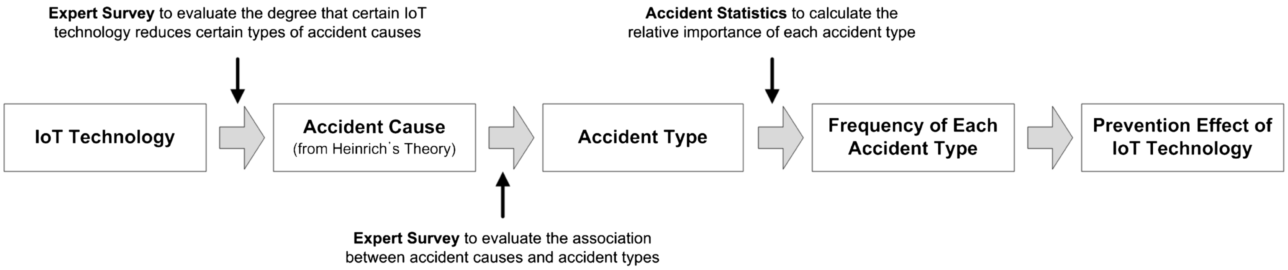

Fig. 2. Proposed process quantifying the effectiveness of IoT technologies for accident prevention.

The second step is to link the association between accident causes and accident types. There are various types of accident on construction sites. A single accident cause is not associated with all accident types, and all causes are not related to a single type. Thus, the associations among various accident causes and accident types should be observed in order to evaluate the effects of preventing accidents due to the elimination of accident causes. In this study, another set of surveys was developed for this. More details about the survey are provided subsequently.

The third step is to calculate the accident frequencies for each accident type. Each accident type has a different impact on construction safety because each has a different occurrence frequency. The ratios of accident types among all accidents are considered and applied to the respective accident types to evaluate the overall accident-prevention effect.

Fig. 3 shows the relationships among IoT technology, accident cause, and accident type. The association between accident causes and types is C_iA_k, the degree of reducing accident causes by IoT technology is TC_i, and the ratio of accident types in all accidents is R_k. When observing each evaluation component, TC_i refers to the degree of accident cause reduction using IoT technology, which evaluates the degree of technical prevention as 0%–100% for n accident causes. Because C_iA_k refers to the association between the accident types and their causes, the association of n (number) causes and m (number) types is represented as 0%–100%. The sum of a single accident type and the association between causes should be 100%. Because R_k refers to the ratios of the accident types making up the entire list of accidents, it is calculated as the number of people injured or killed. At the time, the fact that the importance of those injured and killed differs should be considered when estimating the ratios.

Accordingly, an evaluation of the accident-prevention effect of IoT technology is made using the accident-prevention effect on accident types and the total accident-prevention effect. First, the prevention effect evaluation based on the accident type can be calculated as the accident-prevention degree of the technology with respect to the causes and the association between accident causes and types. In other words, it is calculated as $TC_i \times C_iA$, and, because causes exist for n (number) accidents, the effect (E) can be calculated as shown in Eq. (1)

$$E_k = \sum_{i=1}^{n} (\mathrm{TC}_i \times C_iA_k) \tag{1}$$

where C_i = ith cause of accidents; TC_i = degree of preventing causes (C_i) based on the technology used; and C_iA = association between accident cause (C_i) and type (A).

Fig. 4 provides an example of the evaluation of the accident-prevention effect of technology T for type A. There are four accident causes, namely C_1, C_2, C_3, and C_4. The accident-prevention degrees associated with the four causes are 20%, 50%, 30%, and 0%, respectively. Furthermore, the association between the accident causes and the types is 10%, 20%, 40%, and 30%, respectively. At this time, the accident-prevention effect of technology on accident type A is calculated as 24%. This calculation considers the simple relationship between one type of accident cause and one type of accident, which is different from the multiple causation theory that there are many contributory factors behind a single accident (Petersen 1971). These contributory factors are classified into behavioral and environmental factors. When quantifying the impact of certain accident causes on certain accidents, it is impossible to consider these factors. More discussion is provided in Section 5.

