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Choosing Wearable Internet of Things Devices for Managing Safety in Construction Using Fuzzy Analytic Hierarchy Process as a Decision Support System

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CHOOSING WEARABLE INTERNET OF THINGS DEVICES FOR MANAGING SAFETY IN CONSTRUCTION USING FUZZY ANALYTIC HIERARCHY PROCESS AS A DECISION SUPPORT SYSTEM

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APPROVAL OF THESIS

We, the faculty supervising the work of Sharique Khalid, affirm that the thesis, "*Choosing Wearable Internet of Things Devices for Managing Safety in Construction Using Fussy Analytic Hierarchy Process as a Decision Support System"*, meets the high academic standards for original scholarship and creative work established by the MSE program and the College of Engineering and Computer Sciences. This work also conforms to the editorial standards of our discipline and the Graduate College of Marshall University. With our signatures, we approve the manuscript for publication.

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ABSTRACT

Many safety and health risks are faced daily by workers in the field of construction. There is unpredictability and risk embedded in the job and work environment. When compared with other industries, the construction industry has one of the highest numbers of worker injuries, illnesses, fatalities, and near-misses. To eliminate these risky events and make worker performance more predictable, new safety technologies such as the Internet of Things (IoT) and Wearable Sensing Devices (WSD) have been highlighted as effective safety systems. Some of these Wearable Internet of Things (WIoT) and sensory devices are already being used in other industries to observe and collect crucial data for worker safety in the field. However, due to limited information and implementation of these devices in the construction field, Wearable Sensing Devices (WSD) and Internet of Things (IoT) are still relatively underdeveloped and lacking. The main goal of the research is to develop a conceptual decision-making framework that managers and other appropriate personnel can use to select suitable Wearable Internet of Things (WIoT) devices for proper application/ implementation in the construction industry. The research involves a literature review on the aforementioned devices and the development and demonstration of a decision-making framework using the Fuzzy Analytic Hierarchy Process (FAHP).

CHAPTER 1

INTRODUCTION

Worker safety and an increase in workplace injuries is ongoing issue for all of the industries. According to a recent report by the United States Bureau of Labor Statistics (BLS) in 2019 (Figure 1), the number of fatal injuries in all industries has been rising every year (2013 onwards) with a two percent increase from 2018 to 2019. The report's key findings highlighted how 2019 had the largest annual number of occupational fatalities since 2007, with a worker dying every 99 minutes.

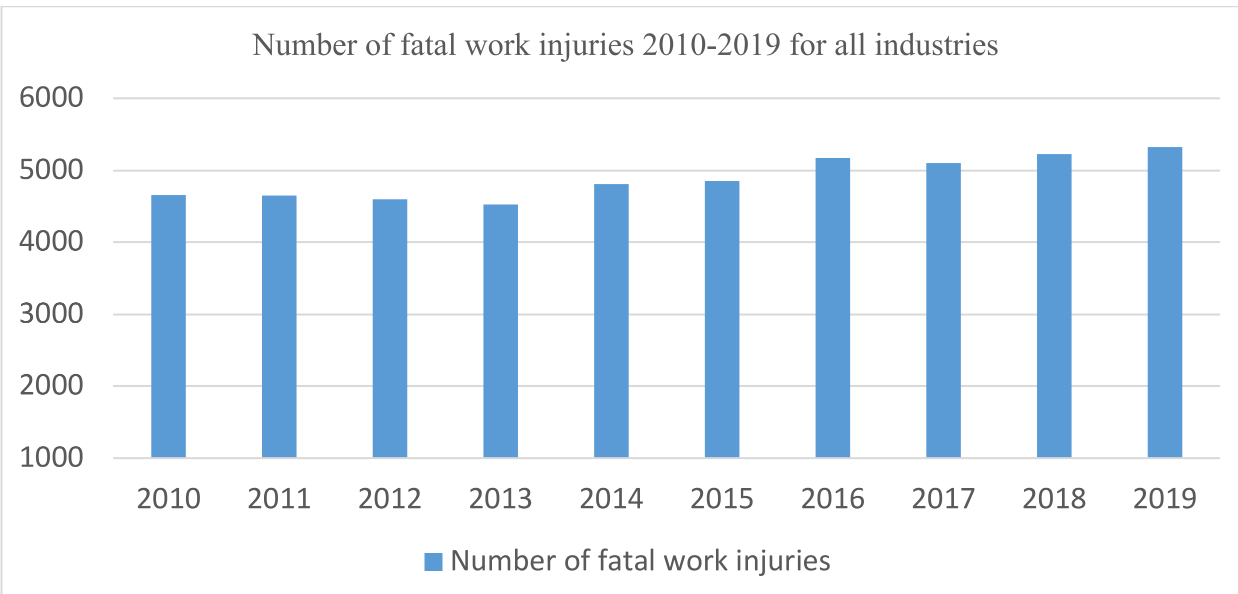

Figure 1. Number of fatal work injuries in all industries, 2010-2019 (BLS, 2020)

That being said, the construction industry is one of the worst for accidents occurring in the workplace. There are all sorts of injuries that can occur, such as slips, trips, falls, struck-by, caught in-betweens, lacerations, cuts, electrocution, chemical asphyxiation, ergonomic injuries, and hearing problems. It is filled with safety hazards and risks that construction workers have to face in their work environment on a day-to-day basis, with each job or task coming with its own specific risks. For example, a forklift driver is going to have different safety risks and concerns in their shift versus a concreter. Figure 2 is taken from a BLS report on Employer-Reported Workplace Injuries, and Illnesses clearly shows the safety condition of construction workers (BLS, 2020). Construction laborers are amongst the top five in regard to the incidence rate of cases involving days away from work, with the problems getting worse yearly. It should be noted, though, that since construction is such a huge field, there can be workers of the field in different categories other than construction laborers as well.

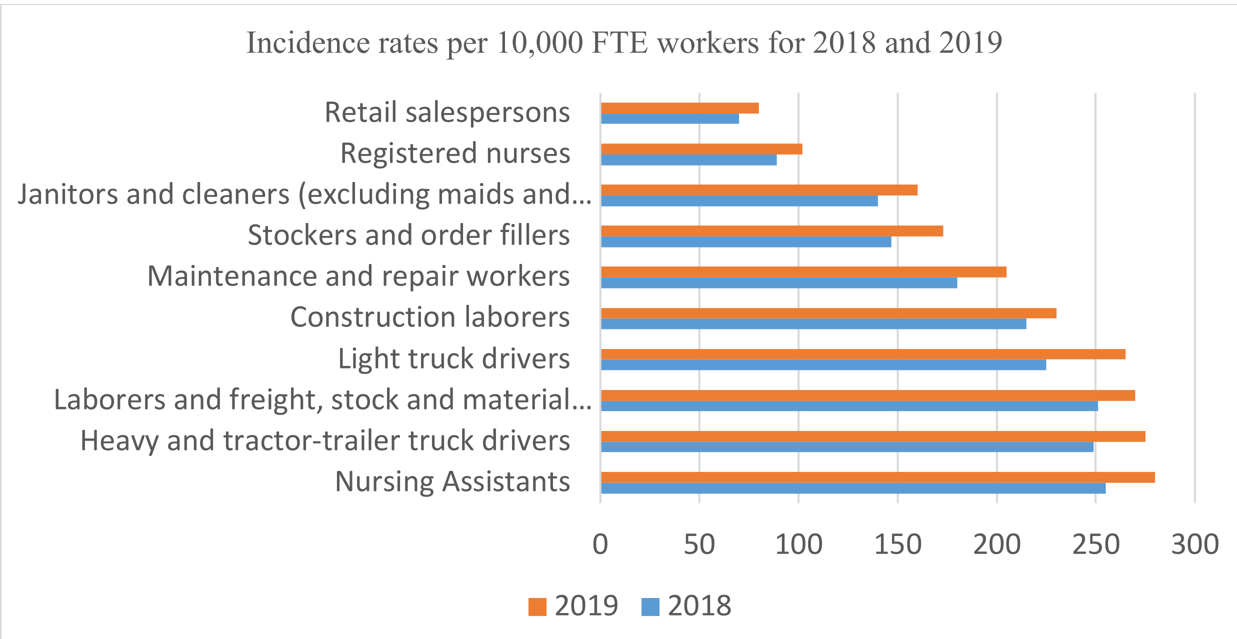

Figure 2. Incidence rates of cases involving days away from work for selected occupations in private industry, 2018-19 (BLS, 2020)

Furthermore, another report published by the Bureau of Labor Statistics in 2020 found that the construction industry was one of the leading industries when it came to the number of fatal and non-fatal injuries at the workplace (Center for Construction Research and Training, 2019). Hence, there is a strong need to eliminate these risks efficiently using all the tools and technology at our disposal.

Some tools and technologies identified that could prove beneficial for the safety of workers in the industry include Wearable Sensing Devices (WSDs) and Internet of Things (IoT), which is used to form the concept of Wearable Internet of Things (WIoT) devices. These devices allow for the monitorization and collection of data in the field, which is used for improving the safety of the workers. According to researchers in the field of ergonomics, the application of technologies such as Wearable Sensing Devices (WSD) and the Internet of Things (IoT) have been recognized as one of the most effective ways of predicting future safety performance and preventing incidents/accidents (Nath et al., 2017). It should be noted that these devices are used in industries other than construction as well, where they are used to collect and monitor data necessary for improving worker safety. However, as the field of wearable sensors and the Internet of Things (IoT) is still emerging, especially in the field of construction safety, their application and implementation in the workplace are underdeveloped and insufficient.

The lack of information in the field on Wearable Internet of Things (WIoT) devices makes informed decisions to recognize and utilize the appropriate safety devices in the workplace harder. There is a need to identify the devices, select the appropriate device (from the commercially available devices) and implement them into the workplace. Therefore, a conceptual decision-making system or framework needs to be set up, so that a criterion can be used to establish and implement the correct WIoT in the construction industry. The decision-making framework that will be utilized to make these conclusions will be the Fuzzy Analytic Hierarchy Process (FAHP).

There are numerous reasons why the device is important. Firstly, and most crucially, it will help save the lives of the employees working in the field. As aforementioned, the construction industry is rife with incidents and near-misses, with the focus four hazards (slips/ trips, struck-by, caught-in-between, and electrocution hazards) being the reason for most injuries in the workplace (Brown et al., 2021). Data collected by the Center for Construction Research and Training (CCRT) shows the percentage of fatalities that were caused by the focus four in the years of 2018 and 2019 in Figure 3 (Center for construction research and training, 2019). From this, it is evident that falls are the cause of most deaths in the industry and that the percentage of injuries due to falls still had a drastic increase in just a year (5.5%). Caught in-between injuries had a slight percentage increase (0.1%) and the other two hazards had slight percentage decreases but nothing statistically significant. All these hazards can be reduced with the usage of Wearable Internet of Things (WIoT) devices, all the while important data/ trends are recorded for future use.

