HUMAN FACTORS ENGINEERING ON THE EDGE OF INDUSTRY 4.0: ANALYSIS FOR IoT-AIDED TECHNOLOGIES

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Abstract

Using advanced technologies and devices in human factors engineering (HFE) processes is becoming a rising trend in international arena, regarding Industry 4.0 philosophy and transformation consummation. Transition to this new technology from traditional HFE applications offers many advantages but also refers to the analysis of a very complex set of numerous emerging criteria conflicting in varying directions and dimensions. This study focuses on that enigma and investigates the problem space to facilitate Ergonomics 4.0 transformation process with the employment of fuzzy sets theory, Delphi method and Best-Worst Method (BWM). New technologies and IoT-aided devices introduced within Industry 4.0 era for instrument based ergonomic assessment, occupational health and safety applications, and, physical environment monitoring were addressed as another contribution of this study to Ergonomics 4.0 aspect. An evaluation framework apropos of related challenging decision structures was proposed in the wake of in-depth literature analysis, where, the validated criteria set was clarified with fuzzy Delphi Method. The elucidated criteria list was than observed with BWM to propose a transition period charter. Main and sub-criteria of the problem were scrutinized according to decision hierarchy; local and global importance levels of criteria, and, outcomes regarding different parties of the decision making process were interpreted comparatively in details, and suggestions has been made in the light of multi-dimensional benchmarking debates.

ENDÜSTRİ 4.0 DÖNÜŞÜMÜNDE İNSAN FAKTÖRLERİ MÜHENDİSLİĞİ: IoT TEMELLİ TEKNOLOJİLER ANALIZİ

Anahtar Kelimeler

Endüstri 4.0, İnsan faktörleri mühendisliği, Bulanık Delfi, BWM, Ergonomi 4.0

Öz

Endüstri 4.0 felsefesi ve tamamlanmaya çalışılan dönüşüm çerçevesinde insan faktörleri mühendisliği (İFM) süreçlerinde ileri teknolojilerin ve cihazların kullanılması uluslararası arenada yükselen bir trend haline gelmektedir. Beraberinde birçok avantaj getiren geleneksel İFM uygulamalarından bu yeni teknolojiye geçiş, aynı zamandada değişen boyutlarda farklı yönde çelişen çok sayıda yeni kriterin analizini de ifade etmektedir. Bu çalışma bu probleme odaklanmakta ve incelenen problem uzayını bulanık küme teorisi, Delphi yöntemi ve En İyi-En Kötü Yöntemini (Best-Worst Method - BWM) birlikte kullanarak Ergonomi 4.0 dönüşüm sürecini kolaylaştırmak adına araştırmaktadır. Endüstri 4.0 ile ortaya çıkan cihaz temelli ergonomik değerlendirme, iş sağlığı ve güvenliği uygulamaları, fiziksel çevre takibi için kullanılabilen yeni teknolojiler ve IoT temelli cihazlar çalışmanın Ergonomi 4.0 literatürüne bir diğer katkısı olarak ele alınmıştır. İncelenen zorlu karar yapılarına uygun olarak önerilen değerlendirme çerçevesi için gerçekleştirilen derinlemesine literatür araştırması sonuçları bulanık Delphi Metodu ile analiz edilerek geçerli kılınan kriter kümesi belirlenmiştir. Daha sonra doğrulanan kriterler listesi bir geçiş süreci yol haritası önermek adına için BWM yöntemi ile ele alınmıştır. Problemin ana ve alt kriterleri karar hiyerarşisine uygun olarak irdelenmiş; yerel ve genel önem seviyeleri ve karar verme sürecinin farklı taraflarına ilişkin çıktılar karşılaştırmalı olarak detayları ile yorumlanmıştır.

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1. Introduction

Today, it is an undeniable fact that all organizations, regardless of their field of activity, have to adopt Industry 4.0 perspective in their operations and switch into Internet of Things (IoT)-based technologies in order to overhaul the epoch, increase operational efficiency and provide remote control and observance.

Industry 4.0 term refers to the fourth industrial revolution phase and was first announced in 2011, as a project related to computerized manufacturing carried out by German Ministry of Education and Research (Yılmaz Kaya & Dağdeviren, 2019). While it retains an ongoing adaptation process, Industry 4.0 preserves a complicated and interlaced structure. Some components i.e. IoT, cyber-physical systems, Industrial Internet of Things (IIoT), big data analytics, robotic systems, cloud systems, smart products, smart factories could be inferred about Industry 4.0 concept to complete this transition. However, since the basic philosophy of Industry 4.0 is to build a system that is completely free of humans, full autonomous, moving by itself based on error-free operations; which reveals that the backbone of it underlies in IoT applications.

IoT, introduced in 1999 by Kevin Ashton, is one of the most significant technological revolutions that enabled several dissimilar physical things to get seamlessly integrated by unique identification and ubiquitous connectivity (Hinduja & Pandey, 2020). IoT expresses the communication of physical devices with each other and remote control of objects; it creates a system that enables both machine to machine (Machine to Machine - M2M) and human to machine (User to Machine - U2M) communication (Adem, Yılmaz Kaya, Çakıt & Dağdeviren, 2022).

IoT is an ever-growing "wearable and mobile device network" generator that not only digitizes but also changes working and monitoring concepts, hence, the way processes be practiced. With the use of IoT technologies in human factors engineering (HFE) applications, labeling and tracking "objects" has been made possible in physical production environment (Adem et al., 2022). This progress makes low-cost computing activities usable in work measurement, ergonomic assessments and business planning, independently from the center or human perception.

This leads us to the biggest change of Industry 4.0; removing the human from production as much as possible with smart factories enabled by efficiently employed IoT technologies will result in enhanced productivity and reduced error rates. According to a Forbes' research, smart factories will increase global economy by 1.5 trillion dollars in 2023, where, approximately 70% of manufacturers are following smart factory initiatives today, which shows a significant increase since 2017 (Giles, 2019). As Siemens, Hewlett Packard, Whirlpool, Bosch, and Volkswagen lead this transformation (Giles, 2019), it is still a dream to completely prune human effect from manufacturing processes in a wider scale; ergo, some different ways to embrace IoT technologies in Ergonomics 4.0 standpoint according to today's circumstances and accelerate Industry 4.0 transformation have to be addressed.

The use of IoT-aided technologies for HFE analysis started after it was primarily used in health sector for medical purposes and subsequently in training management for athlete health control and performance monitoring. Today, in Industry 4.0 phenomena, employment of IoT technologies in industrial HFE applications is especially attention-grabbing in some certain applications; (i) instrument based assessments, (ii) occupational health and safety (OHS) activities, and, (iii) physical environment monitoring. The most frequently encountered Industry 4.0 driven technologies used in industrial HFE activities could be listed as wearable activity or GPS trackers, smart OHS watches, Augmented Reality (AR) goggles, image processing technologies, sensors, robots, smart lighting and energy systems, smart communication devices, smart masks, smart helmets, IoT-aided goggles, IoT-aided gloves, lumbar motion monitor (LMM), motion capturing (MoCap) and electromyography (EMG) technologies.