Second, the total accident-prevention effect is calculated as R_k, the ratios of the accident types about total accidents, and E, the prevention effect of the type calculated using Eq. (1). Moreover,

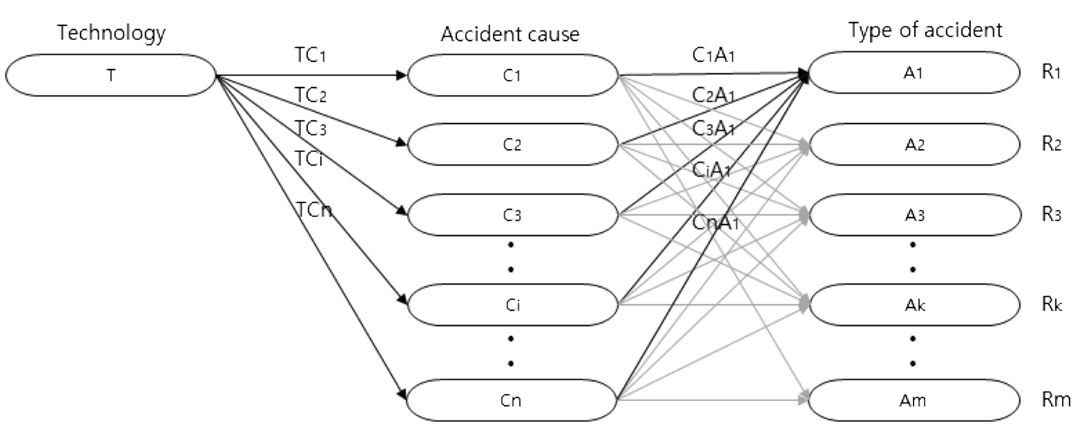

Fig. 3. Relationship among technology, accident cause, and accident type.

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	TC_i		C_iA		
C_1	20%	X	10%	=	2%
C_2	50%	X	20%	=	10%
C_3	30%	X	40%	=	12%
C_4	0%	X	30%	=	0%
Total			100%	=	24%

Fig. 4. Example calculation of accident-prevention effect of technology T for type A.

		TC_i		C_iA		R_k	
	C_1	20%	X	10%			
A_1	C_2	50%	X	20%			
	C_3	30%	X	40%			
E_1			=	24%	X	60%	= 14.4%
	C_1	20%	X	50%			
A_2	C_2	50%	X	50%			
	C_3	30%	X	0%			
E_2			=	35%	X	40%	= 14%
Total							= 28.4%

Fig. 5. Example calculation of total accident-prevention effect of technology T.

because this is the sum of m (number) types, it can be represented by Eq. (2)

$$\mathrm{TE} = \sum_{k=1}^{m}(E_k \times R_k) \tag{2}$$

where R_k = ratio of accident types A_k among entire accidents; and E_k = prevention effect of accident type A_k.

Fig. 5 provides an example of an evaluation of the total accident-prevention effect of technology T. The accident types are A_1 and A_2, and the accident causes are C_1, C_2, and C_3. When the accident-prevention effect (E) is calculated, E_1 is 24%, E_2 is 35%, and the total accident-prevention effect is calculated by applying each accident type ratio (R) to this: A_1 is 14.4% and A_2 is 14%. Therefore, the total accident-prevention effect is 28.4%.

Case Study

The previous section describes the method of evaluating the effectiveness of IoT technology on accident prevention. This section presents the applicability of the proposed method with two different types of IoT technology. Fig. 6 shows the application procedure for the method proposed in this study. The figure designates the roles responsible for each step. As shown in the figure, various types of experts within an organization should be involved in the process. For example, the IT management team within a company knows most about the technologies available for reducing accidents. Thus, if a company considers using IoT technologies to reduce accidents, the team should be able to propose the technologies. For an IoT technology proposed by the team, safety managers should review the technology to determine the impact on accident causes, TC_i in Fig. 3. This is because they know most about accidents occurring on construction sites. The relationships between accident causes and accident types (C_iA_k in Fig. 3) can be evaluated by project managers and safety managers who have expertise on accident causes and accident types. To quantify the impact of a certain accident type, its frequency should be obtained. Accident statistics can be used for this step. In this section, each step is further described in the following subsections.

