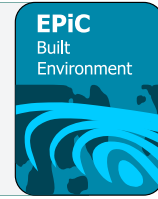




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# Decision Support Framework for Selecting Wearable Internet of Things Devices for Safety Management in Construction

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Construction workers are usually faced with many safety and health risks due to the hazardous nature of the construction work environment. The application of emerging safety technologies such as wearable sensing devices (WSDs) and the Internet of things (IoT) has been identified as one of the most effective means of predicting future performance and preventing these risky events. In spite of the benefits of these devices, their implementation on construction sites to protect workers and improve their safety performance is still limited. Several IoT-based wearable sensing devices are being used in other industries to monitor metrics that are similar to those that can be monitored to manage workers' safety on construction jobsites. Hence, there is a need to develop some criteria for evaluating these devices for their applications in construction. The main purpose of this study is to develop a conceptual decision-making framework that stakeholders can use to select Wearable Internet of Things (WIoT) devices for applications in construction. The research approach involves a review of literature on WIoT devices and the development of a decision-making framework using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). This study presents an initial attempt geared toward providing stakeholders with an effective decision-making tool that can be used to select WIoT devices for implementation in the construction industry.

**Keywords:** Construction Safety, Decision Support Framework, Internet of Things, TOPSIS, Wearable Sensing Devices,

## Introduction

Workers on construction jobsites are often faced with many safety and health risks due to the hazardous nature of the construction work environment. According to the reports of the U.S. Bureau of Labor Statistics, the construction industry accounts for one of the highest counts of fatal and non-fatal injuries among industrial sectors (BLS, 2020). Although different safety management approaches have been developed and are currently being applied for the reduction of the unpalatable trends, these approaches, characterized by the use of lagging indicators have not proven to be effective in achieving zero injuries and fatalities on construction jobsites (Hinze et al., 2013; Awolusi & Marks, 2017). An alternative

approach is the use of leading indicators, which can be utilized to predict future performance and prevent injuries, illnesses, or accidents (Hallowell et al., 2013; Mark et al., 2016).

Researchers and industry practitioners have identified the application of emerging safety technologies such as wearable sensing devices (WSDs) and the Internet of things (IoT) as one of the most effective means of preventing accidents and predicting future safety performance on construction sites (Nath et al., 2017; Choi et al., 2017; Awolusi et al., 2018; Yeo et al., 2020; Nnaji et al., 2020). Advances in wearable and big data technologies provide an effective method of collecting and transforming safety and health data in real-time, which has great potential to improve safety performance by reducing illness and injury-related risks (Wu et al., 2016; Shen et al., 2017; Yeo et al., 2020). Wearable devices perform a wide range of functions including data collection from on-body sensors, preprocessing the data, temporary data storage, and data transfer to internet-connected immediate neighbors such as mobile phones or a remote server (Hiremath et al., 2015; Arias et al., 2015).

The WIoT is a novel concept that provides the possibility of safety and health monitoring using IoT-based WSDs that offer huge potential to collect and analyze rich data and provide insights for improving safety performance. Despite the benefits of these devices, their implementation on construction sites to protect workers and improve their safety and health performance is still limited (Choi et al., 2017; Awolusi et al., 2019). Several IoT-based wearable devices have been used in other industries to monitor metrics that are similar to those that can be monitored and tracked to manage workers' safety on construction jobsites. Because there is little information available to allow the construction manager to make informed decisions to identify and implement suitable devices among these commercially available ones, there is a need to develop some criteria for evaluating these devices for applications in construction. The main purpose of this study is to develop a conceptual decision-making framework for selecting WIoT devices for implementation in the construction industry.

## Literature Review

### *Construction Incident Statistics and Safety Hazards*

Globally, the construction work environment is one of the most dangerous when compared to other industries. In 2019, a total of 1,061 U.S. workers lost their lives in the construction industry (BLS, 2020). A large number of people who work in construction jobsites are regularly exposed to a wide variety of safety and health hazards which increase the potential for developing illnesses, getting injured, disabled, or even losing their life. Some of the common safety and health hazards for construction workers include: falls from height due to improper erection of scaffolding or use of ladders; electrocution due to contact with energized sources; struck by or caught-in or -between moving equipment working close to workers; repetitive motion injuries; and heat exhaustion or heat stroke due to body temperature rising to dangerous levels. There is a need to explore other effective methods of improving construction workers' safety performance and the implementation of emerging safety technologies such as WIoT has been identified as one of the most promising methods. In this study, the construction focus four hazards (falls, electrocution, struck-by, and caught-in or -between) will be used for evaluating WIoT devices that can be selected for use for safety management on construction jobsites.