Wearable activity trackers (Lennefer, Resi, Lopper & Hoppe, 2020) and Smart OHS watches (Gonzalez-Canete & Casilari, 2021) are able to be used to monitor instant situations to intervene in a very short time in health related issues e.g. heart attacks, falls, low blood sugar, and, to enable effective employee follow-up in high-risk working environments e.g. working at height, under water, underground. Wearable GPS trackers could also be used for OHS activities especially in environments having a lot of movement or high risk levels by monitoring not only employees, but vehicles and autonomous devices too; i.e. in case of entrance to a location with any risk factors warnings would be sent to compatible gadgets (e.g. preventing employees from entering chemically contaminated areas). Smart OHS watches are used not only to intervene instant situations but to monitor the physical working environment elements constantly and autonomously. The vibration, noise, pressure, heat, temperature, even stress conditions that employees might be exposed to could be measured, hence, precautions would have been taken accordingly this continuous data flow. AR goggles (Ivaschenko, Stinkov & Krivosheev, 2018) are able to be used for OHS activities and trainings. With these devices, employees could instantly see data e.g. operating manual, transport mode, last maintenance date, by just looking at the objects in their glasses. In this way, even unexperienced or untrained employees would use those objects more efficiently and appropriately; accordingly, training and treatment costs, process times, maintenance and repair costs, and job accidents would decrease. Image processing technologies (He, 2021) are used in instrument based ergonomic assessments and physical environment monitoring; e.g. mental fatigue, a very hard to detect issue, could made possible to be monitored, or, preventive actions could be taken immediately in any temperature rise to avoid a possible fire start, respectively. Robots (Chaari, Abdelfatah, Loreno & Al-Rahimi, 2021) could also be used for OHS activities and physical environment measurements. Output efficiency and job safety could be increased since robots could uninterruptedly perform the tasks that are determined to certainly be harmful to human health (e.g. in environments chemically, biologically, or radioactively contaminated) or to be high-risk jobs. Smart masks (Ma, Wu, Miao, Fan, Kong, Patil, Liu & Wang, 2021) and smart helmets (Wang, Zhang, Lv & Lu, 2018) are other types of Ergonomics 4.0 devices to be used in both OHS activities and physical environment measurements. OHS rules could be checked to be complied with thanks to the sensors that detect whether the device was worn. Some health parameters (e.g. heart rates) or physical environment elements (e.g. gas, temperature, etc.) could be measured too; in case of exceeding critical levels warnings could be send. These devices could also be used as gadgets to notify employees of the approach of dangers by integrated employment with wearable GPS tackers. In addition, smart helmets are able to be used in posture and motion assessments thanks to optional 360-degree navigation 3D depth cameras. IoT-aided goggles and gloves (Yang, Yu, Shirowzhan & Sepasgozer, 2020) are able to be used in OHS activities to reduce occupational accidents by M2M communication; machinery that require the use of these personal protective equipment (PPE) will not work unless they were in use. LMMs (Cerqueira, Ferreira da Silva & Santos, *2019), s*onic based human body posture assessment devices (SBPADs) (Eldar & Fisher-Gewirtzman, 2020), and accelerometer based posture assessment devices (Cerqueira et al., 2019) could be used in instrument based assessments to directly assess the human body posture. Where, LMMs could be considered uncomfortable to use and could modify normal postural behavior; and, thickness of the subcutaneous fat and air properties (e.g. temperature, density) can influence SBPADs' results. MoCap technologies (Asadi & Arjmand, 2020; Chebel & Tunc, 2021) are also able to be used for posture evaluations, providing digitalization of the subjects' motion. Regarding posture strain and muscular fatigue evaluation, the most used method is EMG (Mudiyanselage, Nguyen, Rajabi & Akhavian, 2021), a technique based on the measurement of skin's electrical potential through the use of electrodes. There are two types of EMGs available; intramuscular and surface EMGs. Due to the fact that the first one is invasive, surface EMG sensors are more frequently preferred for ergonomic assessment experiments (Cerqueira, et al., 2019).

As explained by the application examples presented above; such a new technology which is able to communicate M2M, collect and exchange data autonomously could bring enormous opportunities in industrial HFE standpoint for both employees and companies. By enhanced workload adjustment and workforce assignment pursuant to employee performances, staff and energy saving would be enabled by smoother scheduling. Especially for certain tasks where mental workload was assessed to express performance, this new technology is evidently more convenient. Performed operations and related environment parameters could be fully captured, which would improve physical working environment conditions. Evolved OHS conditions could be considered as another advantage, where this brand-new technology enables to minimize occupational risks and dangers in advance, and could be used to create a virtual operational process steps and warnings roadmap for users. Enhancements in predictive maintenance could be realized by proactive actions taken in the light of uninterruptedly monitored and well-interpreted U2M and M2M operational data. Prolonged product lifetime for machinery is another advantage, where, there is no user or device count limit in IoT-aided systems; they provide unlimited and indefinite usage.

Alongside huge potential benefits of employing IoT-aided technologies in HFE activities, deciding which type of this new facility to choose and append into current processes on what performance indicators, operating parameters, or evaluation criteria set is a very complicated task. These facts lead the problem to be a complex multi-criteria decision making (MCDM) problem. Criteria influencing the preferability and performance of IoT-aided technologies can vary across different devices and different user groups, so, it may not be practically possible to identify a valid criteria set and specify weights of decision criteria solely on crude expert choices without employment of suitable and robust techniques. The relative importance of respective criteria will vary on user goals and application domain. Therefore, the model would need to be tailored to the particular context of this generalized research topic.

In this study, 43 initial decision criteria under six main attribute groups, which were determined with regard to a comprehensive literature review research, were handled in five aspects with the fuzzy Delphi method in to this end. Fuzzy set theory (FST) was used to represent the impact of individual perspectives and linguistic judgements on the results with triangular fuzzy numbers (TFNs), which is the most frequently used fuzzy number (FN) type owing to the ease of operation and suitability to intuitive creation of it. After identification of the proto-criteria set and validation of real main and sub-criteria sets for the problem, as a robust and potent technique Best -Worst Method (BWM) was employed to further investigate the problem space.

In this context, contribution of this study to the existing literature can be summarized in four-folds; (i) this is a pioneer study to investigate IoT-aided technologies in terms of proposing a benchmarking debate for industrial use in HFE related applications; (ii) benefits of employing IoT technologies as ergonomic analysis solutions were addressed for HFE practitioners, additionally, different Ergonomics 4.0 devices were collated; (iii) a comprehensive literature review was performed to enlighten diverse criteria for Ergonomics 4.0 applications; (iv) BWM and FDM methods were used as a first in a study of Ergonomics 4.0 research topic. Since previous studies have focused on individual employment of these devices and technologies, and rarely on the factors influencing adoption in industrial scales, hence, little was known about the quality factors about IoT-aided technologies in a specific context such as industrial HFE applications and ergonomic measurements. This study presented a guideline for industrial professionals from different fields. Outcomes of the study were interpreted to highlight the impact of the difference among decision maker (DM) perceptions; additionally, benchmarking of local and global weightings were also presented, which makes the findings presented by this study adding a merit value and different point of view to the existing literature, since there are no such studies introduced.

The remainder of this study is as follows, Section 2 introduces literature review related to IoT-aided device and technologies assessment studies, Section 3 introduces the employed methods, Section 4 was devoted to the definition of the problem and numerical experiments of performed real-life application. Obtained results and findings were examined and discussed in Section 5, where, Section 6 concludes the study and points out some future research directions.

2. Scientific Literature Review

On the extant literature analysis considering IoT-aided technologies and employed MCDM techniques as solution approaches, it can be seen that almost all of the studies handled the problem on the basis of individual use, where, the scopes of papers could be clustered on product features, encountered advantages and disadvantages, fashion design specifications, security and risk assessment problems. Some recent studies in related literature were summarized hereinafter.

Ye and Gao (2014) developed a conceptual model of IoT-aided stadium information system (SIS), and compared it with conventional SISs. Gao, Li and Luo (2015) analyzed factors associated with consumer's intention to adopt IoT-aided wearable technology for health care management. Yang, Yu, Shirowzhan, Sepasgozer and Li (2016) analyzed factors determining perceived value for IoT-aided wearable devices. Jeong, Kim, Park and Choi (2017) validated innovation diffusion theory within the context of IoT-aided wearable devices and tested several features in relationship with purchase intention.