Quantifying the Degree to Which IoT Technology Reduces Accident Causes

The first step is to identify IoT technologies presumably contributing to reducing the number of accidents. The IT management team within a company, which should be familiar with new technologies, can propose IoT technologies contributing to reducing accidents. In this study, two IoT technologies summarized in Table 4 were considered. As indicated in the table, the technologies considered in this study are technology automatically identifying hazardous areas (Kim et al. 2016a) and technology monitoring the worker's heart rate with a photoplethysmography (PPG) sensor on a real-time basis (Hwang et al. 2016).

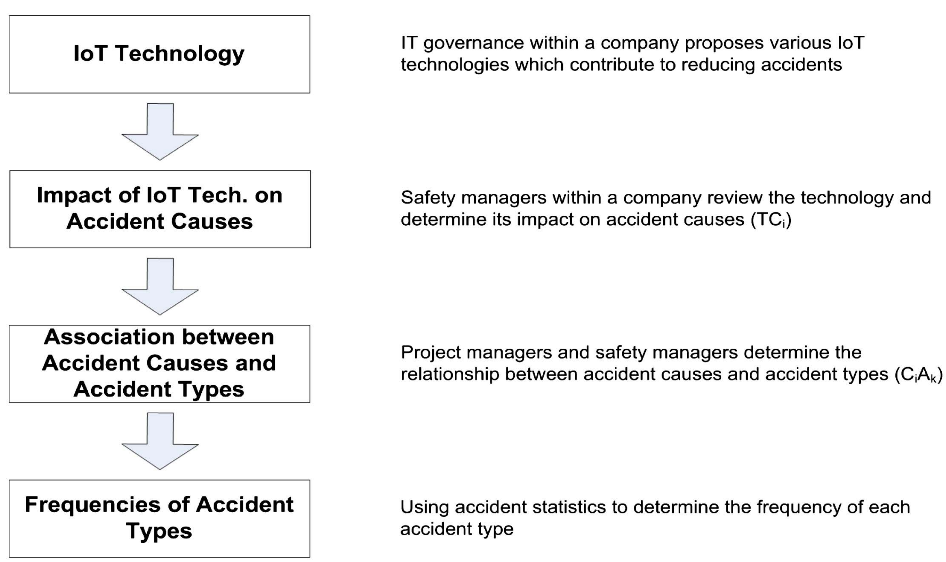

Fig. 6. Application procedure.

Table 4. IoT technologies tested for the proposed method

Category	References	Contents
Tech 1	Hwang et al. (2016)	Real-time heart-rate monitoring of construction workers using a PPG sensor
Tech 2	Kim et al. (2016a)	Automated identification technology of hazardous areas at construction sites using an RTLS BIM

To quantify the degree to which each IoT technology reduces accident causes, a survey was developed. For the IoT technologies in Table 4, the authors prepared a description about each technology. After obtaining general information from respondents in terms of overall working experience and safety management experience, experts were asked how much in terms of percentage values this technology contributes to reducing each accident cause listed in Table 3. For example, if a respondent selects 30%, that means the technology can reduce the accident cause by 30%.

Overall, 10 respondents participated in the survey. Table 5 summarizes the average prevention effects of each technology on each accident cause. As indicated in the table, Tech 1 shows high prevention percentage values for the use of alcoholic beverages and drugs (90%) and poor ventilation (76%). This is reasonable because those accident causes should directly influence the heart rate. By using this technology, such accident causes will be detected in real time, which will contribute to reducing the accident causes and eventually decreasing accidents related to them. Tech 2, however, shows higher percentage values for workplace congestion (76%) and improper loading or placement of equipment or supplies (72%).