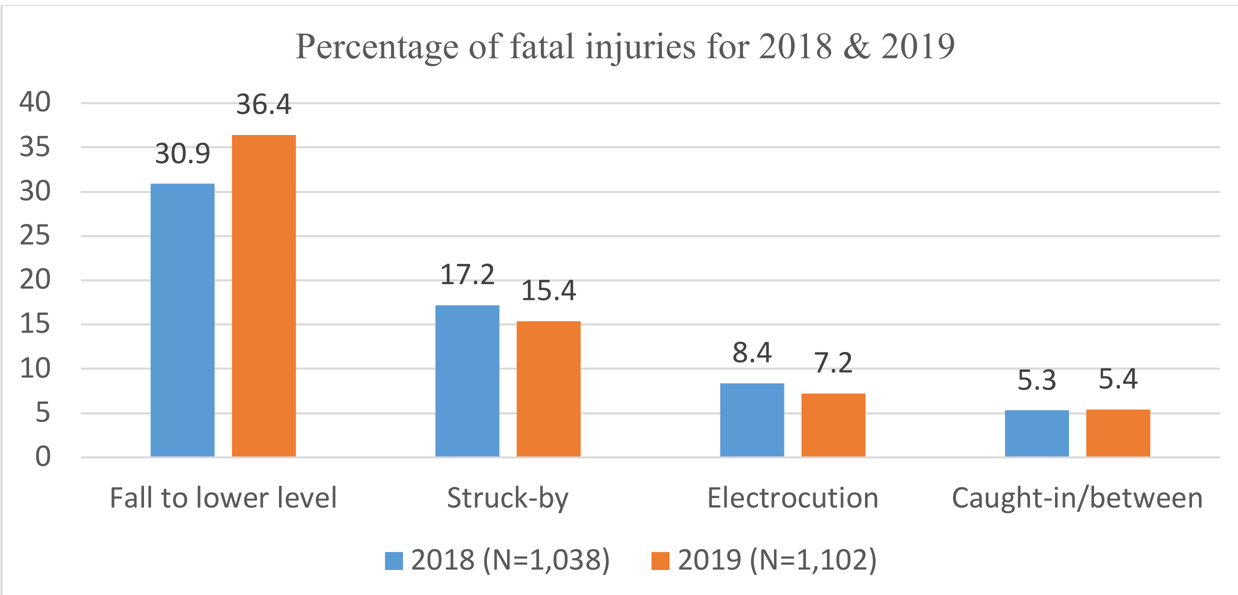

Figure 3. A comparison of the percentage of fatalities associated with the focus four for 2018 and 2019 in the construction industry (CPWR, 2019).

Furthermore, the Wearable Sensing Device will allow the collection and recording of data in real-time. An intriguing characteristic of the device is that it is a leading indicator, meaning it will warn or predict injuries/ failures ahead of time. This is more useful than lagging indicators, such as DART (Days away, restricted, or transferred) and the TRIR (total recordable incident rate), which give the required data and performance results after the incident has occurred (Manjourides et al., 2019).

On top of that, the device will have the added benefit of reducing costs for the company. These include costs associated with worker compensation, days away from work costs, replacement costs, medical and administrative expenses, machinery and equipment replacement, and other legal fees. It can have other indirect positive effects as well. There will be less loss of production days/work hours and delays due to a decrease in incidents. This applies directly to the workers affected by the incident, and the area or space which might have to be closed down due to the incident. Additionally, it can also lead to improved worker morale and job satisfaction, which can be crucial features for a great workforce. This all will help contribute in making the industry safe, and efficient.

CHAPTER 2

LITERATURE REVIEW

WEARABLE SENSING DEVICES AND THE INTERNET OF THINGS

Wearable devices are becoming very popular in various fields (Haghi et al., 2017). The devices are helpful to all workers, as they are able to track vitals, monitor health over long periods of time, and even detect falls. These devices usually work by tracking the motion and vital signs of the workers (pulse, heart function, temperature, pupils, blood flow, etcetera).

Wearable sensors have plenty of safety benefits to offer against physiological and environmental factors in the field. Wearable sensors can be used to identify and mitigate physiological factors in the workplace. It was found that photoplethysmography (PPG) sensors can be useful for identifying physiological problems such as stress, fatigue, and heat strokes through the heart rate of the worker (Hwang et al., 2016). Similarly, in the results of their study, it was found that physical fatigue for workers can be thoroughly monitored using wearable sensors (Ashrant et al., 2017). They suggested that worker fatigue needs to be kept at a minimum, otherwise it would cause a reduction in productivity and a higher chance of accidents. In another study, it was found that human sweat is high in physiological information and can help provide the health state of a worker at a molecular level (Gao et al., 2016). Fully integrated sensors for perspiration analysis were used, and measures of temperature, metabolites and electrolytes were taken non-invasively. Two separate pieces of research done on activity and limb movement of workers, demonstrated how wearable sensors can be used to decrease ergonomic risk factors, prevent fall and loss of balance hazards, and help improve the posture of workers (Reiss et al., 2014) and (Bertolotti et al., 2016). Lastly, real-time wearable motion warning systems can even help fight musculoskeletal disorders and other ergonomic issues (Yan, 2017). The real-time motion warning PPE also enables self-awareness and self-management amongst the workers.

Furthermore, in another study, it was suggested that a worker's physical data can be used to measure the psychological status of that worker (Guo et al., 2017). This can even help explore the mental causes of accidents. Also, it should be noted that where traditional wearable devices cannot be used or have shortcomings (functionality, comfort, accuracy or environmental factors), smart clothing can be used (Chen et al., 2016). The textile clothing has body sensors integrated into it, which can take readings and collect data over time, similar to other wearable sensing device concepts.

Nonetheless, the implementation of wearable technology and IoT in the field of construction has been quite poor. The uptake is considerably slow for the industry, with a lot of older technology being used. Wearable devices are growing but still not integrated optimally into clinical practice and industries (Kumari et al., 2017). Just like wearable devices, IoT is poorly integrated and not used to the maximum capability (Davenport et al., 2015).

From the evaluation of portable single-gas monitors in the industry, the archaic nature of wearable devices can be seen (Hemingway et al., 2012). The same monitoring devices are still being used in the construction industry frequently. While there are multi-gas factors as well, they are still only capable of detecting one factor, and a few constituents at that. Additionally, most of the detectors being used in the various industries are of the type to present data and readings only to the personnel wearing it, and not to other appropriate personnel (Kolavennu et al., 2015). This poses problems in work on remote sites especially. Therefore, a wireless architecture is of utmost importance to be able to share and record data seamlessly. One of these, WSN (Wireless Sensor Network) systems, is an application of IoT in the construction workplace that can be implemented quickly (Cheung et al., 2018). It is a remote way of collecting data and can enhance safety management.

Although wearable sensors and the Internet of Things have many benefits, they have some problems associated with them. The most crucial concern for the Internet of Things is the security (Kumar et al., 2019). Due to it, there can be threats of hackers, cyber-attacks and data breaches. Authentication is another issue faced by Internet of Things, where data and actions between two parties can be intercepted by a different party (Tawalbeh et al., 2020). Apart from those issues, there are no fixed policies, regulating bodies and guidelines for security and privacy on the Internet of Things, and how all these need to be improved upon (Maple, 2017). Moreover, the use of security architecture for Internet of Things based on SDN is suggested (Olivier et al., 2015). This will ensure flexibility, efficiency, and security.

Other than that, worker uptake and acceptance of the technology in the field of construction is an ongoing problem as well. Some workers are reluctant to use Wearable Sensing Devices (WSDs) due to the perceived pervasive nature of the technology. Due to which, only two out of three workers are willing to share their capture data (Nnaji et al., 2021). Furthermore, results from a test conducted found that perceived usefulness, social influence, and perceived privacy risk are directly related to the workers' intent to wear smart technology, such as, vests and wrist bands. (Choi et al., 2017).

TECHNOLOGY SELECTION FRAMEWORK & MCDM

In the process of technology selection, the potential value of technologies and their contribution to the profitability and competitiveness of organizations is gauged (Farshidi et al., 2018). The technology selection process is usually complicated and often modeled as a multi-criteria decision-making problem, as many factors need to be contemplated. MCDM involves taking sets of alternatives and decision criteria highlighted by a user, to find the most suitable result in an uncertain situation (Nnaji et al., 2018). In the MCDM process, decisions are made between several alternatives by determining the decision criteria and their weights. The procedure then allows the discovery of the optimal alternative among a set of options/choices over a set of multiple criteria (Rani et al., 2018).

There are numerous MCDM techniques being utilized in various fields and industries (Milenković et al., 2018). All techniques are equally capable, but they can have their own positives and negatives, making certain techniques more suitable for certain scenarios (Khan et al., 2018). Although, before any of this, a model for multi-criteria decision-making is developed. It includes steps for; finding all alternatives, setting criteria important for alternatives, evaluating the model, and weighing the alternatives observed (Erdogan et al., 2017).

Analytic Hierarchy Process (AHP) is a technique based on the judgments made according to each criterion. In it, the criteria and alternatives are set in pairs, and then comparisons are made (Rochikashvili, & Bongaerts, 2016). AHP is already utilized in some areas of construction management, with it being especially popular in risk management and sustainable construction (Darko et al., 2018). It should be noted though that the AHP technique is not applicable to uncertain relationships between one key factor and all the other factors within the system (Wang et al., 2017). TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is one of the most widely used MCDM techniques (Celikbilek et al., 2020). In which, the chosen alternative should have the shortest distance from the ideal solution. The TOPSIS technique is quick and easily applicable to qualitative and quantitative data. Though, care needs to be taken that the decision-maker (manager) does not display biasness or subjectivity while giving input ratings and making decisions (Awolusi et al., 2021). Grey relational analysis (GRA) is a frequently used technique for safety assessment

(Xu et al., 2018). It is used in a system with a known and unknown part and utilizes the grey relational degree calculations between the factors or indicators of the alternatives. SWOT analysis (Strength, Weakness, Opportunities, Threats), is a technique that evaluates the internal strengths and weaknesses of a company, method or process, along with the external opportunities and threats present for them (Bidin et al., 2019). This enables acquisition of information on several fronts. However, as SWOT does not provide solutions or comparisons with alternatives, failure of interpreting results from an analysis is an issue faced by managers (Namugenyi et al., 2019). Simple Additive Weighing (SAW) is a method of weighted addition (summation) of rating the performance of each alternative on all given criteria (Muslihudin et al., 2018). In it, a decision matrix normalization process is required for the comparison between the alternatives.

VIKOR, standing for Vlsekriterijumska Optimizacija I Kompromisno Resenje, is another frequently used technique, created by Serafim Opricoviv (Ahmad et al., 2015). It is used to optimize multi-criteria complex systems by concentrating on ranking and selecting set choices for an issue with opposing criteria (Sadi-Nehzad, 2017). An additional technique used is MOORA (Multi Objective Optimization on the basis of Ratio Analysis), in it, beneficial and non-beneficial criteria are used for ranking the alternatives from a set of predetermined options (Patel & Maniya, 2015). Lastly, ELECTRE (ELimination and Choice Expressing the REality) is a technique in which actions are ranked from the best option to the least (Hassan et al., 2018).

Moreover, multiple MCDM techniques can be used in conjunction together. This can enhance/ improve the techniques, providing a more accurate and efficient solution. Where, not only an improved grey relational analysis (GRA) is used, but TOPSIS is redesigned with it as well (Yang & Wu, 2019).