### *Wearable Sensing Devices and the Internet of Things*

Wearable devices have attracted much attention from the academic community and industry within the last decade and have recently become very popular. Wearable electronics have been described as

devices that can be worn by humans to continuously and closely monitor an individual's activities, without interrupting or limiting the user's motions (Gao et al., 2016; Haghi et al., 2017). The most commonly used wearable sensors include wearable body temperature sensors, pulse, and blood oxygen level sensors, accelerometers for motion sensing, airflow sensors, electrocardiograms, and galvanic skin response sensors (Davenport & Lucker, 2015; Kumari et al., 2017). These sensors and systems are capable of detecting, monitoring, and tracking both personal and environmental properties or data that can be used for workers' safety management in high-risk work environments such as construction jobsites. Although not currently prevalent in the construction industry, these sensors and systems are deployed in wearable devices used in sectors such as healthcare, athletics, and business for monitoring health, safety, productivity, among others.

The IoT is the network of physical objects which are supported by embedded technology for data communication and sensors to interact with both internal and external objects states and the environment (Haghi et al., 2017). With IoT, digital and physical entities can be linked, using appropriate information and communication technologies, to enable a unique class of applications and services. The concept of IoT provides a solid framework for interconnecting edge computing devices—wearable sensors and smartphones—and cloud computing platforms for seamless interactions (Hiremath et al., 2015). Using the IoT, application-specific solutions can be created by interconnecting physical objects through the internet, and allowed to collaborate to achieve assigned tasks. Although IoT has emerged as a disruptive technology finding its applications in different industrial sectors and areas (Kumari et al., 2017), its adoption in the construction industry, particularly for safety management is still at the nascent stage.

The recent growth in the popularity of interconnected wearable devices with sensing, computing, and communication capability has been very rapid, paving the way for a new category of technology called Wearable Internet of Things (WIoT). Although more prevalent in other industries (such as healthcare, sports, and fitness), the use of IoT-Based wearable devices (i.e. WIoT devices) has only found limited applications in the construction industry for safety management. Given the recent development, there is a pressing need to explore the decision-making process to evaluate and select the most appropriate WIoT devices for safety management on construction sites.

### *Technology Selection Framework*

Technology selection is the process of assessing the potential value of technologies and their contribution to the competitiveness and profitability of organizations (Farshidi et al., 2018). Because so many factors need to be considered, the technology selection process is usually complex and often modeled as a multi-criteria decision-making (MCDM) problem which entails the evaluation of a set of alternatives and taking into account a set of decision criteria (Becker et al., 2013; Nnaji et al., 2018; Farshidi et al., 2018). MCDM is the process of making decisions between several alternatives by defining the decision criteria and their weights. The procedure enables the determination of the optimal choice among a set of options over the set of multiple criteria (Rani & Mishra et al., 2020). The process leads to the ranking of alternatives, from the most to the least favorable, thus allowing comparison of alternatives (Milenković et al., 2018). A few of the MCDM approaches that have been used in different fields (such as management, engineering, and economy) include the analytic hierarchy process (AHP) (Zubaryeva et al., 2012; Kumru & Kumru, 2014; Milenković et al., 2018), the technique for order of preference by similarity to ideal solutions (TOPSIS) (Chen et al., 2014; Milenković et al., 2018), grey evaluation method (GE) (Pai et al., 2007; Milenković et al., 2018), simple additive weighting (SAW) (Jakimavičius & Burinskiene, 2009; Milenković et al., 2018), ELimination and Choice Expressing the

REality (ELECTRE) (Hassan et al., 2018), and Strengths-Weakness-Opportunities-Threat (SWOT) analysis (Milenković et al., 2018). Table 1 presents a summary of these different MCDM approaches.