Association between Accident Causes and Accident Types

The association between accident causes and accident types was determined by another set of survey. The type of accidents was taken from the Construction Safety Management Information System (COSMIS) in South Korea, which manages statistics about construction accidents in South Korea (COSMIS 2019). For each accident type, respondents were asked the degree to which each accident cause leads to a certain type of accident with a range of 0–100%. A higher percentage value means that the accident cause tends to lead to the type of accident more.

A total of 32 safety management experts participated in the survey. They had more than 5 years of work experience by average at construction sites. Table 6 summarizes the mean values for each association. As indicated in the table, the sum of the associations between accident causes and each accident type is 100%. The table provides some interesting findings. First, failure to use PPE is the accident cause most contributing to falling. This finding is consistent with other studies asserting that the use of PPE is the most important aspect to reduce fall accidents (Kang 2018). Workplace congestion is the accident cause most related to hit (collision) and hit by falling or flying objects. This indicates that managing the workplace in a way to distribute various resources evenly, such as material, equipment, and labor, is important to reduce accidents by being hit. Managing the ventilation is important to reduce the accident type "contact with harmful material," because the accident cause has the highest percentage value for the accident type.

Frequency of Accident Types

Regarding the frequency of accident types, construction accident statistics provided by COSMIS were used. The system has collected

Table 5. Prevention effects of each IoT technology on each accident cause

Accident cause	Accident-prevention capability (%)	
	Tech 1	Tech 2
Inadequate supports or guardrails	18	40
Defective tools, equipment, or supplies	22	26
Workplace congestion	34	76
Inadequate warning systems	40	64
Fire and explosion hazards	32	50
Poor housekeeping	32	58
Hazardous atmospheric conditions (gases, dust, fumes, and vapors)	66	54
Excessive noise	34	8
Poor illumination	24	28
Poor ventilation	76	40
Radiation exposure	44	32
Operating equipment at improper speeds	30	48
Operating equipment without authority	2	6
Using equipment improperly	22	26
Using defective equipment	20	22
Disabling safety devices	18	52
Failure to warn coworkers or to secure equipment	38	44
Failure to use PPE	34	26
Improper loading or placement of equipment or supplies	18	72
Taking an improper working position	38	6
Improper lifting	8	18
Servicing operating equipment	4	28
Horseplay	20	10
Use of alcoholic beverages and drugs	90	14
Lax safety assurance	52	38
Failure to conduct work procedures properly	27	32
Approaching dangerous locations	42	68
Improper positions for performing work	68	62

recordable incidents and fatalities. By using the data for accidents that occurred for two recent years (2016 and 2017), the significance of each accident type was calculated such that one fatality is regarded as five recordable incidents. This is based on an article in the law of South Korea, Article 3.2 of the Enforcement Decree of the Industrial Safety and Health Act.

Table 7 presents the significance for accident type. The significance value was calculated by the ratio of overall impact of an accident type to the total overall impact. For example, the numbers of fatalities and recordable incidents were 32 and 48, respectively. So, the overall impact was 208 ($32 \times 5 + 48$). The significance was calculated by the ratio of overall impact of falling (208) to the total of overall impact (1,915). From the table, it was found that destroying is the accident type with the highest significance.

Calculation of Prevention Effect of IoT Technology

Based on the results presented in the previous subsections, the prevention effects of IoT technologies were evaluated. The results are summarized in Table 8. Tech 1 was most effective in preventing contact with harmful material (44.8%). As indicated in Table 6, poor ventilation is the accident cause highly associated with contact with harmful material. Because Tech 1 has a high accident-prevention capability, as indicated in Table 5, Tech 1 shows the highest prevention effect in Table 8. Tech 2, however, shows the greatest effect on preventing destroying (48.6%) and traffic accidents (48.3%). Improper loading or placement of equipment or suppliers and approaching dangerous locations are the accident causes

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Table 6. Evaluation results of association between accident types and their causes