Özgüner Kılıç (2017) presented a field research for employment of available smart garment products. Park and Shin (2017) proposed a security assessment framework for IoT services, based on fuzzy DEMATEL (Decision Making Trial and Evaluation Laboratory) and fuzzy AHP (Analytical Hierarchy Process) MCDM methods. Hsiao and Chen (2018) proposed a conceptual model to investigate antecedents of intention to purchase a smartwatch for individual use. Ly, Lai, Hsu & Shih (2018) used FST and AHP to evaluate influential factors in building IoT systems. Abdel-Basset, Mohamed, Chang and Smarandache (2019) suggested a methodology using bipolar FNs with TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) for blood sugar tracker smart medical devices for diabetic patients. In another study, Abdel-Basset, Manogaran and Gamal (2019) proposed a combined neutrosophic FNs and TOPSIS method to evaluate the performance of IoT-aided applications and services in organizations. Balog, Băjenaru and Cristescu (2019) assessed affecting factors on the quality of IoT-aided smart wearable devices by D-ANP (DEMATEL-based Analytic Network Process). Bharathi (2019) designed "IoT risk taxonomy" and prioritized IoT security risks with AHP. Büyüközkan and Göçer (2019) employed intuitionistic fuzzy Choquet integral (IF-CI) approach on wearable monitoring device selection for cardiac patients with comparisons on several MCDM methods. Mashal and Alsaryrah (2019) adopted a fuzzy AHP approach to rank problem criteria and and alternatives for IoT applications selection. Büyüközkan and Güler (2020) handled an IoT-aided smart watch selection problem with HFL-SAW (Hesitant Fuzzy Linguistic Simple Additive Weighting) and ARAS (Additive Ratio Assessment) methods. Hinduja and Pandey (2020) evaluated security features of IoT-aided equipment with ANP and GRA (Grey Relational Analysis) for healthcare devices.

As a last instance, Mashal, Alsaryrah, Chung and Yuan (2020) selected the most suitable IoT applications for individual users in their study with AHP and SAW methods.

3. Methods

This section describes the methods used in the study. Research and publication ethics were complied with in this study.

3.1 Fuzzy Delphi Method

The DELPHI method, developed by Rand Co. in the 1950s, is a powerful decision-making tool that can develop common decisions by combining DM opinions in a single point while providing consistency. Fuzzy DELPHI, like DELPHI method, is based on expert opinions, but while DELPHI method requires a sequence of multidimensional researches to ensure consensus of expert opinions, a single research will be sufficient in fuzzy DELPHI management.

Fuzzy Delphi was developed to consider ambiguity of DMs' judgments and improve output reliability and efficiency besides achieving a consensus (Murray, Pipino, Gigch and John 1985; Ishikawa, Amagasa, Shiga, Tomizawa, Tatsuta and Mieno 1993; Lee, Wang & Lin, 2010). Also, while DELPHI method forces experts to change their opinions to meet at a common debate, fuzzy DELPHI method respects expert opinions by assigning a different degree of membership for each possible consensus. Moreover, where original DELPHI method might be considered as resource, effort- and time-consuming due to need of sequential data collecting from a broad board of experts, fuzzy Delphi offers a more cost-effective and rapid process, and yet more trustable results by reflecting uncertainties in DMs' assessments to results. Padilla-Rivera, Telles do Carmo, Arcese and Merveille (2021) identified that the number of respondents, despite being smaller, would be sufficient to ensure the robustness of fuzzy Delphi results with advantage of offering a more effective evaluation process based on linguistic references.

To provide a clearer ground for the readers, preliminarily referring FST basically will be proper. FST is suggested to handle subjective and imprecise data and to transfer the input information into the solution space with minimum loss by Zadeh (1965).

Considering the traditional set theory, an element x has to have the membership value of "1" if it belongs to the set A, and the value of "0" if it does not. According to FST; element x can belong to set $\tilde{A}$ to a degree of $\mu\tilde{A}(x)$ which is the membership function of element x, and, is defined between [0,1]. There are various types of membership functions used in FST applications, where some commonly used types could be listed as singular FNs, TFNs, trapezoidal FNs, Gaussian FNs, sigmoidal FNs, intuitionistic FNs, Pythagorean FNs, Spherical FNs (Yılmaz Kaya, Adem, Dağdeviren, 2021a). TFNs were used in this study to represent the linguistic definitions of DMs, which could be denoted as a triplet (α, β, γ), where, $\alpha \leq \beta \leq \gamma$. TFNs were employed in this study, since triangular membership function is the most frequently used FN type owing to the ease of operation, stretchable and intuitive creation feature of it (Sanchez & Gomez, 2003; Yılmaz Kaya et al., 2021a). The membership function of a triangular FN x $\mu\tilde{A}(x)$ could be defined as (Zimmermann, 1990) (Equation 1);

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{(x-\alpha)}{(\beta-\alpha)} & x \in [\alpha, \beta] \\ \frac{\gamma-x}{\gamma-\beta} & x \in [\beta, \gamma] \\ 0 & otherwise \end{cases} \quad (1)$$

The algebraic operations of any two fuzzy numbers $\tilde{A}(1)$ and $\tilde{A}(2)$ could be observed from the studies of Zadeh (1965), Zimmermann (1990), Chang (1996), Sanchez and Gomez (2003), Dağdeviren (2007), Dağdeviren and Yüksel (2008), Kılıç Delice (2016), Yılmaz Kaya and Dağdeviren (2016), Abdel- Basset et al. (2019), Yılmaz Kaya et al. (2021a) for interested readers.

As the first step of fuzzy Delphi method, expert x from the committee having n experts evaluates the importance of attribute y as $p_{xy} = (a_{xy}; b_{xy}; c_{xy})$; $x = 1, 2, 3, ..., n$; $y = 1, 2, 3, ..., m$; after that, DM scores of each attribute was integrated with geomean function, where p_y represents the weight of attribute y presented as $p_y = (a_y; b_y; c_y)$ with $a_y = min(a_{xy})$, $b_y = (\prod_1^n b_{xy})^{1/n}$, $c_y = max(c_{xy})$. Thereafter, DMs' linguistic preferences were converted into TFNs (Table 1), where the convex combination values use the coefficient ε; $\varepsilon = [0, 1]$, as; $u_y = c_y - \varepsilon (c_y - b_y)$; $p_y = a_y - \varepsilon (b_y - \varepsilon a_y)$; $b = 1, 2, ..., m$. Here, ε represents the positive or negative bias of DMs' perception, and usually considered as 0.5, to reflect a non-biased evaluation as a general condition. Next, the inferred fuzzy evaluations were translated into exact H_y number for each attribute (Equation 2).

$$H_y = \int(u_y, p_y) = \sigma[u_y + (1-\sigma)p_y] \quad (2)$$

Here σ indicates optimistic equilibrium assessment of DMs'. Hence, after the fuzzy Delphi threshold value was obtained to refine the validated attributes from the original set (Equation 3, Equation 4).

$$T = \left(\sum_{y=1}^{m} H_y\right) / \, m \quad (3)$$

$$\begin{matrix} H_y \geq T, & b \text{ is valid} \\ H_y < T, & \text{reject } b \end{matrix} \quad (4)$$

Table 1
DMs' linguistic scale in fuzzy Delphi

Linguistic terms (importance)	Corresponding TFNs
Extreme - Very high	(0.75, 1.0, 1.0)
Demonstrated - High	(0.5, 0.75, 1.0)
Strong - Low	(0.25, 0.5, 0.75)
Moderate - Very low	(0, 0.25, 0.5)
Equal - No	(0, 0, 0.25)

3.2 Best-Worst Method

BWM developed by Rezai (2015, 2016) is a subjective pairwise comparison-based MCDM method which requires two different information (i) preference vector of the most important criterion over other, (ii) preference vector of all criteria over the least important criterion (Yılmaz Kaya, Adem, Dağdeviren, 2021b). BWM has become very preferable in a short time because it reduces the number of comparisons in calculations (Kılıç Delice & Can, 2020). In comparison with its rivals like DEMATEL, AHP or ANP, BWM also provides the reliability information of final weightings by computing the consistency ratio of comparisons; as a plus, the consistency could be improved with BWM while it reduces required pair-wise comparisons in regards with the other subjective weighting methods; i.e. BWM requests fewer comparisons compared to AHP, the comparisons in BWM were reduced from "n*(n - 1) / 2" to "(2n – 3)" for n decision criteria (Rezaei, 2015; Sotoudeh-Anvari, Sadjadi, Molana, & Sadi-Nezhad 2018). Furthermore, BWM provides the optimal solutions considering the handled problem space by employing a maximin model to compute the weights of selection criteria, as an improvement and the main distinctive advantage of the method.