Table 1  
*Common MCDM Approaches for Technology Selection*

<b>MCDM Approach</b>	<b>Description</b>	<b>Strengths</b>	<b>Weaknesses</b>
Analytical hierarchy process (AHP) applications	Based on decomposing a complex MCDM problem into hierarchies.	<ul style="list-style-type: none"> <li>• Seeks consistency in judgments.</li> <li>• Enables users to formulate their opinions.</li> </ul>	<ul style="list-style-type: none"> <li>• Ineffective handling human's subjective judgments.</li> </ul>
ELimination and Choice Expressing the REality (ELECTRE)	Deals with the "outranking relations" using pair-wise	<ul style="list-style-type: none"> <li>• Treats qualitative and quantitative scales of criteria.</li> <li>• Treats reasons for and against an outranking.</li> </ul>	<ul style="list-style-type: none"> <li>• Inappropriate for scoring actions.</li> <li>• No property of independence with respect to irrelevant actions.</li> </ul>
Grey relational analysis (GRA)	Estimates a set of alternatives in terms of decision attributes.	<ul style="list-style-type: none"> <li>• Suitable to handle both incomplete information and unclear problems.</li> </ul>	Does not attempt to find the best solution.
Simple additive weighting (SAW)	Based on weighted summation of rating the performance of each alternative on all alternative criteria.	<ul style="list-style-type: none"> <li>• Can be used to perform judgments more precisely because it is based on pre-defined value and preference weight.</li> </ul>	<ul style="list-style-type: none"> <li>• Requires normalizing decision matrix to a scale comparable to the ratings of existing alternatives.</li> </ul>
Strengths-Weakness-Opportunities-Threat (SWOT) analysis	Structured method that evaluates the strengths, weaknesses, opportunities, & threats of alternatives.	<ul style="list-style-type: none"> <li>• Allows expert knowledge acquisition from both explicit and implicit knowledge.</li> </ul>	<ul style="list-style-type: none"> <li>• Does not provide solutions or offer alternative decisions.</li> <li>• Cannot be used to choose the best ideas</li> </ul>
Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)	Basic concept is that the chosen alternative should have the shortest distance from the ideal solution and the farthest from the negative ideal solution.	<ul style="list-style-type: none"> <li>• Limited amount of subjective input is needed.</li> <li>• Identifies the best alternative quickly.</li> <li>• Applicable to qualitative and quantitative data</li> </ul>	<ul style="list-style-type: none"> <li>• Risk determination of decision maker while giving different input ratings.</li> </ul>

## Research Method

This section explains the research methodology implemented for this study. The research approach involves a review process and the presentation of the elements of the decision-making framework developed in this study. The study is divided into two major phases which are phase I – review of

literature on WIoT devices and phase II – decision-making benchmarking of the WIoT devices. In consideration of those two phases, a mixed-method research design was used in this study. During phase I, a qualitative method was adopted through a systematic literature review. The implementation of the systematic literature review focused on commercially available WIoT devices and information publicly available for the devices. This was done by probing the “Google” search engine and using keywords informed by preliminary and previous studies conducted by the research team. In phase II, a decision-making framework is developed to evaluate and select the WIoT devices that can be applied for safety management in construction. The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is used in the development of the decision-making framework and will be implemented as a quantitative method to evaluate and select the WIoT devices. TOPSIS is considered a powerful MCDM approach for the study because it requires a limited amount of subjective input and permits the quick identification of the best alternative. However, the elements of the decision-making framework and metrics for evaluating the WIoT devices are presented in this paper.

### Decision Support Framework for WIoT Devices Selection

This section presents the development of a decision support framework that supports construction stakeholders in making decisions on suitable WIoT devices. The implementation Phase II - Decision Making Benchmarking of the IoT Wearable Devices through the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) will focus on developing the decision-making parameter to rank the IoT Wearable Devices to mitigate the fatal four. This phase II will be grounded on the results from phase I - review of literature on WIoT devices. For each WIoT, the device name, manufacturer, and source of information will be recorded in a dataset. Each WIoT device will have a unique identifier composed of the letters “WIoT” followed by a sequential number (i.e. WIoT-1). A second dataset will be created with the following decision-making characteristics of the device that include: metrics monitored or captured, device type, alert methods, dimensions, weight, battery life, wireless connectivity, data log, and functions. The two datasets will be linked by the unique identifier. The decision to create two datasets was made as the information in the first dataset will not be used as part of the decision-making process. This phase II will be done in nine stages: Stage II.1 – Identify Measures; Stage II.2 – Identify measures needed to mitigate the fatal four; Stage II.3 – Establish Fuzzy Decision Matrix; Stage II.4 – Define Linguistic Values to Triangular Fuzzy Value; Stage II.5 – Normalize Linguistic Values (if needed); Stage II.6 – Calculate Objective Weight; Stage II.7 – Normalize Objective Weight; Stage II.8 – Determine Distance; Stage II.9 – Determine Ranking Values.