	Accident types											
Accident causes	Falling (collapse)	Buried/capsized (reversal)	Hit by falling or flying objects	Hit (collision)	Stuck (cramped)	Destroying (destruction or crumble)	Contact with harmful material	Electric shock	Explosion	Rupture	Traffic accident	Stumble (conversion)
Inadequate supports or guardrails	0.5	1.4	0.5	1.8	3.6	4.5	3.6	3.2	0.5	3.2	0.5	0.5
Defective tools, equipment, or supplies	8.2	2.7	2.8	0.0	1.8	2.3	3.2	11.1	11.9	14.2	0.0	7.0
Workplace congestion	3.5	11.8	15.7	16.1	5.5	2.3	10.9	8.8	1.8	2.8	23.8	22.9
Inadequate warning systems	1.2	2.3	3.2	10.3	1.8	2.7	10.0	4.6	6.4	5.0	11.2	1.4
Fire and explosion hazards	0.9	0.0	1.9	0.0	0.0	12.7	2.7	0.0	33.0	6.0	0.0	0.0
Poor housekeeping	1.4	8.2	12.0	4.5	5.5	12.7	5.5	12.5	6.4	7.3	4.5	10.7
Hazardous atmospheric conditions (gases, dust, fumes, and vapors)	0.0	0.0	0.0	0.0	0.5	0.0	2.7	0.5	3.2	0.0	0.0	0.0
Excessive noise	0.0	0.0	0.0	2.7	0.9	0.0	2.7	0.9	0.0	0.0	1.8	1.9
Poor illumination	5.4	5.5	0.9	3.4	2.3	0.0	6.4	7.4	2.8	7.3	3.0	15.9
Poor ventilation	0.0	0.0	0.0	0.0	0.0	0.0	18.2	0.0	11.5	0.0	0.0	0.0
Radiation exposure	0.0	0.0	0.0	0.0	0.5	0.0	0.5	0.0	0.0	0.0	0.0	0.0
Operating equipment at improper speeds	0.0	5.5	2.3	15.7	8.6	1.8	0.0	0.0	0.0	2.8	14.5	5.6
Operating equipment without authority	0.5	2.3	1.4	5.9	2.3	1.8	0.0	1.9	2.3	6.9	6.5	3.3
Using equipment improperly	8.1	14.5	2.3	4.3	4.5	5.0	0.0	0.9	0.9	7.3	0.9	0.9
Using defective equipment	6.8	9.5	0.5	3.6	11.4	1.4	0.5	0.9	0.9	6.9	2.7	2.3
Disabling safety devices	2.0	3.2	0.6	1.4	8.2	0.5	0.0	7.4	1.4	4.1	2.7	1.4
Failure to warn coworkers or to secure equipment	2.7	0.9	1.9	6.4	7.7	4.5	2.3	2.3	0.9	1.4	3.2	2.3
Failure to use PPE	21.2	0.0	4.6	2.3	5.5	0.0	9.5	2.8	0.0	1.4	0.0	0.0
Improper loading or placement of equipment or supplies	0.0	1.8	8.1	0.5	3.2	10.5	1.4	3.7	0.9	2.3	2.3	5.6
Taking an improper working position	6.8	0.0	0.0	0.0	5.5	0.0	0.0	0.0	0.0	0.9	0.0	4.7
Improper lifting	3.9	2.3	7.4	0.9	3.6	1.4	0.0	0.0	0.0	0.0	0.0	0.5
Servicing operating equipment	0.9	5.0	0.9	1.2	0.0	0.0	0.0	0.9	0.0	1.8	5.9	0.5
Horseplay	0.2	0.2	0.0	2.0	0.5	0.0	0.9	0.0	0.0	0.0	0.9	0.5
Use of alcoholic beverages and drugs	1.5	3.3	0.0	2.7	0.9	0.0	3.2	0.9	0.0	0.0	6.8	1.4
Lax safety assurance	3.0	2.7	5.6	2.5	3.6	9.5	5.9	13.0	3.7	4.1	3.2	2.3
Failure to conduct work procedures properly	7.5	7.7	4.8	8.2	6.4	14.1	1.4	10.2	10.5	9.6	2.7	0.9
Approaching dangerous locations	7.7	3.8	15.1	2.1	0.5	10.5	7.7	4.2	0.9	3.7	1.8	6.1
Improper positions for performing work	6.3	5.5	7.4	1.5	5.5	1.8	0.9	1.9	0.0	0.9	0.9	1.4
Total	100	100	100	100	100	100	100	100	100	100	100	100