Linear BWM handles the decision making problem including *n* criteria $\{c_1, c_2, ..., c_n\}\}$, where $j=1, 2, ..., n,$ in a comparison debate, where, the criteria having the highest, and, the least importance have to be identified, at first. After that, "*the best-to-others*" comparison vector was identified, which was denoted as $A_B= (a_B1, a_B2, ..., a_Bj, ..., a_Bn)$; a_{Bj} represents the preference value of the criterion *B* over the criterion *j*, in regards with the determined preference of criterion with the highest importance over all other criteria on a scale of 1 to 9 (Table 2).

Table 2
DMs' linguistic scale in BWM

Linguistic scales	Scores
Equally	1
Weakly	2
Moderately	3
Moderately plus	4
Strongly	5
Strongly plus	6
Very strongly	7
Very, very strongly	8
Extremely	9
Reciprocals	from 1/9 to 1

Thereafter, "*the others-to-worst*" comparison vector, which was denoted as $A_W= (a_{1W}, a_{2W}, ..., a_{jW}, ..., a_{nW})$, was obtained according to the preferences of all criteria over the criterion with the least importance on the same scale (Table 2). Inferred precedence information then is used to build a linear mathematical programming model to find the optimal weighting scores of criteria. The optimal weighting scores ($w_1^*, w_2^*, ..., w_n^*$) and the index of judgement consistency (ξ^*) were calculated by solving the identified linear programming model denoted in Equation (5) – Equation (9) to minimize the maximum absolute difference of $\{|w_B/w_j - a_{Bj}|, |w_j/w_W - a_{jW}|\}$; for $\{c_1, c_2, ..., c_n\}, j=1, 2, ..., n.$

$$\min \xi \tag{5}$$

Subject to

$$\left|\frac{w_B}{w_j} - a_{Bj}\right| \leq, \ \xi, \quad for\ all\ j \tag{6}$$

$$\left|\frac{w_j}{w_W} - a_{jW}\right| \leq \xi, \quad for\ all\ j \tag{7}$$

$$\sum_j w_j = 1 \tag{8}$$

$$w_j \geq 0, \quad for\ all\ j \tag{9}$$

This linear mathematical model aims to minimize the maximum absolute difference value "ξ" (Eq. 5), where, Eq. (6) represents "*the comparison of best-to-others*" vector, Eq. (7) represents "*the comparison of others-to-worst*" vector, Eq. (8) ensures the sum of optimal weighting scores to be equal to "1", and, Eq. (9) stands as the positivity constraint. The acceptability of the input problem data of DMs' initial pair-wise comparison could be calculated by consistency ratio (CR) values, where CR = $\xi^* /CI,$ in means of the input-based CR and consistency index (CI) threshold values proposed by Rezaei (2015). ξ^* = [0, 1], where, the closer the optimal auxiliary variable ξ^* values to zero will address higher consistency. The computation procedure of BWM was proposed to clarify the importance levels by investigating the superiority of the criteria, where this procedure is also able to be used to investigate the superiority of alternatives with respect to a criteria set, especially for the cases where the performance values of alternatives could not be quantified.

4. Application

Data collection was performed on Google Scholar and Scopus databases to engage a broader publication array for literature reviews based on introducing an affecting criteria set for the handled problem. The search terms used were "("iot" and "ergonomics"); ("wearable devices" and "ergonomics"); ("iot" and "ergonomics" and "wearable devices" and "multicriteria decision making"); ("iot" and "ergonomics" and "multicriteria decision making"); ("iot" and "multicriteria decision making"); ("wearable devices" and "multicriteria decision making")" generating in titles, abstracts, or keywords. From the literature analysis and expert knowledge 43 criteria were identified in terms of six main attribute groups representing cost-, technology-, HFE-, design-based attributes and attributes related to security and product life cycle management (PLCM) issues; to scrutinize factors affecting Ergonomics 4.0 applications (Rijsdijk & Hultink, 2009; Yang et al., 2016; Jeong et al., 2017; Abdel-Basset et al., 2019; Balog et al., 2019; Büyüközkan & Göçer, 2019; Mashal & Alsaryrah, 2019; Büyüközkan & Güler, 2020; Mashal et al. 2020).

4.1 Fuzzy Delphi Computations

Five DMs to represent five differing aspects related to the handled problem evaluated the problem space to validate the attributes (Table 3). DM board assessed criteria significance levels using a five point Likert scale, then their linguistic assessments were converted into TFNs using Table 2. Assessment scores were aggregated, defuzzified and tested for expert consensus using Equations (2) – (4); there were 19 criteria which were eliminated, where, a total of 24 criteria grouped under six different main groups were accepted with the threshold value T= 0.277 through the validation procedure.

Table 3
DMs profiles

Expertise field	Title	Background	Experience (years)
HFE, OHS	Academician	Industrial Engineering (Ph.D.)	15
HFE	Technical works & repair chief	Mechanical Engineering (B.Sc.)	12
OHS	Job safety expert	Industrial Engineering (M.Sc.)	8
Purchasing	Purchasing expert	Business Administration (B.Sc.)	10
Informatics	Data security expert	Computer Engineering (M.Sc.)	13

The proto-set of factors consisting of 43 criteria under 6 main attribute groups, criteria definitions, calculation values and acceptance status are shown in Table 4, where, input data of DMs' evaluations were presented in Appendix 1.

Table 4
Fuzzy Delphi calculations and results

Main-attributes	Criteria	py	uy	Hy	Status
Cost	Investment cost	-0,287	0,787	0,322	Accept
	Operational costs	-0,294	0,794	0,324	Accept
	Maintenance cost	-0,294	0,794	0,324	Accept
Technology	Computing performance	-0,066	0,879	0,314	Accept
	Storage capacity	-0,006	0,694	0,172	Reject
	Ubiquity	-0,066	0,879	0,314	Accept
	Measurement variety	0,228	0,897	0,267	Reject
	Energy consumption	-0,358	0,858	0,339	Accept
	Communication network	-0,098	0,911	0,319	Accept
	Operating temperature rate	0,153	0,972	0,272	Reject
	Functional stability	-0,123	0,935	0,322	Accept
	Magnetic immunity	0,000	0,500	0,250	Reject

	Battery life	-0,006	0,694	0,172	Reject
	Work environment integration level	0,018	0,669	0,171	Reject
	Interoperability	-0,338	0,838	0,334	Accept
	Mobile application	0,000	0,500	0,250	Reject
	Actuation comfort	-0,358	0,858	0,339	Accept
	Inertial motion comfort	-0,338	0,838	0,334	Accept
Ergonomics	Movement prohibition	-0,098	0,911	0,319	Accept
	Vibration comfort	0,204	0,921	0,268	Reject
	Weight	0,228	0,897	0,267	Reject
	Dimensions	-0,075	0,888	0,315	Accept
	Need of physical effort to use	-0,098	0,911	0,319	Accept
	Need of mental effort to use	-0,066	0,879	0,314	Accept
	Need of proficiency to use	-0,098	0,911	0,319	Accept
	Easy to learn	0,438	1,000	0,173	Reject
	Ease of configuration	0,438	1,000	0,173	Reject
	Attention requirement	-0,358	0,858	0,339	Accept
	Modular design	-0,287	0,787	0,322	Accept
Design	Design aesthetics	0,000	0,500	0,250	Reject
	Usefulness	0,438	1,000	0,173	Reject
	Output reliability	-0,358	0,858	0,339	Accept
	Safe to use	0,153	0,972	0,272	Reject
	Data security	0,438	1,000	0,173	Reject
Security	Defense against malware/attacks	-0,098	0,911	0,319	Accept
	Input info precision	-0,358	0,858	0,339	Accept
	Vendor reputation	-0,006	0,694	0,172	Reject
	Brand reputation	-0,054	0,866	0,312	Accept
	Maintenance requirements	-0,098	0,911	0,319	Accept
	Service life	0,228	0,897	0,267	Reject
	Technical service quality (vendor)	0,204	0,921	0,268	Reject
PLCM	Number of customers (vendor)	0,000	0,375	0,141	Reject
	Customer reviews (vendor)	-0,054	0,866	0,312	Accept