CHAPTER 3

METHODOLOGY

SCOPE AND OBJECTIVE

There are various risks and unpredictable events found in construction worksites. For these risks to be minimized and the efficiency of processes to be improved, management needs to analyze the situation first and then make a decision using all the tools at their disposal. These tools include WIoT devices, which, when implemented correctly, can be highly beneficial.

The problem persists that it is unknown which available WIoT devices are the best for worker safety and which devices are better suited for various situations/ tasks and environments. Therefore, this study has two main objectives. First, it is to highlight and compile a list of most of the various WIoT devices being used (and their variables) in the field of construction. Second, a Fuzzy AHP Multi-Criteria Decision-Making (MCDM) tool will be used to select the best devices out of the list. This will enable managers to determine the best devices to be used in the construction field to improve costliness, efficiency, and most importantly worker safety.

RESEARCH METHOD AND DESIGN

An extensive review of prior literature on Wearable Sensing Devices (WSD), Internet of Things (IoT) devices, Wearable Internet of things (WIoT) devices, and technology selection frameworks was conducted. WIoT devices and their implementation in the construction workplace safety was found to be fairly new and thus, underdeveloped and not fully utilized. WIoT devices currently in the market and being used in the industry were identified and sorted.

A hybrid technique of Fuzzy Analytical Hierarchy Process (FAHP), based on a Multi-Criteria Decision-Making model (MCDM), is developed. It provides a framework for quantifying criteria and all the alternatives to make a rational decision. The FAHP model will allow for the selection of the best WIoT. After this, the model will be validated, and the outcome reviewed. In the end, the conclusions and results drawn from this study are discussed. Figure 4 shows the proposed methodology flow chart.

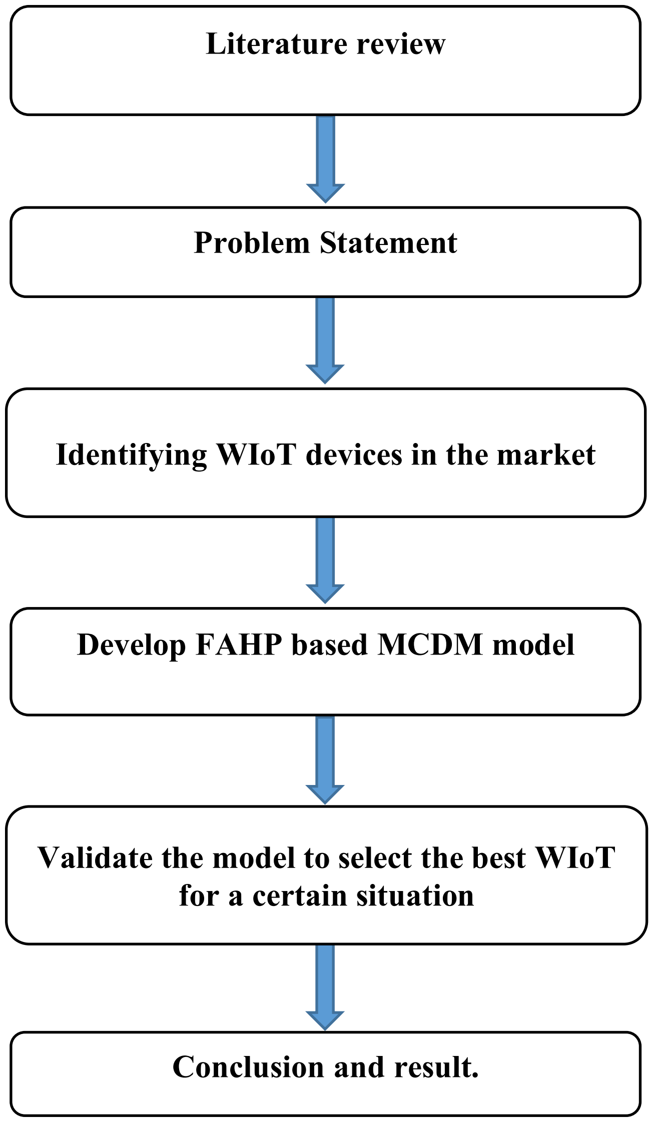

Figure 4. Methodology flow chart

MULTI-CRITERIA DECISION-MAKING (MCDM)

Decision-making is crucial for attaining progress and efficiency, especially in a multidisciplinary, information-filled field such as construction. Many uncertainties and variables in the work environment can cause accidents and need to be considered. Due to this, the manager needs to take decisive actions immediately to avoid accidents in construction safety.

Some decision choices or situations involve a plethora of decision criteria and alternatives that can be inaccurate or in opposition to each other. Here, decision analysis, through various methods, can highlight the best choice of action to a decision-maker in a risk-filled environment. This helps in allowing the decision-makers to choose between a set of preestablished alternatives (Köksalan et al., 2011). There are plenty of MCDM tools and techniques, but the Analytical Hierarchy Process will be emphasized for this study.

ANALYTICAL HIERARCHY PROCESS

Analytical Hierarchy Process (AHP) is one of the most utilized decision-making techniques (Eydi et al., 2016). It is a decision-making process that helps establish priorities to make decisions. The process makes use of pairwise comparisons based on the judgments of an expert (Saaty, 2008). AHP works by breaking down long complicated problems into simpler ones and then uses the decision maker's experience to ascertain the priority of criteria and alternatives.

Even though the technique has many applications, such as providing greater efficiency and consistency in traffic planning (Pogarčić et al., 2008). The traditional Analytical Hierarchy Process is not regarded as an ideal technique in its ability to deal with involved risks in the criteria (Pan, 2008). Traditional AHP has a big disadvantage due to subjectivity, with risks being associated with the opinions of a decision-maker being potentially biased.

However, this issue can be resolved by using AHP with Fuzzy Logic to create the Fuzzy Analytical Hierarchy Process (FAHP) hybrid approach. The hybrid FAHP will have the advantage of mitigating subjectivity from the process, thus making the results more accurate and reliable. It should be noted that this approach has seen use (albeit limited) in the construction industry by various researchers in the field (Filippo et al., 2007).

FUZZY LOGIC

The Fuzzy Set concept was first founded by Zadeh in 1965 (Zadeh, 1978). It was inspired by observations that human thinking uses ideas that do not have rigid, defined borders (Mehrdad & Abbas, 2011). Fuzzy Logic is a technique that provides accurate deduction from ambiguous and inaccurate data.

Fuzzy Logic and its hybrid methods have been used in construction to improve project management and workforce by identifying, and then analyzing risk (Jamsandekar & Mudholkar, 2013). Fuzzy Logic encapsulates expert judgment and knowledge functionally, combining these biased factors with project data to improve decision-making in the construction industry (Fayek & Jose, 2010). Additionally, a common shape of Fuzzy Logic is the Triangular Fuzzy Number (TFN), which is defined as a triplet consisting of a1, aM, and a2. Figure 5 shows a triangular fuzzy number.

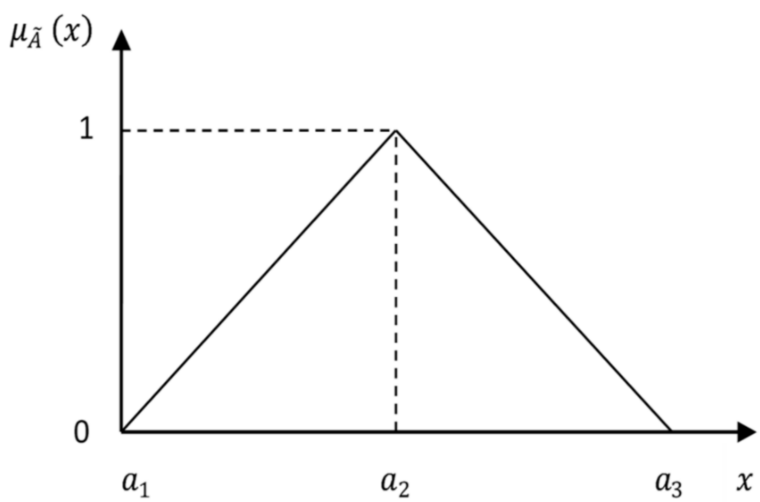

Figure 5: Triangular Fuzzy Number

As stated by (Dutta et al., 2011), the functions (a_1 and a_3) are defined as the two limits of the triangular fuzzy number (TFN), whereas the point (a_2, 1) is considered as the peak. The parameter for a1 represents the minimum value, a_2 represents the most likely value, and a_3 represents the maximum value (Kaufmann & Gupta, 1991). For example, a score allocated to a device may include the values (2, 3, 4) for a moderately favored preference. In this, 2 would be a_1 (min value), 3 would be the most likely or middle value (a_2) and 4 would be the max or peak value (a_3).

$$\mu A(x) = \begin{cases} \dfrac{x - a_1}{a_2 - a_1} & for\ a_1 \le x \le a_2 \\ \dfrac{x - a_3}{a_2 - a_3} & for\ a_2 \le x \le a_3 \\ 0 & otherwise \end{cases}$$

CHAPTER 4

COLLECTION OF WIOT DEVICES

Wearable Internet of Things (WIoT) devices and other Wearable Sensing Devices (WSDs) have the potential to enhance worker safety through efficient data collection, communication, and analysis of information instantaneously (Yeo et al., 2020). While wearable devices can be considered as Personal Protective Equipment (PPE), they have engineering control elements heavily involved with them as well, meaning they are crucial and higher up in the hierarchy of controls for safety (Karakhan et al., 2018). The devices being used need to suit the work environment and task, incorporating functions deemed crucial to the safety of the workers. Some WIoT devices presently being used in the field include smart watches, wrist bands, hats, vests, boots, and goggles (Nnaji & Okpala et al., 2020). These devices are performance tested and integrated into the field smoothly afterwards.

MEASURABLE FUNCTIONS AND SENSING TECHNOLOGIES INVOLVED

Table 1 shows all the WSD functions present in the construction field and what kind of sensing technology is required to gauge and monitor them (Nnaji et al., 2021). There is a total of 11 WSD functions identified, with the first four of them being physiological in nature (1-4) and the rest of the seven being environmental (4-11). Physiological functions or measures include body temperature, heart rate, ergonomic factors, emotional levels and stress. Whereas environmental factors can include noise levels, open spaces or trenches, falling objects, bad terrain and toxic gases at the worksite. Also, more focus is placed in construction on the physiological side of WSD's and WIoT devices, than on the environmental functions (Awolusi et al., 2019). Even though in actuality, environmental factors are a greater problem in the field. Furthermore, the three major concerns workers and managers have in the workplace are in regard to the energized cable/ equipment detection, toxic gas detection, and fire/smoke detection in the vicinity of the worker (Nnaji et al., 2018). All three of these functions are environmental in nature and provide credence that WIoT devices can be utilized to reduce these risks. Also, it should be noted that some sensing technology overlaps between various functions as well, so the same technology could be used to find out two or more measurements or functions simultaneously.

With the passage of time, even more functions and sensing technology might be identified in the environment, such as measure of light or visibility in the workplace. Similarly, new biosensor systems in technology have enabled constant measurement and information for physical demands being placed on the workers body (Hwang et al., 2017).

Table 1. Functions for sensing devices and the associated sensor technologies (1-4 are physiological functions, whereas 5-11 are all environmental).