**Stage II.1:** This stage will focus on identifying the measurements about the workers and the environment needed to predict and prevent construction injuries and accidents as shown in Table 2.

Table 2  
*Worker and Environmental Measurements*

ID	Measurements	Unit of Measure
<i>Worker Measurements</i>		
WM1	Body Position	x-y-z
WM2	Body Direction (rotation and orientation)	Azimuth & Zenith (Degree)
WM3	Body Velocity (Vector)	ft/sec
WM4	Body Acceleration	ft/sec <sup>2</sup>
<i>Environmental Measurements</i>		
EM1	Environment Objects Position	x-y-z

EM2	Environment Object Composed Volume / Surface with respect to Person	ft <sup>3</sup> /ft <sup>2</sup>
EM3	Environment Objects Direction	Azimuth & Zenith (Degree)
EM4	Environment Objects Velocity (Vector)	ft/sec
EM5	Environment Objects Acceleration (Vector)	ft/sec <sup>2</sup>
EM6	Environment Objects Type	Mass, Empty Space, Energized

During this stage, technical and publically available information for each unique WIoT summarized in phase I will be converted to the specific measurements and units of measure shown in Table 2. This will be done to ensure homogeneity of the data to be analyzed. It is anticipated that for some of the WIoT devices, the information will not be explicitly found in technical and publicly available information and therefore, the research team will infer the information to create the most comprehensive and accurate dataset to make decisions using Table 2.

**Stage II.2:** This stage will correlate the worker measurement (WM) and environment measurements (EM) needed to predict and prevent construction injuries and accidents with each of the construction hazards (CH) identified as the construction fatal four (Falls, electrocution, struck-by, and caught-in or -between) as described under the literature review section.

**Stage II.3:** This stage will ascertain for each WIoT device the WMs and EMs with possible Construction Hazard Adaptations (CH) as illustrated in Table 3. This stage is particularly important, as it is anticipated that most of the WIoT devices that will be found in phase I would not have been designed to mitigate a particular construction hazard. In fact, it is anticipated that most of the WIoT devices might not have been designed for the construction industry. Therefore, this dataset will allow the linking of the WIoT devices for workers and environment measures with their potential capability to be adapted to mitigate one or more construction hazards. Furthermore, this dataset will be composed of fuzzy measurement allowing the research team to evaluate each measurement in a range of linguistic metrics with five options (Very High, High, Medium, Low, and Very Low) likelihood to adapt for this measurement and/or construction hazard as shown in Table 3.

Table 3  
*Derived Measurements and Fuzzy Decision Matrix (Linguistic Values)*

Device ID	Workers Measurements				Environmental Measurements						Construction Hazard Adaptation			
	WM1	WM2	WM3	WM4	EM1	EM2	EM3	EM4	EM5	EM6	CH1	CH2	CH3	CH4
WIoT 1	VH, H, M, L, VL				VH, H, M, L, VL						VH, H, M, L, VL			

VH = Very High (If purpose indicated in Information Source)  
 H = High (If research consider easy to adapt for this measurement/construction hazard)  
 M = Medium (If research consider possible to adapt for this measurement/construction hazard)  
 L = Low (If research consider hard to adapt for this measurement/construction hazard)  
 VL = Very Low (If research consider very unlikely to adapt for this measurement/construction hazard)

**Stage II.4:** This stage will define the linguistic values to triangular fuzzy values (from the dataset developed in the previous stage). Three fuzzy value options will be considered as shown in Table 4 because as part of this decision support framework, only five linguistics options (VH, H, M, L, VL) will be allowed for simplicity and consistency (of the decision-making framework) as opposed to the traditional seven linguistic options on fuzzy decision matrix that also include Medium High (MH) and Medium Low (ML). Therefore, Option 1 will use the regular values for each of the fuzzy values. Option 2 will use the average fuzzy values of High and Medium High to represent High and the average fuzzy

values of Low and Medium Low to represent Low. Option 3 will use the fuzzy values corresponding Medium High to represent High and the fuzzy values of Medium Low to represent Low. The three fuzzy value options (Alpha1..3, Beta1..3, and Gamma1..3) will be recorded in three different datasets each containing for each WIoT device all the values for WM1...4, EM1...EM6, and CH1...CH4. It is expected that an analysis of the three options will serve as a sensitivity evaluation of the decision support framework to identify the need or not to increase the five linguistics options (used in the framework) to seven linguistics options.