As Table 4 indicates, the validated criteria set with FDM calculations which will be employed in the further analysis of the study is composed of 24 sub-criteria grouped under 6 main-criteria identified for the handled problem. The three sub-criteria related to the "*Cost*" main-criteria represent the magnitude of the required financial resources for purchasing and initial investment, operating (costs related to (i) possible modifications to enhance technical capabilities in the future, (ii) power consumption, etc.), and, the maintenance actions (costs related to (i) ongoing maintenance, (ii) data storage unit maintenance, etc.), respectively. "*Computing performance*" represents how well a device can perform under varying parameters e.g. measurement speed, measurement accuracy, calculation reliability, etc. "*Ubiquity*" indicates the degree of the device to be operational and accessible anytime and anywhere when needed to be used, including mobility, connectivity, availability and computability. "*Energy consumption*" represents the amount of power that the device consumes per unit of time. "*Communication network*" represents being capable of communicating accurately with other devices and outsider environment without functional input-output redundancy problems. "*Functional stability*" represents the functional correctness of the device which could be explained as the degree to which a device provides correct and precise data independently from the operational conditions. "*Interoperability*" represents the ability of the device to work with other devices fabricated by different manufacturers. "*Actuation comfort*" and "*Inertial motion comfort*" sub-criteria represent the usage comfort of the device while it was being and not being used, respectively. "*Movement prohibition*" represents the degree of the device on which state it restricts the range of motion. "*Dimensions*" are the physical dimensions of the device. Sub-criteria of "*Need of physical effort to use*", "*Need of mental effort to use*" and "*Need of proficiency to use*" represent the needed efforts on physical and cognitive aspects, and, the proficiency level to operate the device, all underlining the capability of the device to be apprehended, learned, utilized and memorized by employees. "*Attention requirement*" represents the need of focus while the device was being used. "*Modular design*" represents the adaptability degree of the design of the device to varying urges. "*Output reliability*" represents the ability of the device to operate accurately under varying conditions in pre-specified operation time limits and provide reliable data to serve the aimed purposes. "*Defense against malware/attacks*" represents the ability of the device to protect data and information. "*Input info precision*" represents the degree of the accuracy and reliability of the data collected by the device. "*Brand reputation*" and "*Customer reviews (vendor)*" sub-criteria represent the judgements about the product manufacturer and provider companies' venerability, authenticity and stability, respectively. "*Maintenance requirements*" represents the planned and unforeseen degree of the performed maintenance activities regarding that device.

4.2 BWM Computations

Seven new sets of main- and sub-criteria were defined according to the refined results covering six main and 24 sub-criteria validated by fuzzy Delphi method (Table 5). These new criteria sets were then evaluated by the same DMs by the employment of the scale represented in Table 2 according to analyze the dominance level of each criterion in the afore-mentioned five different aspects (Table 3). The DM assessments regarded in constituting linear programming models considering referred criteria sets were presented in Table 5, hereinafter. As it was indicated in the table, the first variable before the slash mark in each assessment represents the value assigned to that criterion by that DM in accordance with the "*best-to-others*" vector, where, the second one after the slash mark represents the value assigned in accordance with the "*others-to-worst*" vector. To explain the computation mechanism of BWM method in more details, the linear programming model considering the assessments of DM_1 on both main attributes and sub-criteria groups were presented in Equation (10) – Equation (16).

Table 5
BWM decision matrix assessments

		Best to others / Others to worst									
Main-criteria	Sub-criteria	DM_1		DM_2		DM_3		DM_4		DM_5	
	C_{11}-Investment cost		B/9		B/7		2/4		B/4		B/5
C_1-Cost	C_{12}-Operational costs	7/3	5/3	6/5	2/5	9/W	B/7	B/9	2/3	4/6	5/W
	C_{13}-Maintenance cost		9/W		7/W		7/W		4/W		3/2
	C_{21}-Computing performance		4/6		B/8		2/9		3/6		B/7
	C_{22}-Ubiquity		B/9		3/6		3/6		4/5		3/5
C_2-Technology	C_{23}-Energy consumption	B/8	8/W	B/9	5/5	3/6	9/W	3/6	B/9	B/8	7/W
	C_{24}-Communication network		6/4		8/W		4/5		8/W		2/6
	C_{25}-Functional stability		4/7		7/6		3/6		4/5		4/5
	C_{26}-Interoperability		3/8		6/4		B/9		3/4		1/6
	C_{31}-Actuation comfort		6/3		B/9		B/4		1/3		B/5
C_3-Ergonomics	C_{32}-Inertial motion comfort	6/6	9/W	6/6	9/W	B/9	3/W	9/W	4/W	4/5	5/W
	C_{33}-Movement prohibition		B/9		3/4		2/2		B/3		2/4
	C_{41}-Dimensions		8/3		6/5		9/W		8/W		9/W
	C_{42}-Need of physical effort to use		B/9		1/9		2/8		3/5		5/5
C_4-Design	C_{43}-Need of mental effort to use	5/5	1/9	7/4	B/9	2/9	2/8	5/6	3/5	5/6	5/5
	C_{45}-Need of proficiency to use		3/6		2/7		3/7		B/8		4/6
	C_{46}-Attention requirement		5/5		4/6		B/9		4/6		B/9
	C_{47}-Modular design		9/W		9/W		6/5		5/4		5/7
	C_{51}-Output reliability		B/5		1/6		2/4		B/3		B/5
C_5-Security	C_{52}-Defense against malware/attacks	4/8	2/3	4/7	B/6	4/7	5/W	4/8	2/W	2/7	2/3
	C_{53}-Input info precision		5/W		4/W		B/5		1/3		4/W
	C_{61}-Brand reputation		6/W		8/W		3/3		3/3		5/3
C_6-PLCM	C_{62}-Maintenance requirements	8/W	B/5	9/W	3/5	7/5	6/W	5/6	6/W	8/W	8/W
	C_{63}-Customer reviews (vendor)		3/3		B/8		B/5		B/5		B/8
	Best (B)	C_2; C_{11}; C_{22}; C_{33}; C_{42}; C_{51}; C_{62}		C_2; C_{11}; C_{21}; C_{31}; C_{43}; C_{52}; C_{63}		C_3; C_{12}; C_{26}; C_{31}; C_{46}; C_{53}; C_{63}		C_1; C_{11}; C_{23}; C_{33}; C_{45}; C_{51}; C_{61}		C_2; C_{11}; C_{21}; C_{31}; C_{46}; C_{51}; C_{63}	
	Worst (W)	C_6; C_{13}; C_{23}; C_{32}; C_{47}; C_{53}; C_{63}		C_6; C_{13}; C_{24}; C_{32}; C_{47}; C_{53}; C_{61}		C_1; C_{13}; C_{23}; C_{32}; C_{41}; C_{52}; C_{62}		C_3; C_{13}; C_{24}; C_{32}; C_{41}; C_{53}; C_{63}		C_6; C_{12}; C_{23}; C_{32}; C_{41}; C_{53}; C_{62}	

$\min \xi$

s.t.