		WSD Functions	Sensors and Tech involved
Physiological Functions	**1**	Worker Body Temperature	Thermistors, thermometers, infrared
	2	Worker Heart Rate and Blood Pressure	ECG/ EKG, infrared, PPG
	3	Stress Level of worker	ECG, EEG, infrared, perspiration analysis sensors
	4	Body Posture and Repetition	Gyroscope, accelerometer, magnetometer
Environmental Functions	**5**	Detect toxic gases or chemicals	Infrared, Multi-gas monitors
	6	Detect Smoke and Fire	Infrared, FLIR cameras
	7	Energized cables and high voltage	GPS, RFID, Radar, Bluetooth
	8	Noise Level	Decibel Meter, a noise sensor
	9	Proximity detection	GPS, RFID, Radar, Bluetooth, Radio waves, LiDAR
	10	Open trenches or uncovered holes	GPS, Infrared, Bluetooth, BIMS
	11	Falling objects, Struck-by	Gyroscope, accelerometer, magnetometer

WIOT DEVICES USED IN CONSTRUCTION

A lot of the WIoTs utilized in the field are still in the development/ prototype phase. For instance, wireless wearable rings, fitted with chemical and electrochemical sensors, are being created and tested for detecting chemical threats (Sempionatto et al., 2017). Nonetheless, some commercial types of WIoTs being used in the industry, their examples and percentage of usage in construction are given in Table 2 (Nnaji et al., 2021). The types of WSD's can be divided into three categories. The first category would be for WSD being integrated into the PPE, which would include smart safety hats, safety vests, glasses and boots (1-4). The second category (5-10) consists of WSD being incorporated into common/ everyday wearable accessories such as smart watches, rings, bracelets, necklaces and even applications for smartphones. The last category (11-13) contains other attachable sensing devices used in construction sites such as wearable lights, cameras, patches and other attachable devices. Here, we are most interested in the category of wearable sensing devices (first category) that have an IoT component, as they are necessary factors for WIoT devices. Still, identification of most hazards in the construction industry depends on human judgment and perception (Yang et al., 2017).

While smartphone apps are indeed the most popular and used WSD (both overall and for WSD integrated into typical personal accessories), they should not be. Many workers prefer this type of WSD as it is most convenient, cost-effective, and they do not want to wear or carry any additional PPE (Choi et al., 2017). However, smartphones are inherently distracting and for a worker to look away from the hazardous machinery, work environment or jobsite and focus on a screen (that they nonetheless have to get out of their pocket or holder) is unwise and unsafe. It is thus crucial to use smart apparel or PPE with an IoT component to them instead. After smartphone applications, smart hard hats and smart safety vests are the most popular devices, having 72% and

65% usage in the industry, respectively. This is due to the ease in implementation of these devices into the workplace. The base equipment is already established and required in the work area, with no need for additional PPE either.

Table 2. WIoT devices and WSDs used on construction projects (1-4 are devices integrated into PPE, 5-10 are devices integrated into personal accessories, and 11-13 are other additional types of wearable devices). (Nnaji et al., 2021).

		Type of WSDs	Examples	Percentage of Use
Integrated into PPE	1	Smart Safety Hard hats	Cat Detect, Smart Cap, Compass	72%
	2	Smart Safety Vests	Redpoint	65%
	3	Smart Safety Boots	SolePower	40%
	4	Smart Safety Glasses	Vuzix Blade, XOEye	62%
Integrated into Personal Accessories	5	Smartphone apps	Ios, android applications, Redpoint app, BIMS app	84%
	6	Smartwatches	Apple watch, Samsung watch	48%
	7	Smart bracelet	FitBit	19%
	8	Smart necklace	Zephyr Biomodule	12%
	9	Smart Rings	NIMB smart ring	17%
	10	Smart Band	Proxxi, Proxxi Contact	33%
Additional Types	11	Wearable Lights	Halo Lights	64%
	12	Wearable Cameras	Veho Muvi, FLIR Camera	40%
	13	Attachable/Carriable Device	Vigifall, Gentag	58%

EXAMPLES OF WIOT DEVICES

The following are some examples of commercial devices available in the market currently. Smart Cap, a form of a smart hard hat that can monitor many vitals and fatigue. It uses electroencephalography (EEG) sensors built-in to determine this information (Hwang et al., 2018). It can even detect microsleep in workers and relay the information onwards instantly (Smart Cap technology, 2021).

Sole Power is an example of an IoT-based PPE that is OSHA approved (Sole Power technology, 2021). It has built-in sensors that can provide information on falls, walking coordination, weight being carried, relative positioning, fatigue, etcetera. There are alerts that can be sent in real-time to appropriate personnel automatically via cloud access.

Vigifall, a wearable sensor that alerts to slips, trips and falls that utilizes gyroscopes and accelerometers. Again, it utilizes an internet connection to deliver the information and location in real time. The whole setup can cost upwards of $2000 for a three-year plan (Health Management, 2021). Spot-R clips are similar devices that have built-in gyroscopes to detect falls.

Gentag is a wearable adhesive sensor pack that sticks to the body. It measures body temperature, heart rate, blood pressure, and electrolytes in the body. The device is very responsive as it is attached straight onto the body.

Proxxi, wearable smart bands that can sense voltage in energized cables and save workers from electrocution. They have another wearable device Proxxi Contact, that can help detect COVID-19 early, provide contact tracing and oxygen levels in the blood (Proxxi voltage detector, 2021).

Voltage Compass, another energized system detector for detecting voltage in equipment before contact. It also has multiple variations, including one that mounts underneath the hardhat and runs on rechargeable batteries. It has other built-in sensors as well such as proximity detection, fall detection and location tracking (Safeguard equipment, 2022).

Zephyr performance system’s biomodule is a wearable GPS sensor that can record and relay vitals of a worker in an instant (Zephyr, 2021). It can give accurate physiological and accelerometry data of the workers, such as measuring blood pressure, oxygen levels and heart rate. They are of high quality but a bit costly, with each unit coming in around $700.

Wireless decibel or sound level meters, such as the Omega NSRTW-mk3 can be used to determine the sound level in the work environment (Convergence Instruments, 2021). This can be important to see if a worker is being exposed to sound levels greater than the set limit of 85 Hertz. Higher quality decibel meters such as the NSRTW-mk3 can be costly (upwards of $800) though. They can have problems with being bulky, having to be buckled on or attached to clothing, and only serve one function with only one sensor.

Red point safety vests are wearable IoT devices that work together with an application to provide real-time information on hazards found in the immediate vicinity and physiological performance of a worker. The system has very low latency but suffers from offering no warning indications to the wearer without the app (Redpoint positioning solutions, 2021).

Vuzix Blade are smart safety glasses that come with an ANSI (American National Standards Institute) certification (Z87.1). These glasses can provide eye and fatigue tracking, AR features, offsite assistance, enclosed space monitoring, and monitoring or management of other IoT devices by the wearer through the display (Vuzix Smart Glasses, 2021). However, these smart safety glasses can be quite expensive (upwards of $500, and $800 for the Vuzix Blade series), especially when compared to regular safety glasses.

NIMB smart rings are capable of alerting preselected contacts the exact location of the wearer in case of emergencies (Buy smart rings, 2019). They are useful for employees working in enclosed spaces, remote locations, late shifts or when they are out of sight from other workers. However, they can be inconvenient to wear (especially with other PPE such as safety gloves) and provide limited functionality. They are not that cheap either, with each unit costing around $200.

PERSONALIZED WIOT DEVICES AND SYSTEMS

Personalized devices and systems can be highly beneficial to any company in the field of construction. The companies can choose to have exactly what they want and remove the features they deem unnecessary. Personalization of the devices can usually be done by either modifying and building on existing devices, or by combining multiple devices or sensors to make another. This fusion of sensors can provide more applications and uses in the field (Changbum et al., 2019). While this can also be more cost-efficient, sometimes modifying the devices can be expensive, require expertise or connections (with people who can make the changes), and even additional parts. Similarly, the systems for the WIoT devices can be tweaked as well. It can be chosen to who can have access the information or data being collected, along with whom the information should be conveyed to (safety manager, project manager only for example) (Bayo-Monton et al., 2018).

CHAPTER 5

FAHP MODEL

INTRODUCTION AND BRIEF HISTORY

Analytical Hierarchy Process is a decision-making tool that works by dissecting complicated problems into smaller, fairly straightforward problems based on a hierarchy of criteria, alternatives, and goals. It helps in highlighting the top alternatives and making the best possible decision. However, as previously mentioned, traditional AHP has a drawback of subjectivity when making a selection, on the behalf of the decision-maker.

Therefore, Fuzzy Logic is applied to AHP to form Fuzzy Analytical Hierarchy Process (FAHP) (Liu et al., 2020). Thus, this technique was first introduced in order to enhance traditional AHP (Chang, 1996). In it, pairwise evaluations of criteria and alternatives are achieved via linguistic variables, using fuzzy triangular numbers. A linguistic variable is different from a numerical one, as the value for the linguistic variable is exhibited as phrases and expressions rather than numbers (Permana et al., 2017). The four stages in the FAHP model are given in Figure 6.