Table 7. Relative importance of accident types

Accident types	Fatality (A)	Recordable incident (B)	Overall impact ($A+B$)	Significance (ratio)
Falling (collapse)	32 (160)	48	208	0.109
Buried/capsized (reversal)	44 (220)	51	271	0.142
Hit by objects (falling or flying)	36 (180)	29	209	0.109
Hit (collision)	15 (75)	18	93	0.049
Stuck (cramped)	8 (40)	18	58	0.030
Destroying (destruction or crumble)	150 (750)	213	963	0.503
Contact with harmful material	2 (10)	2	12	0.006
Electric shock	0 (0)	1	1	0.001
Explosion	8 (40)	14	54	0.028
Rupture	2 (10)	3	13	0.007
Traffic accident	3 (15)	3	18	0.009
Stumble (conversion)	0 (0)	15	15	0.008
Total	300 (1,500)	415	1,915	—

Table 8. Results of effects on accident prevention by accident type

	Prevention effect (%)	
Accident types	Tech 1	Tech 2
Falling (collapse)	32.8	34.1
Buried/capsized (reversal)	29.9	41.7
Hit by objects (falling or flying)	0.0	0.0
Hit (collision)	31.6	44.6
Stuck (cramped)	30.3	39.1
Destroying (destruction or crumble)	31.5	48.6
Contact with harmful material	44.8	46.0
Electric shock	31.9	44.8
Explosion	36.4	43.9
Rupture	26.1	37.8
Traffic accident	33.1	48.3
Stumble (conversion)	30.6	47.5

Table 9. Results of evaluation of total accident-prevention effects

		Prevention effect (%)	
Accident types	Rate of accident types	Tech 1	Tech 2
Falling (collapse)	0.109	3.57	3.72
Buried/capsized (reversal)	0.142	4.25	5.93
Hit by objects (falling or flying)	0.109	0.00	0.00
Hit (collision)	0.049	1.55	2.19
Stuck (cramped)	0.030	0.91	1.17
Destroying (destruction or crumble)	0.503	15.83	24.44
Contact with harmful material	0.006	0.27	0.28
Electric shock	0.001	0.03	0.04
Explosion	0.028	1.02	1.23
Rupture	0.007	0.18	0.26
Traffic accident	0.009	0.30	0.43
Stumble (conversion)	0.008	0.24	0.38
Total accident-prevention effect		28.15	40.07

highly associated with destroying, as revealed in Table 6, and Tech 2 shows high prevention effects on these accident causes, as indicated in Table 5. Construction companies have different proportions of accident types. Information in Table 8 should be helpful for construction companies to select appropriate technologies with the consideration of accident types they mainly experience.

The overall accident-prevention effect can be calculated with the frequencies of accident types provided in Table 7. Table 9 summarized the results. Techs 1 and 2 achieved 28.15% and 40.07% of prevention effect, respectively. Destroying shows the highest accident significance in South Korea. Thus Tech 2, which has a high prevention effect on destroying, shows higher total accident-prevention effectiveness than Tech 1.

As a way to validate the method, a series of interviews was conducted with industry experts who participated in the surveys. They were asked about the accuracy, objectivity, and rationality of the proposed method. In general, most of the respondents agreed that the method can be accurate, objective, and rational. One concern that some raised was that the evaluation can be subjectively quantified based on the respondents' experience. To resolve the issue, some interviewees recommended ways to screen the survey respondents by work experience (i.e., respondents should have more than 5 years of experience) or expertise (i.e., only safety managers should participate in the survey). More discussion about this is provided in the next section.