$\left|\frac{w_{12}}{w_{11}} - 7\right| \leq \xi$, $\left|\frac{w_{12}}{w_{13}} - 6\right| \leq \xi$, $\left|\frac{w_{12}}{w_{14}} - 5\right| \leq \xi$, $\left|\frac{w_{12}}{w_{15}} - 4\right| \leq \xi$, $\left|\frac{w_{12}}{w_{16}} - 8\right| \leq \xi$, $\left|\frac{w_{11}}{w_{16}} - 3\right| \leq \xi$, $\left|\frac{w_{12}}{w_{16}} - 8\right| \leq \xi$, $\left|\frac{w_{13}}{w_{16}} - 6\right| \leq \xi$, $\left|\frac{w_{14}}{w_{16}} - 5\right| \leq \xi$, $\left|\frac{w_{15}}{w_{16}} - 8\right| \leq \xi$

$$w_{11}+w_{12}+w_{13}+w_{14}+w_{15}+w_{16}=1,$$
$$w_{1j}\geq 0, \quad j=1,\dots,6 \tag{10}$$

$\min \xi$

s.t.

$$\left|\frac{w_{11}}{w_{12}}-5\right|\leq \xi, \left|\frac{w_{11}}{w_{13}}-9\right|\leq \xi, \left|\frac{w_{11}}{w_{13}}-9\right|\leq \xi, \left|\frac{w_{11}}{w_{13}}-3\right|\leq \xi$$

$$w_{11}+w_{12}+w_{13}=1,$$
$$w_{1j}\geq 0, \quad j=1,\dots,3 \tag{11}$$

$\min \xi$

s.t.

$$\left|\frac{w_{12}}{w_{11}}-4\right|\leq \xi, \left|\frac{w_{12}}{w_{13}}-8\right|\leq \xi, \left|\frac{w_{12}}{w_{14}}-6\right|\leq \xi, \left|\frac{w_{12}}{w_{15}}-4\right|\leq \xi, \left|\frac{w_{12}}{w_{16}}-3\right|\leq \xi, \left|\frac{w_{11}}{w_{13}}-6\right|\leq \xi, \left|\frac{w_{12}}{w_{13}}-9\right|\leq \xi, \left|\frac{w_{14}}{w_{13}}-4\right|\leq \xi, \left|\frac{w_{15}}{w_{13}}-7\right|\leq \xi, \left|\frac{w_{16}}{w_{13}}-8\right|\leq \xi$$

$$w_{11}+w_{12}+w_{13}+w_{14}+w_{15}+w_{16}=1,$$

$$w_{1j}\geq 0, \quad j=1,\dots,6 \tag{12}$$

$\min \xi$

s.t.

$$\left|\frac{w_{13}}{w_{12}}-6\right|\leq \xi, \left|\frac{w_{13}}{w_{12}}-9\right|\leq \xi, \left|\frac{w_{11}}{w_{12}}-3\right|\leq \xi, \left|\frac{w_{13}}{w_{12}}-9\right|\leq \xi$$

$$w_{11}+w_{12}+w_{13}=1,$$

$$w_{1j}\geq 0, \quad j=1,\dots,3 \tag{13}$$

$\min \xi$

s.t.

$$\left|\frac{w_{12}}{w_{11}}-8\right|\leq \xi, \left|\frac{w_{12}}{w_{14}}-3\right|\leq \xi, \left|\frac{w_{12}}{w_{15}}-5\right|\leq \xi, \left|\frac{w_{12}}{w_{16}}-9\right|\leq \xi, \left|\frac{w_{11}}{w_{16}}-3\right|\leq \xi, \left|\frac{w_{12}}{w_{16}}-9\right|\leq \xi, \left|\frac{w_{13}}{w_{16}}-9\right|\leq \xi, \left|\frac{w_{14}}{w_{16}}-6\right|\leq \xi, \left|\frac{w_{15}}{w_{16}}-5\right|\leq \xi$$

$$w_{11}+w_{12}+w_{13}+w_{14}+w_{15}+w_{16}=1,$$

$$w_{1j}\geq 0, \quad j=1,\dots,6 \tag{14}$$

$\min \xi$

s.t.

$$\left|\frac{w_{11}}{w_{12}}-2\right|\leq \xi, \left|\frac{w_{11}}{w_{13}}-5\right|\leq \xi, \left|\frac{w_{11}}{w_{13}}-5\right|\leq \xi, \left|\frac{w_{12}}{w_{13}}-3\right|\leq \xi$$

$$w_{11}+w_{12}+w_{13}=1,$$

$$w_{1j}\geq 0, \quad j=1,\dots,3 \tag{15}$$

$\min \xi$

s.t.

$$\left|\frac{w_{12}}{w_{11}}-6\right|\leq \xi, \left|\frac{w_{12}}{w_{13}}-3\right|\leq \xi, \left|\frac{w_{12}}{w_{11}}-5\right|\leq \xi, \left|\frac{w_{13}}{w_{11}}-3\right|\leq \xi$$

$$w_{11}+w_{12}+w_{13}=1,$$

$$w_{1j}\geq 0, \quad j=1,\dots,3 \tag{16}$$

The local and global importance levels regarding analyzed seven different criteria set were determined in terms of the optimal weighting scores by the employment of 35 different linear programming model systems which were formulated separately for each DM and related assessment set. The importance levels, and, local and global rankings related to problem criteria calculated by solving these linear mathematical modelling systems separately, and, by synthesizing the calculated importance scores according to the problem hierarchy, respectively, were presented in Table 6. CR values regarding each criterion set assessment were also calculated (Table 6); the fact that all CR values were found very close to zero (< 0.10) proves the reliability of calculated weighting scores.

Table 6
BWM results, CR values, local and global importance scores

Main-criteria	Sub-criteria	Local Weights		Global Weights	CR Values (Sub-criteria)				
					DM_1	DM_2	DM_3	DM_4	DM_5
C_1	C_{11}	0,155	0,096	0,089					
	C_{12}		0,051	0,048					
	C_{13}		0,020	0,018	0,066	0,058	0,021	0,042	0,025
C_2	C_{21}	0,340	0,042	0,086					
	C_{22}		0,034	0,068					
	C_{23}		0,021	0,042					
	C_{24}		0,015	0,031					
	C_{25}		0,019	0,039					
	C_{26}		0,036	0,073	0,041	0,049	0,024	0,027	0,024
C_3	C_{31}	0,149	0,079	0,071					
	C_{32}		0,018	0,016					
	C_{33}		0,070	0,063	0,087	0,043	0,077	0,063	0,075
C_4	C_{41}	0,133	0,007	0,006					
	C_{42}		0,038	0,031					
	C_{43}		0,038	0,031					
	C_{44}		0,034	0,027					
	C_{45}		0,037	0,029					
	C_{46}		0,012	0,009	0,023	0,023	0,026	0,033	0,045
C_5	C_{51}	0,164	0,076	0,074					
	C_{52}		0,046	0,045					
	C_{53}		0,045	0,044	0,028	0,083	0,075	0,077	0,063
C_6	C_{61}	0,059	0,028	0,010					
	C_{62}		0,040	0,014					
	C_{63}		0,098	0,035	0,089	0,100	0,089	0,089	0,083
CR Values (Main-criteria)					0,053	0,045	0,033	0,042	0,036

5. Findings and Discussion

In terms of selection criteria, the threshold value (T=0.277) was applied to validate the proto-attribute set of 43 criteria clustered under 6 main-groups (App. 1) and to select the final indicators according to the fuzzy Delphi outcomes. Figure 1 shows the relationship between 24 retained and 19 discarded problem criteria on the same solution space to schematize fuzzy Delphi results (Table 4). The significant cut is explained by the trend line of indicators' H_y values that distinguishes the attributes regarded as hardly essential into the Ergonomics 4.0 implementation activities according to the DMs assessments. Fuzzy Delphi method made it possible to determine a group consensus while simultaneously addressing the ambiguity of DMs' apprehension to validate a genuine criteria set representing the factors to be considered in such decisions. The validated attributes also represent the intersection of different high-level DMs (academia, industry, and government) insights, expertise and know-how about early HFE applications in the age of Industry 4.0.