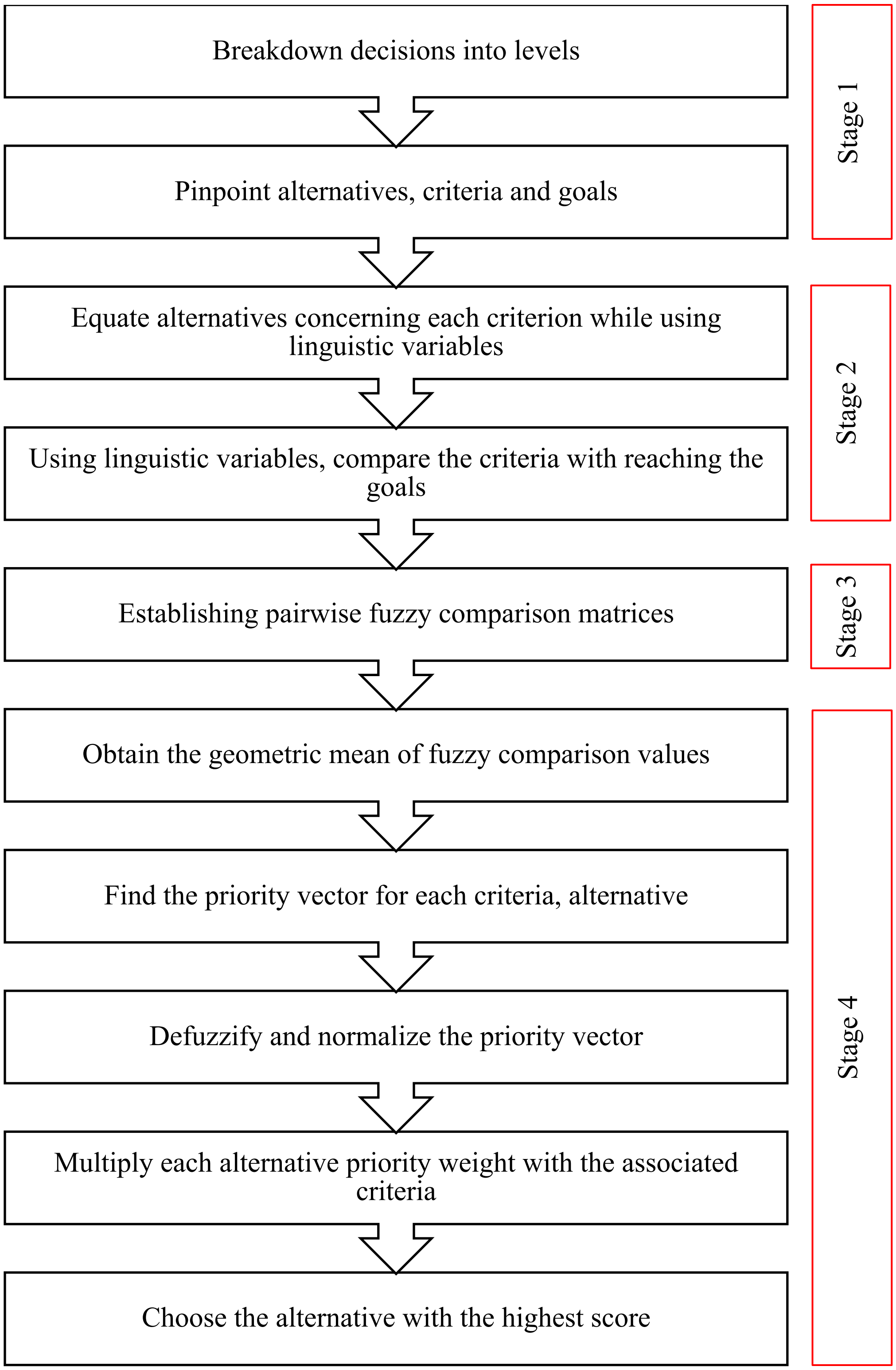

Figure 6. FAHP Model plan flowchart

FAHP STAGE 1

In this stage, all the problem factors or elements are sorted into levels by the decision maker. After that, arrangement of levels takes places according to the goal, criteria and alternative levels. Figure 7 shows the hierarchy levels for Analytical Hierarchy Process, where the main goal is to select the best WIoT device. As the elements are separated into hierarchal levels in the same cluster, the comparison of elements, and thus, the decision-making process becomes easier. This is crucial for the next stage of the process. It is also important to make sure that in this stage, the factors in the same level/ tier do not affect or influence each other, with the same case being for alternatives (Wulf, 2020).

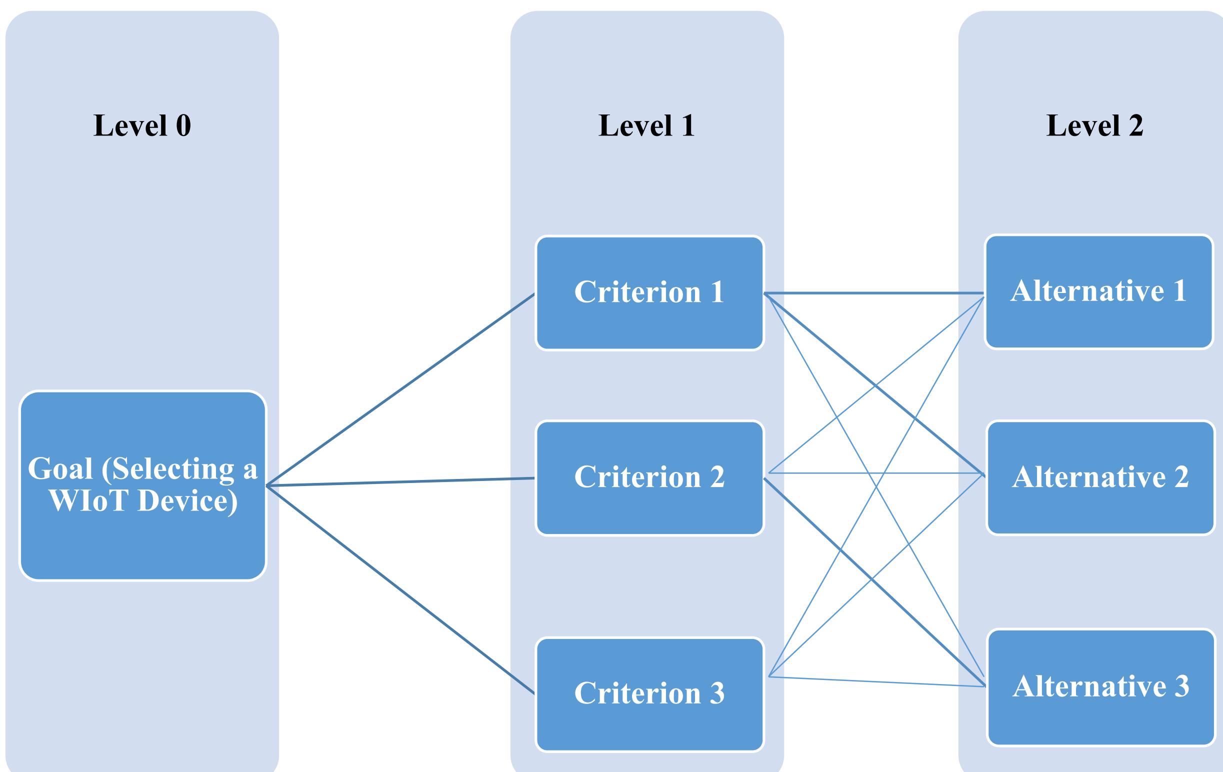

Figure 7. AHP Hierarchy Levels

FAHP STAGE 2

This stage has two main goals, comparison of alternatives with criteria, and comparison of criteria with goal. A scale of real numbers from one to nine is apportioned to preferences in a traditional Analytical Hierarchy Process (Saaty, 2008). It is also proposed that the pairwise comparison measurement scale (Table 3) can be utilized to measure the importance of the assigned value, when two alternatives are compared (Yildirim et al., 2021). Additionally, the intermediate values in the table are used to provide further clarity to the decision-making process.

Table 3. Scale for Traditional AHP

Definition	Numerical Scale
Extremely Favored (E.F)	9
Very Strongly Favored (V.S.F)	7
Strongly Favored (S.F)	5
Moderately Favored (M.F)	3
Equal (EQ)	1
Moderately Disfavored (M. Df)	1/3
Strongly Disfavored (S. Df)	1/5
Very Strongly Disfavored (V.S. Df)	1/7
Extremely Disfavored (E. Df)	1/9
Intermediate Values	2, 4, 6, 8

Since the traditional AHP can succumb to subjectivity and uncertainty, Triangular Fuzzy Numbers (TFN) are used to fuzzify the numeric scale (Putra et al., 2018). Thus, TFN are used to represent uncertainty found in the traditional AHP model. Table 4 shows the fuzzy triangular scale and the linguistic variables involved, as suggested by (Mahad et al., 2019).

Table 4. FAHP and the Fuzzy Triangular Scale

Definition	Fuzzy Triangular Scale
Extremely Favored (E.F)	(9, 9, 9)
Very Strongly Favored (V.S.F)	(6, 7, 8)
Strongly Favored (S.F)	(4, 5, 6)
Moderately Favored (M.F)	(2, 3, 4)
Equal (EQ)	(1, 1, 1)
Moderately Disfavored (M. Df)	(1/4, 1/3, 1/2)
Strongly Disfavored (S. Df)	(1/6, 1/5, 1/4)
Very Strongly Disfavored (V.S. Df)	(1/8, 1/7, 1/6)
Extremely Disfavored (E. Df)	(1/9, 1/9, 1/9)
Middle value of 1 and 3	(1, 2, 3)
Middle value of 3 and 5	(3, 4, 5)
Middle value of 5 and 7	(5, 6, 7)
Middle value of 7 and 9	(7, 8, 9)

Using the linguistic terms, the user compares the criteria with the matching triangular fuzzy number of those values. As an example, if criteria 1 (quality) is said to be strongly favored in comparison to criteria 2 (cost), the fuzzy triangular scale of (4, 5, 6) is taken.

FAHP STAGE 3

The third step is to develop pairwise fuzzy comparison matrices. The dimensions of these matrices are dependent on the number of alternatives or elements. The alternatives are compared in pairs and are found to be consistent due to identical criteria being compared. Thus, the diagonal elements of all three matrices are seen to be (1, 1, 1). A pairwise fuzzy comparison Matrix, *M* can be seen in Figure 8. Here in d_{ij}, the i^{th} criterion represents the larger value over j^{th} criterion, which is also always preferred by the user or decision maker.

$$M = \begin{pmatrix} d_{11} & d_{12} & d_{1n} \\ d_{21} & d_{22} & d_{2n} \\ & & \\ d_{n1} & d_{n2} & d_{nn} \end{pmatrix}$$

Figure 8. A pairwise fuzzy comparison matrix

FAHP STAGE 4

Stage four involves multiple steps which include finding the geometric mean of fuzzy comparison numbers, finding the priority vector for each criterion, defuzzifying the priority vector and normalizing it afterwards, then finally multiplying each priority weight with the appropriate criteria. This all will enable the decision-maker to choose the alternative with the best score. The geometric mean, which is a prioritization method, helps in estimating the priority vector for finding the weights (Helmy et al., 2021).

In this stage, the priorities of each element (at a certain level) are deduced. After that, relative weights of all the elements at different levels are computed to determine a vector of composite weights. The vectors for the weights will provide ratings to the alternatives, so that a decision can be made. Additionally, relative weights are represented by the vector W, known as the priority vector.

There are numerous techniques that can used to find the relative weights. It is suggested that the following steps and calculations be used to compute the relative priorities of each element in the model by using the following steps (Kabir et al., 2019).

Firstly, Equation 1 can be used to calculate the geometric mean of fuzzy comparison values of each alternative. Then the geometric mean (R) for each alternative and step are added together, and the reciprocal of the value is found and arranged in increasing order ($1/\Sigma$ R). Then, the answers from the previous steps are used to calculate the priority vector *(W)* for each criterion (Eq 3).

Equation 1: $R = \left(\prod_{j=1}^{n} d_{ij}\right)^{1/n}$

Where R is the geometric mean, n is the number of alternatives

Equation 2: $Reciprocal\ value = \left(\frac{1}{\Sigma R}\right)$

Equation 3: $W = R * \left(\frac{1}{\Sigma R}\right)$

Where W is the priority vector and R is the geometric mean.

As the priority vectors are still Triangular Fuzzy Numbers (TFN), a technique called the center of gravity method is needed to de-fuzzify the numbers. The de-fuzzified value is given by the equation 4, where the low, medium and high values of priority vectors in the comparison rating are utilized. Finally, the value from the previous step is normalized using equation 5 and the normalized weights are determined. These are then used, by the decision-makers, to provide scores to the alternatives, with the criteria having the highest score chosen as the best recommendation.

Equation 4: $W_{df} = \frac{lW+mW+hW}{3}$

Where, W_{df} is the defuzzified priority vector, whereas lW, mW and hW are the low, medium and high value of priority vector in the comparison rating

Equation 5: $W_{norm} = \frac{W_{df}}{\Sigma W_{df}}$

Where, W_{norm} is the normalized, defuzzified value priority vector and W_{df} is the defuzzified value priority matrices.