Table 4  
*Linguistic Values and Correspondent Fuzzy Values to Evaluate WIoT Adaptation*

Abbreviation	Scale	Option 1	Option 2	Option 3
		Fuzzy Value H=H L=L	Fuzzy Value H=Avg (H, MH) L=Avg (L, ML)	Fuzzy Value H=MH L=ML
Very High	VH	(0.9 1.0 1.0)		
High	H	(0.7 0.9 1.0)	(0.6 0.8 0.95)	(0.5 0.7 0.9)
Medium	M	(0.3 0.5 0.7)		
Low	L	(0.0 0.1 0.3)	(0.05 0.2 0.4)	(0.1 0.3 0.5)
Very Low	VL	(0.0 0.0 0.1)		

**Stage II.5:** In this stage, linguistic values from the previous stage will be normalized (if needed). The normalization is expected for the WIoT decision-making characteristics quantitative values as well as for the WMs, EMs, and CHs with no extreme values (VH or VL). The normalization will consist of adjusting the values (through a Min-Max scaling) to establish a scale from a minimum value of zero (0) to a maximum value of one (1) for all parameters that will be considered in the decision-making framework.

**Stage II.6:** In this stage, the objective weight (Entropy Method) will be calculated. This will be performed in three steps: a- Defuzzification, b- Projection Variable, and c- Objective Weights Calculations. The defuzzification will involve turning all the fuzzy values back to a single value. The single value will be calculated by adding Alpha plus twice Beta plus Gamma and then dividing the results of the addition by four. This calculation will be done for each of the parameters. The projection variable will be calculated as the coefficient dividing each defuzzified value by the corresponding summation of all defuzzified values for each WIoT device. The objective weight calculation will be done for each of the parameters by using entropy (e) as expressed in the following equation:

$$e_j = -k \sum_j p_{ij} * (\ln (p_{ij}))$$

Where j corresponds to the particular parameter to be evaluated (i.e. 1, 2, to n), k is calculated as 1 / ln (m), m is the total number of WIoT devices been evaluated, and p<sub>ij</sub> corresponds to the particular parameter been evaluated for each of the WIoT devices.

**Stage II.7:** In this stage, the objective weight will be normalized using the weights for measurements and adaptation. The first step in this process will be to calculate the dispersion. The dispersion will be the opposite of the entropy and will be calculated by subtracting the entropy for each parameter from 1 (e.g. 1 - 0.42 = 0.52). The objective weight for each parameter will be the dispersion of each parameter divided by the summation of all parameter weights (normalized). The researchers will then fuzzify the objective weight using Table 4 to select one of the five proposed linguistic values of VH, H, M, L, or

VL. Using the fuzzy objective weight, each of the parameters to be considered in the decision-making framework will be normalized.

**Stage II.8:** This stage will involve the determination of the distance of each WIoT device for its corresponding WM, EM, and CH. This decision-making framework will take advantage of the TOPSIS ability to identify a solution that is the closest to the positive ideal solution (PIS) with a fuzzy value of (1,1,1) and the farthest to the negative ideal solution (NIS) with a fuzzy value of (0,0,0). Thus, the PIS and NIS will be calculated for each parameter of each WIoT using the Pythagorean Theorem. Then all of the PIS for each WIoT device will be added to create an overall PIS for each WIoT device and then all of the NIS for each WIoT device will be added to create an overall NIS for each WIoT device.

**Stage II.9:** This stage will involve the determination of the ranking (Nearness Values) for each WIoT device to mitigate each of the construction hazards. A coefficient will be created by dividing the NIS of each WIoT device by the summation of the PIS and NIS, the higher the coefficient, the further from the NIS, and therefore the higher the rank of the WIoT device.

## Conclusion

In this paper, a comprehensive literature review on the emergence of IoT-based wearable or WIoT devices and their usefulness for safety management was presented. A search of commercially available WIoT devices that can be used in the construction industry was also conducted. The findings of the literature search were used in the development of a decision-making framework for evaluating and selecting WIoT devices. The elements of the decision-making framework are presented in this study. This study presents an initial attempt geared towards providing construction stakeholders with an effective decision-making tool that can be used for evaluation and selecting WIoT devices for implementation in the construction industry. The framework presented in this study will be deployed and tested in further studies by the research team.

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