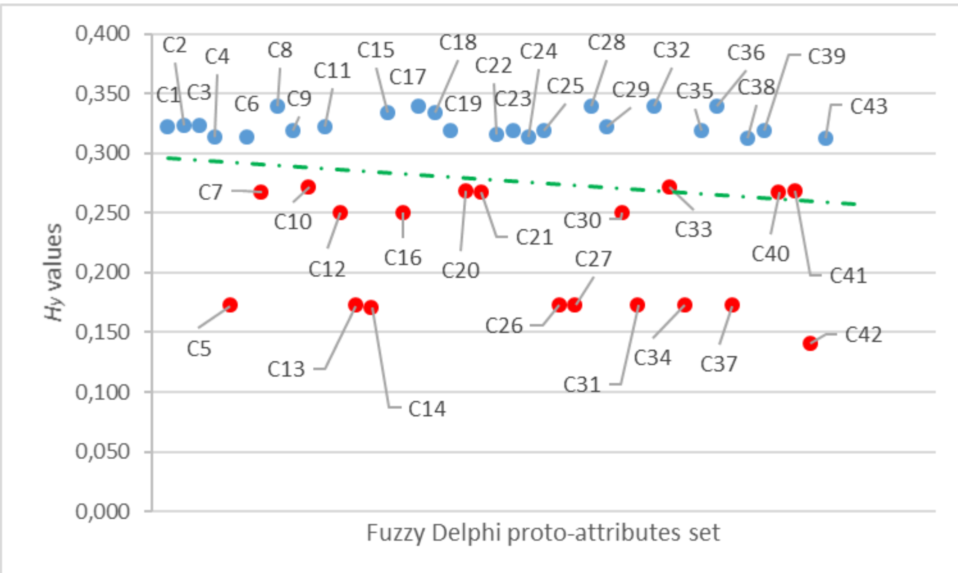

Figure 1. Fuzzy Delphi solution space and validated attributes plot

According to the BWM results, "*C_{11}- Investment cost*", "*C_{21}-Computing performance*", "*C_{51}-Output reliability*", "*C_{26}-Interoperability*" and "*C_{31}-Actuation comfort*" were found to have the most impact on IoT-aided technology assessment in terms of HFE applications regarding the global rakings, where, "*C_{63}-Customer reviews (vendor)*", "*C_{11}-Investment cost*", "*C_{31}-Actuation comfort*", "*C_{51}-Output reliability*", and "*C_{33}-Movement prohibition*" were found to be the essential ones regarding the local rankings. As endorsed also by DMs assessments (Table 5) the global rankings were found to be more accurate and suitable to reflect the input data, where the criteria did not claimed to be in the top impact list yet were selected by local rankings such as "*C_{63}-Customer reviews (vendor)*" or "*C_{33}-Movement prohibition*" were ranked as the thirteenth and seventh according to the global ranking scores, and, criteria representing the costs, which is considered as all-time most important criteria, and computing performance of the technologies in question was not ranked as the most important one(s) in the local rankings. The trade-offs and relationship between local and global rankings of decision problem were illustrated in Figure 2, where the benchmarking of validated criteria in regards of impact levels on HFE implementation activities according to the DMs assessments were visualized in Figure 3.

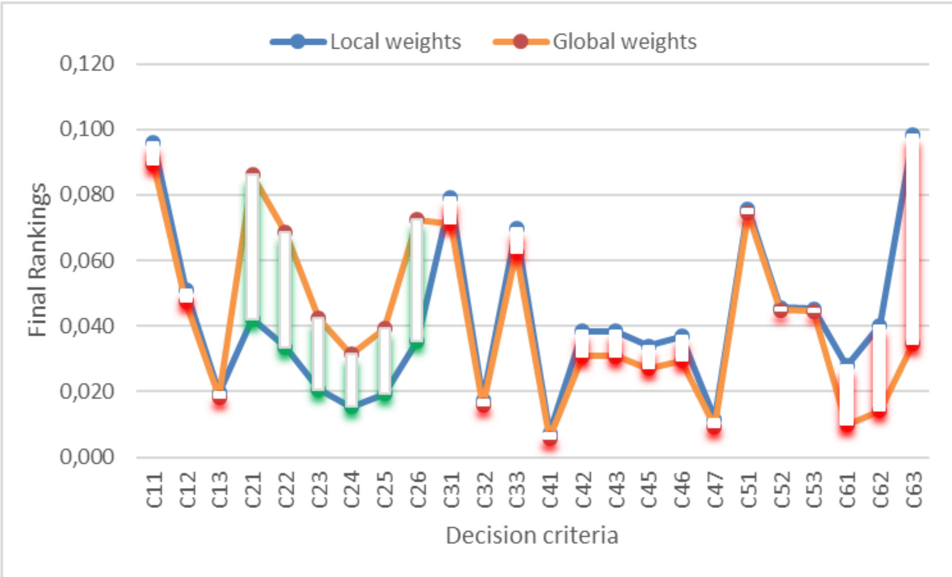

Figure 2. Local and global importance results' trade-offs

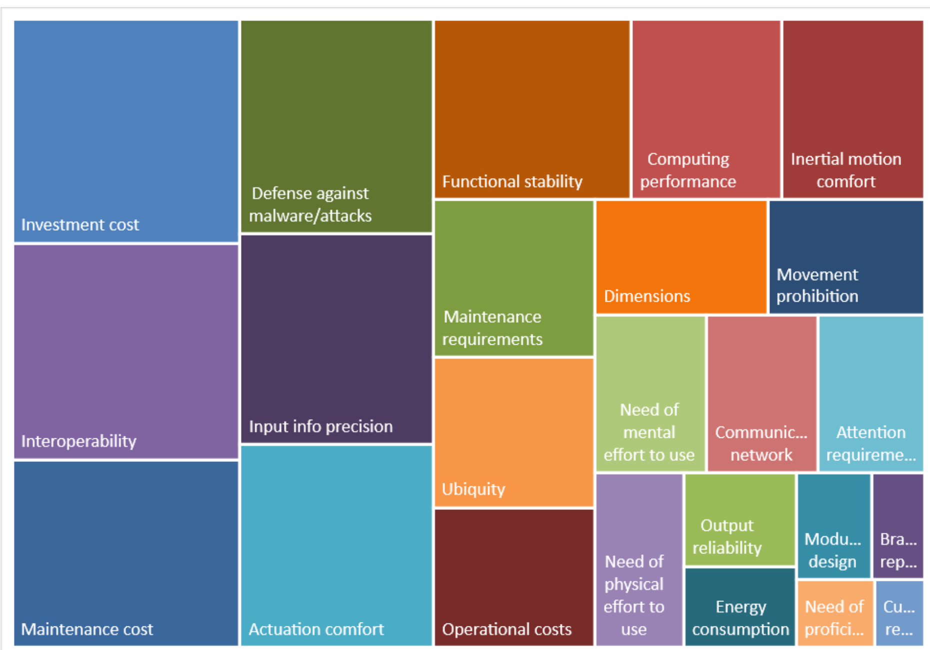

Figure 3. Impact domain distribution according to the global ranking scores

According to the main-criteria weightings, device attributes representing technological capabilities (C_2) has a robust driving effect on the decision problem, where security concerns represented by the fifth attribute group (C_5) plays also an important role according to DMs raw assessments regarding the alternative devices. Furthermore, criteria representing cost related issues (C_1) and ergonomic suitability (C_4) of the handled device were found to have a medium impact on the decision, as a surprising outcome of this detailed research, where "*C_{11}- Investment cost*" from the first main-attribute set and "*C_{31}-Actuation comfort*" from the third main-attribute set were found to be in the top list according to the global ranking scores. This situation proves the advantages exploited from creating both main and sub-criteria sets for decision problem according to the extent literature review, and, the improvement brought to solution by observing the decision hierarchy between the criteria sets by computing global scores when entrusting the overall results for the order of criteria importance.

Figure 4 visualizes the difference between criteria impacts (overall importance levels) on a IoT-aided HFE application investment decision according to different DMs perspectives. As it was indicated with Figure 4, the perception of DMs on product features and the order of importance of the criteria for each DM vary considerably (Table 3 and Table 5). The three most important criteria were found as "*C_{22}-Ubiquity*", "*C_{51}-Output reliability*" and "*C_{26}-Interoperability*" according to DM1; "*C_{21}-Computing performance*", "*C_{22}-Ubiquity*" and "*C_{52}-Defense against malware/attacks*" according to DM2; "*C_{31}-Actuation comfort*", "*C_{33}-Movement prohibition*" and "*C_{46}-Attention requirement*" according to DM3; "*C_{11}-Investment cost*", "*C_{12}-Operational costs*" and "*C_{23}-Energy consumption*" according to DM4, and "*C_{51}-Output reliability*", "*C_{21}-Computing performance*" and "*C_{26}-Interoperability*" according to DM5, representing different standpoints related to Ergonomics 4.0 applications in industry such as "Academician", "Technical works & repair chief", "Job safety expert", "Purchasing expert", "Data security expert" point of views, respectively. The diversity in DMs views and the differences between the overall global ranking results and the global weights calculated in each DM's own reference shows its benefits on making it important to formulate the problem by adding different perspectives to the problem space, and thus to consider the decision problem in a broader frame which will lead the results higher validity.