Equation 6: $CI = (\lambda \max - n) / n - 1$

Where CI is the consistency index, λ max is the highest eigenvalue of the matrix and n is the number of elements.

Equation 7: $CR = CI/RI$

Where CR is the consistency ratio, CI is the consistency index and RI is the random consistency index. Saaty suggested the use of *CI and CR* as a way to compute consistency in a model, which is of extreme importance to AHP and thus FAHP as it helps in the selection of the right criteria, elimination of subjectivity and makes the judgments by the decision-maker more congruent (Tecknomo, 2006). The value obtained from the consistency ratio has to be less than ten percent, otherwise the decisions/ hierarchies made, and the model derived is inconsistent and needs to improve.

FAHP MODEL HAND CALCULATIONS

After the alternatives and criteria were decided by the author of the paper (more about it in chapter 6), a test run was conducted to check all the equations and the system. Table 5 shows the calculation summary for the hierarchy of alternative devices for the element of cost. It should be noted that the information for prices of the devices were taken straight from the companies (suggested MSRP). All the calculations were made to the third decimal place. From the table it can be seen that Voltage Compass is ranked the highest for the criterion of price. The Voltage Compass is not the best WIoT device for the other alternatives, but only judging on how low the cost is, and the high preference placed on that criterion, it can make the device seem better than it actually is.

Table 5. Summary of comparison between alternatives with respect to cost.

	HMT-1Z1	HC1-Comm	Volt Compass	Geometric Mean	Fuzzy Weights	Crisp Weights	Normalized weights
HMT-1Z1	(1,1,1)	(1/7, 1/6, 1,5)	(1/8, 1/7, 1/6)	(0.2614, 0.2877, 0.3218)	(0.0516, 0.0644, 0.0829)	0.0663	0.0647
HC1-Comm	(5,6,7)	(1,1,1)	(1/5, 1/4, 1/3)	(1.0000, 1.1447, 1.3264)	(0.1973, 0.2561, 0.3417)	0.2650	0.2589
Volt Compass	(6,7,8)	(3,4,5)	(1,1,1)	(2.6207, 3.0366, 3.420)	(0.5171, 0.6795, 0.8809)	0.6925	0.6764

CHAPTER 6

MODEL DESIGN, RESULTS AND VALIDATION

SELECTION OF CRITERIA

It was decided that only three major elements would be chosen for this case study. These three elements were Cost, Wearability, and Technical Features, with all three criterions consisting of sub-elements as well. This was done as all factors considered most important are covered by these three main objectives/ elements. The Cost includes sub elements such as cost of the device, cost of repairs (if applicable) or maintenance and any other infrastructure/ set-up costs needed. As for the criteria of Technical Features, sub-elements such as sensors (plus number of sensors), wireless connection and geolocation capabilities, and resistivity to electric shocks. Wearability on the other hand, includes sub-levels for weight of the device, ergonomics, compatibility with other personal protective equipment and general comfort. The elements and sub-elements can be seen in Table 6**.** Moreover, for further consistency in the model, all the sub-levels are given the same weightage.

Even though the criteria/elements for this model were selected from a safety viewpoint, cost is always a big factor and that is why it was given preference over the other elements in the FAHP model. The cost had slight preference over technical features and great preference over wearability. The lower the cost the better it is. However, if a device has a much higher cost, it might not be completely disregarded, given that the quality and technical features of the device are superb. Moreover, a price cap is not placed as elements that are listed with a set target are not helpful for assessing alternatives (Keeney, 2005). After that, while wearability is important, the technical features are given a higher preference as that is what is deemed to be more important in achieving the main objective of improved safety at the workspace (the greater the number of technical features the better). Here, it should be noted that features that directly influence safety are given a higher preference over other features. For example, heat sensor will be preferred over Bluetooth connectivity when comparing features in different devices.

The number of elements were kept lower on purpose (only 3), as the biggest problem in selecting objectives in a hierarchy in analytical methods is choosing too many objectives or by going into more detail than needed (Edwards et al., 2007). This causes a quick escalation of objectives and can provide distorted data. For example, 144 objectives were developed in an objective hierarchy to assess school desegregation plans, which in retrospect were deemed as too many elements (Edwards, 1979). Instead of trying to be as thorough as possible, the main focus should be on the reason for the analysis, which is to provide a clear dissection and examination of the alternatives (WIoT devices).

Another example of this can be seen by the tritium analysis conducted for the expiring (decaying half-life) nuclear warhead stockpile of the United States (Winterfeldt, D. and Schweitzer, E., 1998). The number of elements were drastically reduced to just four from an initial pool of 23, as those were deemed the most important by the decision-makers and stockholders. Thus, the focus should be on the objectives that matter and can clearly distinguish between the alternatives.

One more technical aspect of this FAHP Model is that it exhibits both natural and constructed attributes or criteria (no proxy attribute is observed) (Edwards et al., 2007). The elements of cost and technical features are natural attributes as they can be counted and physically measured. However, the criterion of weight is a constructed attribute as there is no set way to measure “wearability”. However, due to the use of the TFN Saaty scale in the FAHP model a number is assigned to the perceived wearability and can then be compared with ease to the other criterion.

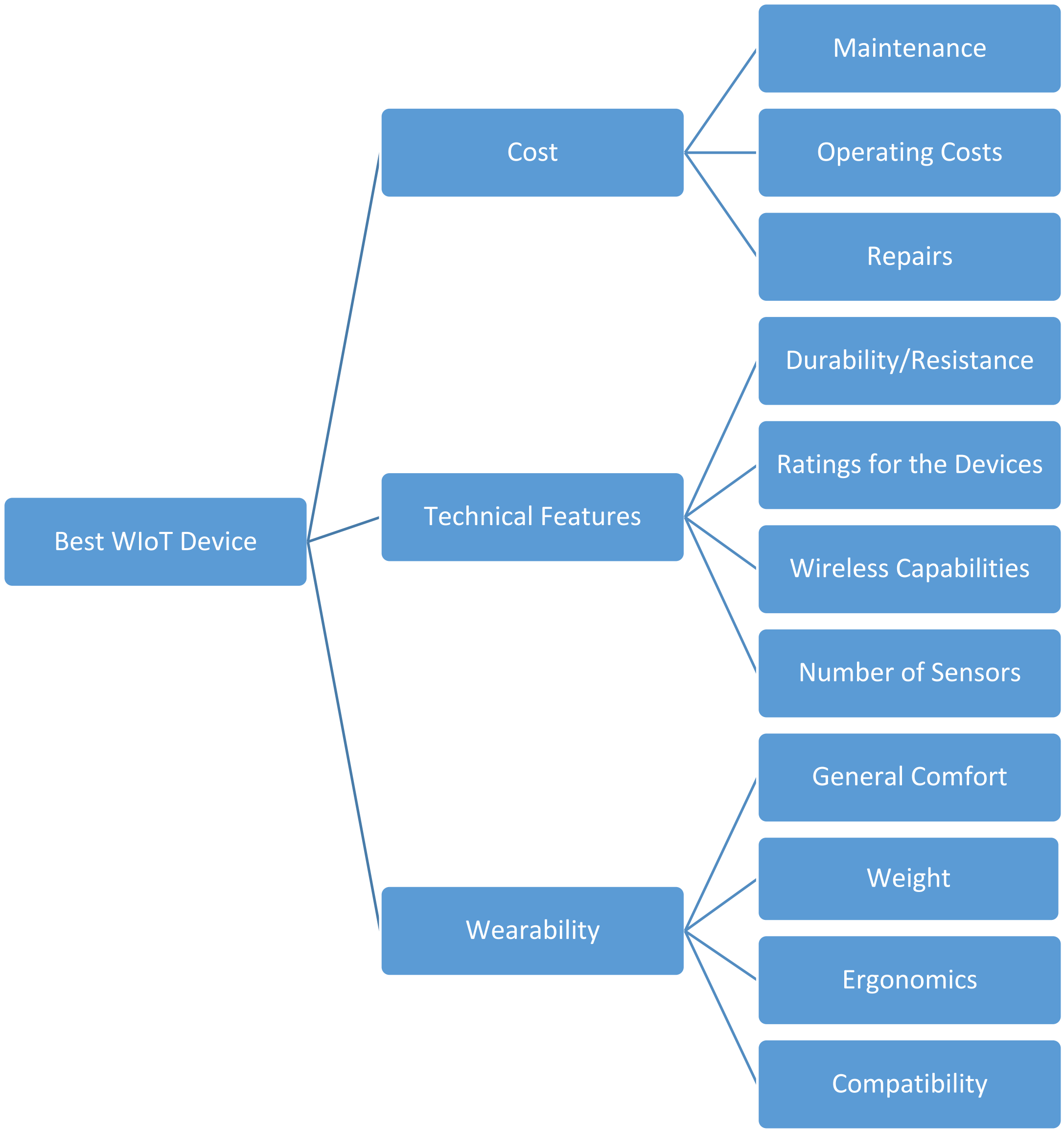

Figure 9. Hierarchal Levels and sub-levels for the elements of the FAHP Model for the best WIoT device.

DEVICE SELECTION FOR MODEL (ALTERNATIVES)

As previously mentioned, after an extensive review of the WIoT devices currently available in the market, a list of all the devices was compiled. From those alternatives, any devices that did not have the proper ratings or adhere to the standards and guidelines set up by regulatory bodies and other organizations in the United States were outright rejected. These bodies can include but are not limited to OSHA (Occupational Safety and Health Administration), ANSI (American National Standards Institute) and UL (Underwriters Laboratories). The unapproved ones can be unsafe for use at heavy worksites and besides that, the ratings are a good judgement for the quality and efficiency of a device. Similarly, any apps or devices that needed constant mobile phone connection were instantly rejected too as they can raise privacy issues, be inconsistent and can lead to issues with worker distraction. It should be noted though that devices with mobile connections as a secondary feature were not excluded but were also not given any special preference over other devices over the basis of technical features.

In addition, there was a time cap placed on the selection of the initial devices from the market, which was at the start of the research. This was done to have a limit to the total number of devices for consistency in the model, as there are newer devices or updated models released frequently. A similar time cap was placed for selecting the alternatives for evaluation of plutonium disposition options for the United States, so that the decision frame for the analytical model did not shift (Butler et al., 2005). That coupled with a high number of alternatives to begin with can cause unnecessary complexity and may not get the decision maker closer to the core alternative.

In similar fashion to the selection of the criteria for the model, the device selection followed a very focused and structured approach as well. The costs associated with the devices were found, alongside the number of features the device had. Three WIoT devices, which were in-line with the criteria and parameters set up by the decision-maker, were observed and chosen at the end to be used in the FAHP model. These devices were seen to be the most exceptional of the bunch for the selected criteria. This was done to further decrease subjectivity in the model by reducing the options to only the devices of the utmost importance.

This also helped in removing devices that might skew the data. For example, Vigifall a wearable fall detection device was eliminated from the selection phase due to its potential to skew the data for the model (Health management, 2021). Apart from the device only having one technical feature, the price for it is very low. Thus, it has the possibility of ranking higher than other, better devices as we have established low cost as a high priority. All this helps in identifying and clarifying key relationships between the alternatives and criterions.