Discussion and Conclusion

Various IoT-based safety management technologies have been proposed to prevent accidents. However, the current body of knowledge lacks a method for quantitatively evaluating the effectiveness of such technologies, which presumably is one reason why they have not been deployed widely. To fill the research gap, this study proposes a method quantitatively measuring the effectiveness of IoT-based safety management technology on accident prevention. Based on the Heinrich's domino theory, this method takes three aspects into account: technology's capability to prevent accident causes, association between accident types and causes, and relative importance of accident types in terms of their frequency. The capability of certain IoT technology to prevent accident causes, as provided by Heinrich and presented in Table 3, can be evaluated by a survey responded to by safety managers in the field. The association between accident types and accident causes can be measured by another survey responded to by safety and project managers. The importance of each accident type can be represented by the frequency of each accident type.

To test the applicability of the proposed method, two IoT technologies were applied to the proposed method. The capability of two types of IoT technology in preventing accidents was measured by a survey responded to by 10 safety managers with 5 years of safety management experience on average. The association between accident types and accident causes was evaluated by a survey in which 32 safety and project managers participated. Accident statistics from COSMIS in Korea were used for the relative importance of each accident type. The results, as presented in Tables 8 and 9,

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successfully provide the effectiveness of each technology for preventing certain types of accident as well as the overall accident-prevention effect. A series of interviews softly validated the accuracy, objectivity, and rationality of the proposed method.

The main contribution of this study is that practitioners can quantify the effectiveness of certain IoT technologies that they are considering for implementation. This should help them compare various kinds of IoT technology, prioritize them, and justify the investment to execute them. Because the lack of a method for quantifying the effectiveness of a certain IoT technology has been a main barrier in deploying IoT technologies in the construction industry, the method is expected to eliminate this shortcoming. This can lead to deploying more IoT technologies for safety management. This should eventually contribute to decreasing accidents in the construction industry.

For the process of applying the proposed method, it is important that practitioners using the technology and benefitting from the use of technology participate in the evaluation process. Even for a single technology, the effectiveness for accident prevention can differ by project. This is because factors influencing the impact, such as site circumstances, ways to manage construction sites, resources being used for a project, and risks about safety, should vary depending on project characteristics and the management philosophy of a company, as well as the project manager. Indeed, the overall benefit, as well as the impact of IoT technology application, should differ by company and by project because of the aforementioned factors. Thus, for companies to quantify the prevention effect of IoT technology properly, they should evaluate the effects according to their own employees.

This study is not free from limitations. The first limitation is related to the multiple causation model proposed by Petersen (1971). The model has been used in many studies investigating the root causes of accidents in the construction industry (Abdelhamid and Everett 2000; Eteifa and El-adaway 2018; Wong et al. 2018). In the model, there are many contributory factors, classified into behavioral factors and environmental factors, behind a single accident. Thus, although the approach proposed in this study considers the one-to-one relationships between accident causes and accident types, there probably exist many-to-many relationships among them. However, it is impossible to consider these relationships when quantifying the impact of certain accident causes on certain accidents. The expert survey data necessary for the evaluation of the association between accident causes and accident types, as well as the actual accident data (if any), would not be sophisticated enough to capture these many-to-many relationships. In addition, when comparing the two different IoT technologies, the relationships among accident types and accident causes are applied equally. Therefore, the result from the comparison should still help practitioners compare various IoT technologies and prioritize them.

The second limitation of this study is validation. By interviewing practitioners, this study tried to validate the usefulness and suitability of the proposed method. They agreed that the method made sense and should be useful to quantify the effects of certain IoT technologies for safety management. However, the accuracy of the results from the method could not be strictly validated.

Even though the accuracy cannot be validated, there are certain ways to improve it. First, if a company keeps the accident record by accident cause and accident type, the results from the proposed method can be more accurate and convincing for the company. This should be particularly true for quantifying the overall effect of certain IoT technologies on safety management. The second source of inaccuracy from the method is that the surveys done for the method can be subjective. Thus, results from the method are highly dependent on the respondents. Because the effect varies depending on characteristics of projects and companies, as discussed previously to produce accurate and consistent results from the proposed method, many respondents from different fields of expertise, including project management, safety, and information technology, should participate in the survey. Case studies employing this method and showing the improvement of safety performance are also recommended in the future to validate the usefulness of the proposed method.

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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