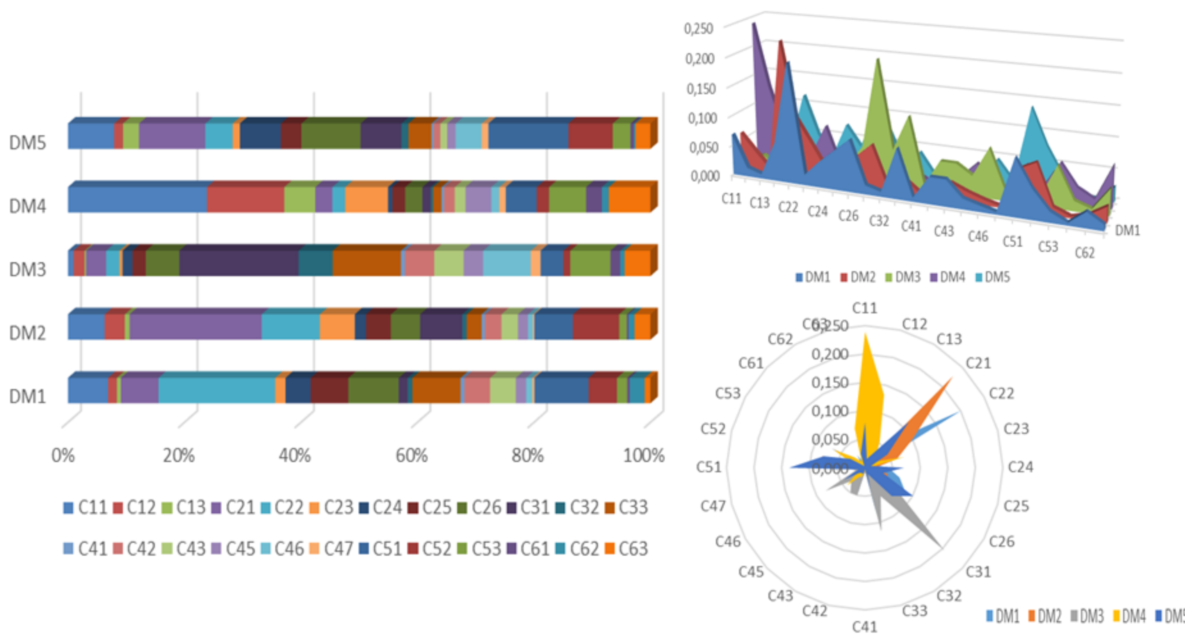

Figure 4. Benchmarking of overall impact of decision criteria on different DM standpoints

6. Conclusion

A general road map for industrial purpose IoT-aided HFE measurement device assessment in terms of different needs of five different aspects for field practitioners who seek the most appropriate alternatives was presented in this study to support their decision making process.

The proto-set of 43 affecting attributes were handled with fuzzy Delphi method, and then, validated 6 main- and 23 sub-criteria were analyzed with BWM.

Results were interpreted separately and then comparatively in different dimensions in terms of local rankings, global ranking scores, impact domains, and, for different DMs as further analysis.

The width of DMs set identified to take part in the assessment of the research could be considered as a limitation, where, as a suggestion for future works this number could be increased; furthermore, different standpoints could be included into the research to enlarge managerial impacts by introducing DMs with different experience fields, e.g. human resources, business excellence or strategical executives. Likewise, as another suggestion, an additional objective MCDM weighting method could be also employed subsequently as a spare assessment to analyze the handled problem in a data driven decision making environment, since BWM is a DM driven subjective MCDM method.

Fundamentally, enhancements on workload adjustment pursuant to personal performances, better working environment organization, enhanced predictive maintenance, enhanced OHS practices as well as preventive action scenarios for possible health problems could be yielded by the employment of IoT-aided Ergonomics 4.0 measurement and data collection devices.

The proposed approach is competent to be utilized as a base model for field experts and organizations from differing activity fields, and could easily be adjusted for possible other specific devices in terms of their exclusive point of views or requirements. The proposed approach is also suitable to be used to assess narrower groups of specific alternative devices prior to be employed while practicing peculiar measurements in differentiated working environments, where BWM is also competent to assess alternatives with respect to ranked criteria weightings, as a further research suggestion.

Contribution of Authors

In this study scientific literature review, application design, analysis, calculations, interpretation of the results, and writing of the paper were performed by Burcu YILMAZ KAYA.

Conflict of Interest

The author acknowledge that this paper is a contribution of original research work and bears no conflict of interest, and has not been funded by any agency or institution.

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Appendices

Appendix 1.
Fuzzy Delphi DM assessments

Main-groups	Criteria	DM_1	DM_2	DM_3	DM_4	DM_5
Cost	Investment cost	*VH*	*L*	*L*	*VH*	*VL*
	Operational costs	*H*	*L*	*L*	*H*	*VL*
	Maintenance cost	*H*	*L*	*H*	*VH*	*VL*
Technology	Operating temperature rate	*VH*	*VH*	*VH*	*L*	*L*
	Storage capacity	*H*	*H*	*H*	*L*	*L*
	Ubiquity	*VH*	*VH*	*VH*	*L*	*L*
	Measurement variety	*H*	*H*	*VH*	*H*	*H*
	Energy consumption	*VH*	*VH*	*VH*	*VL*	*H*
	Communication network	*VH*	*H*	*VH*	*L*	*VH*
	Computing performance	*VH*	*VH*	*VH*	*H*	*VH*
	Functional stability	*VH*	*VH*	*VH*	*L*	*VH*
	Magnetic immunity	*H*	*VH*	*VH*	*N*	*VH*
	Battery life	*H*	*H*	*L*	*H*	*L*
	Work environment integration level	*H*	*H*	*L*	*L*	*L*
	Interoperability	*H*	*H*	*VH*	*VL*	*VH*
	Mobile application	*L*	*L*	*L*	*N*	*VH*
Ergonomics	Actuation comfort	*VH*	*VH*	*VH*	*VL*	*H*
	Inertial motion comfort	*VH*	*VH*	*H*	*VL*	*H*
	Movement prohibition	*VH*	*VH*	*VH*	*L*	*H*
	Vibration comfort	*VH*	*VH*	*VH*	*H*	*L*
Design	Weight	*H*	*VH*	*H*	*H*	*H*
	Dimensions	*L*	*VH*	*H*	*VH*	*H*
	Need of physical effort to use	*VH*	*VH*	*VH*	*L*	*H*
	Need of mental effort to use	*VH*	*VH*	*VH*	*L*	*L*
	Need of proficiency to use	*H*	*VH*	*VH*	*L*	*VH*
	Easy to learn	*VH*	*VH*	*VH*	*VH*	*VH*
	Ease of configuration	*VH*	*VH*	*VH*	*VH*	*VH*
	Attention requirement	*H*	*VH*	*VH*	*VL*	*VH*
	Modular design	*VH*	*VH*	*L*	*VL*	*L*
	Design aesthetics	*H*	*VH*	*L*	*N*	*L*
	Usefulness	*VH*	*VH*	*VH*	*VH*	*VH*
Security	Output reliability	*VH*	*VH*	*H*	*VL*	*VH*
	Safe to use	*VH*	*VH*	*VH*	*H*	*VH*
	Data security	*VH*	*VH*	*VH*	*VH*	*VH*
	Defense against malware/attacks	*VH*	*H*	*VH*	*L*	*VH*
	Input info precision	*VH*	*VH*	*H*	*VL*	*VH*
PLCM	Vendor reputation	*L*	*L*	*H*	*H*	*H*
	Brand reputation	*H*	*L*	*H*	*VH*	*H*
	Maintenance requirements	*VH*	*H*	*H*	*VH*	*H*
	Service life	*H*	*H*	*H*	*VH*	*H*
	Technical service quality (vendor)	*VH*	*H*	*VH*	*H*	*H*
	Number of customers (vendor)	*VL*	*N*	*VL*	*L*	*N*
	Customer reviews (vendor)	*L*	*L*	*VL*	*L*	*H*