MATLAB MODEL

An FAHP model was created on MATLAB (figure 9), where a 3x3 matrix was set up to select the best WIoT device out of three contending devices. The three criteria chosen were cost, technical features and wearability (mentioned in the section above). The three WIoT devices chosen were the HMT-1Z1 (Realwear, 2022), HC-1 Communicator (Guardhat, 2022), and the Voltage Compass (Safeguard equipment, 2022), discussed in section 5.6. Two of these devices are smart hardhats, HMT-1Z1 and HC-1 Comm, with the Voltage Compass being an attachable WIoT device. The HMT-1Z1 was the most expensive device, whereas the Voltage Compass was the least expensive amongst the three. However, with the low cost, the voltage compass only excelled in two features. Meanwhile, the other two devices happened to have numerous features, where HC-1 Communicator was seen to be the superior device, due to the number and strength of its sensors

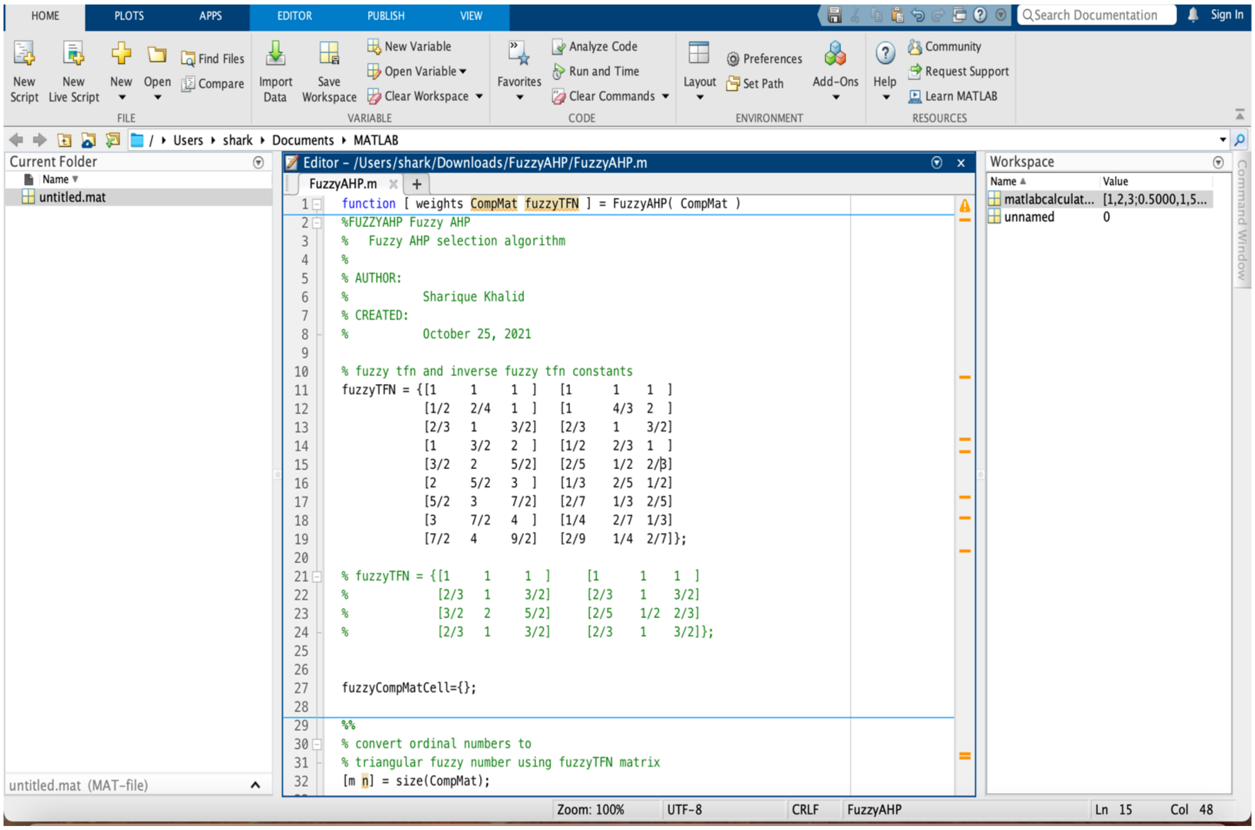

Figure 10: MATLAB Model for FAHP

The researcher (decision maker for this case study) assigned scores to the alternatives, relative to the weights they had for the specific element. Those scores were then translated into the TFN-scale and the overall weights were then calculated (figure 10 shows some of the script for the model). The program would then provide a matrix for comparison of all alternatives with all criteria and then find the overall fuzzy weights of each alternative (including the geometric means). For the criteria, cost was favored over technical features and moderately strongly favored over wearability, whereas technical features were also moderately strongly favored (in-between value) over wearability. As for the ratings of the devices for the element of cost, Voltage Compass was very strongly favored over HMT-1Z1 but favored only moderately over the HC-1. The HC-1, in turn, had a middle value between strongly and very strongly favored over the HMT- 1Z1 device.

For the element of technical features, HC-1 Communicator was slightly favored over the HMT-1Z1 and very significantly favored over the Voltage Compass, whereas the HMT-1Z1 was favored very strongly over the Voltage Compass. Finally, for the third element, the HC-1 was moderately strongly favored over the Voltage Compass and only slightly favored over the HMT-1Z1. On the other hand, the HMT-1Z1 was moderately favorable over the Voltage Compass.

Similar to the hand calculations, to be consistent all numbers computed were taken to the third decimal place. At the end, the higher the weight an alternative had, the better it performed for that criterion and was the preferred device. An average of all the weights for the criteria was then taken to find out the highest weighted WIoT device.

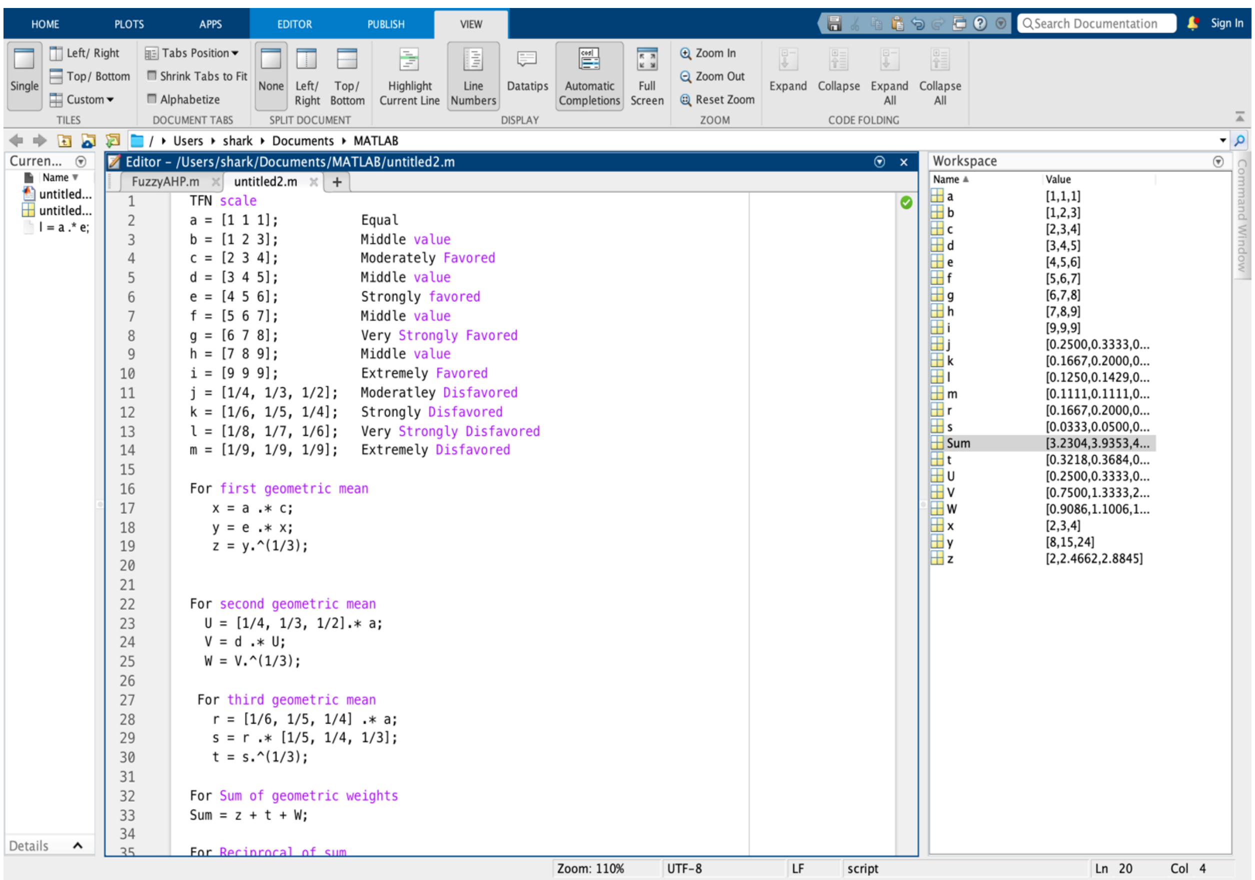

Figure 11. MATLAB FAHP Model sample calculations.

RESULTS AND VALIDATION

After running the FAHP model with the criterions, alternatives and data mentioned above, it was observed that the best WIoT device out of the bunch was the HC-1 Communicator (Device 2), having the highest weight of 0.432. After that it was the Voltage Compass (Device 1) with a weight of 0.362, followed by the HMT-1Z1(Device 3), having a weight of 0.206. The results from the model can be seen in figure 11.

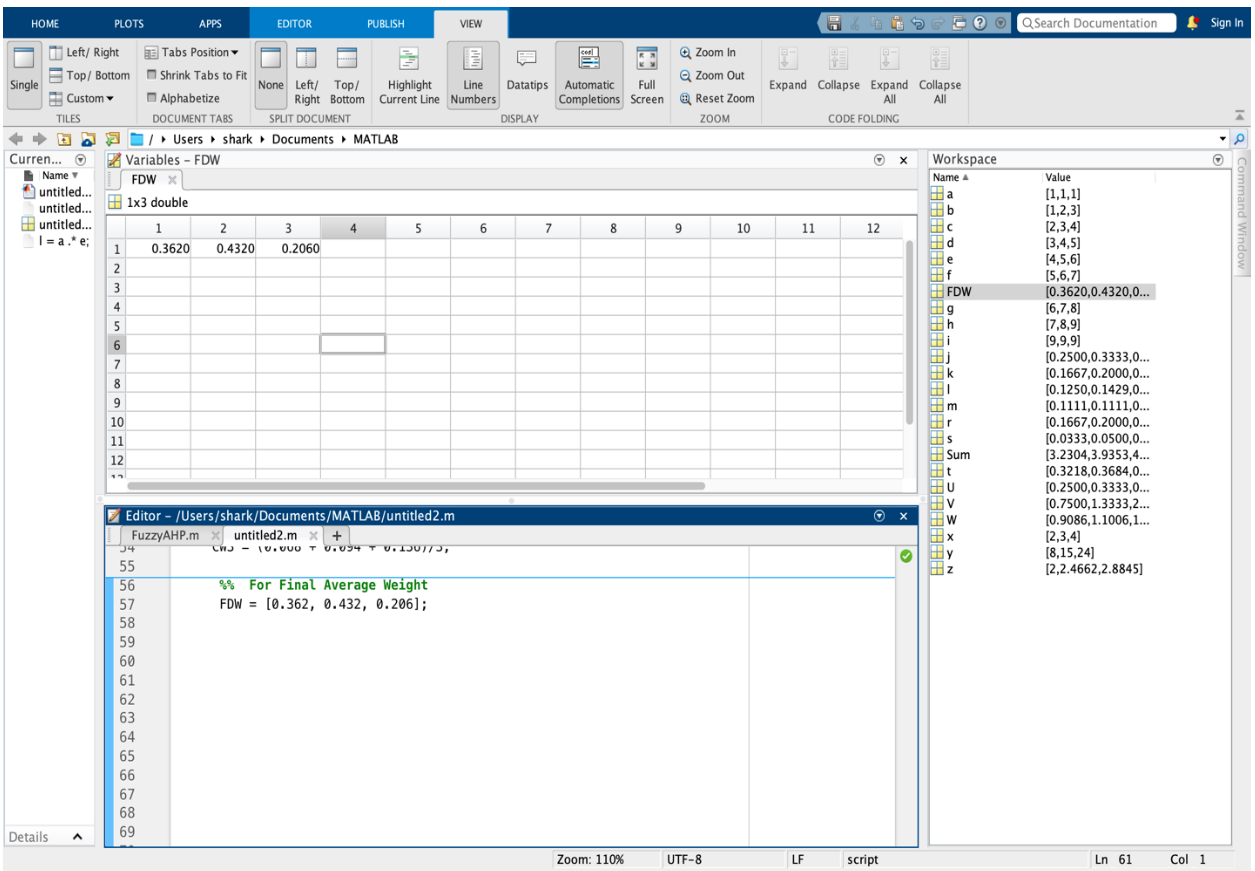

Figure 12: MATLAB model results showing the average normalized, de-fuzzified weights for the three devices.

From the data collected from the model, the eigen value, λ_{max} of the 3x3 matrix was found to be 3.077. Using this, the consistency index (CI) was found to be 0.03854 ((3.07708-3)/3-1). As N= 3, the random consistency index (RI) was taken to be 0.58. Then, by dividing the consistency index by the random consistency, the consistency ratio of 0.065 was found. As the value was smaller than 0.1 or 10%, it showed that the answer was within the acceptable limit and had minimal deviation in consistency. This means that the judgements taken by the decision maker are up to par and no revisions

The results from the model were then compared to the scratch work and an online free AHP software (123AHP, 2022), which can be seen below in figure 13. The specific software was chosen as it follows the same scale as the FAHP MATLAB model.

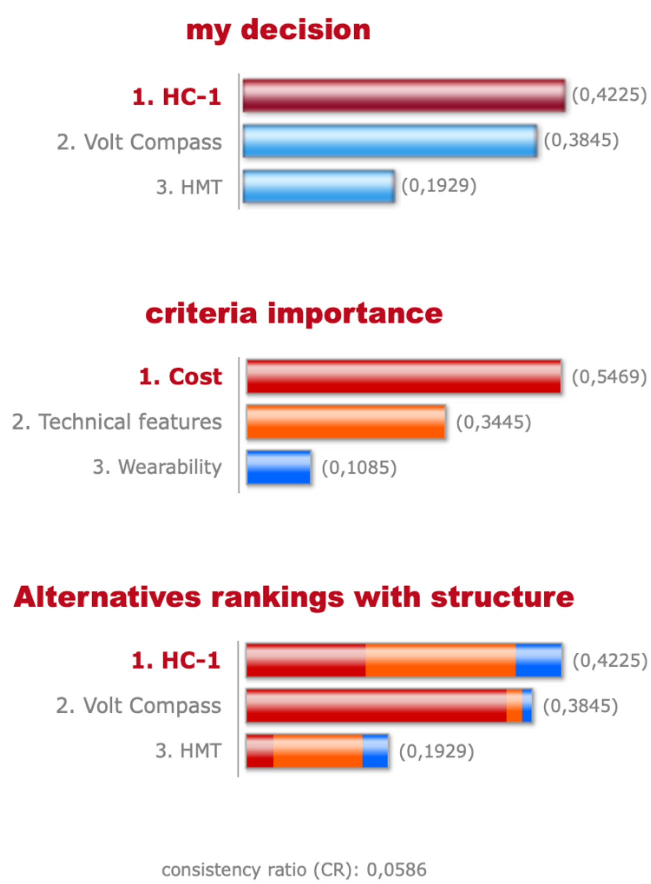

Figure 13: Overall weights for each WIoT device using AHP software (123AHP, 2022)

While it did reiterate the preferences/ ranking for the devices, with the HC-1 communicator having the highest weight and the HMT-1Z1 being the least favored, the FAHP weights were a bit higher than the AHP weights for both of the mentioned devices. The FAHP weight for the Voltage Compass was lower than the other model by about 6.4 percent, due to which both the HC-1 Communicator and HMT-1Z1 had slightly higher weights. Moving on, Table 6 shows the weights for the alternatives from both the FAHP MATLAB model and the commercial AHP software.

Table 6: Weights for the three alternatives for both AHP and FAHP.

	AHP Weights	FAHP Weights
HMT-1Z1	0.193	0.206
HC-1 Communicator	0.423	0.432
Voltage Compass	0.385	0.362

Lastly, an analysis of variance (ANOVA) was conducted to determine the significance of the results between AHP and FAHP. Here, it was found that the difference between the averages of the groups was substantial enough to be statistically significant. The p-value equaled to 0.000681, which was considerably lower than the cutoff point of 0.05. Table 7 shows the p-value amongst others using an online ANOVA calculator (Statistics Kingdom, 2022)

Table 7: ANOVA Results (Statistics Kingdom, 2022).

	Sum of Square	Mean of Square	P-value
Factor	0.05678	0.02839	0.000681

CHAPTER 7

CONCLUSION

With the high number of injuries and fatalities present in the construction industry, use of emerging technology is of utmost importance in order to improve the safety of the workers. Wearable Internet of Things devices are a type of this technological advancement and can, not only help improve the workplace safety, but the productivity, consistency and profits for a company as well. These WIoT devices need to be easily wearable in the workplace and should have a smart device aspect to it. After a large-scale examination of all the WIoT devices available in the market, the three best devices out of all the categories were highlighted and chosen (from a safety perspective). Then, using a decision-making framework the superior device was chosen out of the final three.

The decision-making framework used for this purpose was the Fuzzy Analytical Hierarchy Process (FAHP). Where, a fuzzified version of the AHP was used to establish a hierarchy and determine the best device, using criteria that the decision-maker deems is most valuable. A fuzzy version of AHP was used to eliminate user subjectivity by providing a range of values (fuzzy triangular numbers). The criteria selected for picking the superior device included the cost, technical features and wearability of the device, each with their own subcategories or sublevels. Whereas, the final three devices included the HMT, the HC-1 and the Volt Compass. After the selection of the devices, and assigning scores to them, a MATLAB model was created to make the necessary calculations. From the results of the model, it was observed that out of the three devices, from a safety perspective, the best overall device was the HC-1 from the criteria that the decision-maker had established. The Volt Compass came in at second and the HMT came in at last place.

Moving on, the results for the FAHP model were then compared with those from a free online AHP software, to check for the consistency of the model and the significance of the results. It was found that the results were similar, with both displaying the same ranking. Without a doubt, the selected device, especially in conjunction with other PPE being used (personal protective equipment), can improve the workplace safety in the construction industry.

LIMITATIONS

There were certain limiting factors for the research. Firstly, there was a time constraint for the research. The whole research was conducted in under six months, over two semesters. More time could have meant an even more detailed study of the devices. While the process is straight forward, it has to be repeated multiple times, with each time the alternatives needing a new score to be allocated by the decision maker. Secondly, in-person or hands-on testing, and observation of the devices could not occur. Therefore, the decision maker had to go off of all the data available for the devices online or through other means such as company representatives, customer service and reviews.

Additionally, the devices picked for the study were limited to only the ones available in the North American market. Thus, great devices from other places in the world (not available locally) could have been potentially overlooked.

Lastly, the devices chosen by the decision maker were picked to place an emphasis, and eliminate, (or mitigate where possible) the biggest safety hazards at a construction worksite (including the big four; slips/trips, falls, struck-by/caught-in-between, and electrocution). Though, this focus on hazards could be very different for different sites, depending on the situations, environment and work being done. This would mean that the devices would have to be chosen according to the biggest hazards and safety concerns associated with that particular work. Besides that, the devices were selected for a general, standard workplace. Otherwise, specific or special work sites may need a lot of other considerations to be made when selecting the best WIoT device.

Another thing to consider is that the best WIoT device being selected right now does not mean that it is still going to be the best in the market in the near future. With fast improvements in technology and its increased incorporation into devices means that there will inevitably be a better device in the foreseeable future. Whether it is in the form of brand-new models coming out, prototypes being finally released, or older models being refreshed and updated with gradual improvements.

FUTURE IMPROVEMENTS AND CONSIDRERATIONS

There are numerous ways in which the model can be improved. Firstly, as wearability can already be very subjective, if possible, more accurate results can be obtained if the devices can be worn or placed on subjects and all factors such as fit and ergonomics can be observed firsthand in real-time.

Another thing to mention is that prices are very arbitrary in general and can change. Not only can the prices of products/ devices increase or decrease, but they can vary vastly depending on the country and currency exchange rates. This can cause some criteria, such as costs, having to be reevaluated. Other than that, inflation can change the data overtime as well. Having a known number of employees for a certain company or workplace can also be advantageous in coming up with the best WIoT device as well. It lets you know how many workers you have to cater to and how much budget the person can allocate towards the devices.

An improvement that can be made in respect to the criteria of cost is to take other economic factors such as break-even time into account. This can help observe the costs of the device better, especially if there is a subscription or software service involved with the WIoT device. Similarly, calculations for other hidden costs can prove beneficial as well.

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APPENDIX A: APPROVAL LETTER

MARSHALL UNIVERSITY
www.marshall.edu

Office of Research Integrity

September 16, 2021

Sharique Khalid
1020 10th Street, Apt 1 B
Huntington, WV 25701

Dear Sharique:

This letter is in response to the submitted thesis abstract entitled *"Choosing Wearable Internet of Things Devices for Managing Safety in Construction Using Analytical Hierarchy Process as a Decision Support System."* After assessing the abstract, it has been deemed not to be human subject research and therefore exempt from oversight of the Marshall University Institutional Review Board (IRB). The Code of Federal Regulations (45CFR46) has set forth the criteria utilized in making this determination. Since the information in this study does not involve human subjects as defined in the above referenced instruction, it is not considered human subject research. If there are any changes to the abstract you provided then you would need to resubmit that information to the Office of Research Integrity for review and a determination.

I appreciate your willingness to submit the abstract for determination. Please feel free to contact the Office of Research Integrity if you have any questions regarding future protocols that may require IRB review.

Sincerely,

Bruce F. Day

Bruce F. Day, ThD, CIP
Director