Analyzing the Factors Affecting the Quality of IoT-based Smart Wearable Devices Using the DANP Method

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Abstract. This paper proposes the DANP (DEMATEL-based Analytic Network Process) method so that the factors that affect the quality of IoT (Internet of Things)-based smart wearable devices can be adequately assessed. The proposed method helps to identify and visualize the importance of certain factors (dimensions and criteria), the causal relationship among the factors, the mutual influence upon each other, and their influential weights. A numerical example was presented to illustrate the feasibility and effectiveness of the proposed method. The results of this study demonstrated that the quality dimensions can be divided into a causal group (the technical and ergonomic dimensions) and an effect group (the functional and symbolic dimensions). The functional dimension proved to be the most important factor and the most important core problem to be solved. The most influential driving factor was the ergonomic dimension. The results of this study provide insights into critical design criteria to better meet the users' needs and can be used by manufacturers to develop strategies for improving the quality of IoT-based smart wearable devices, in a priority order.

Keywords: Internet of Things (IoT), smart wearable devices, DANP (DEMATEL-based ANP), quality model.

1. Introduction

The Internet of Things (IoT) is a "new technology paradigm, a global network of machines and devices capable of interacting with each other" (Kao, Nawata & Huang, 2019). The IoT-based smart wearable devices (e.g., smartwatches, activity trackers) can be used for various tasks in our daily life (Voicu et al., 2019), can improve individuals' quality of life and provide benefits in the context of assistive services (Băjenaru, Ianculescu & Dobre, 2018) and business processes.

Due to the potential benefits of IoT-based wearable devices, it is essential to identify their quality characteristics and understand the factors that drive consumers' decisions to adopt and use these devices. This knowledge will provide designers and manufacturers of wearable devices with useful information about the important features and capabilities that should be incorporated in these devices in order to win consumers over. Previous studies have focused on the technological features of these devices and the factors influencing the adoption of wearable devices. Yet, little is known about the quality factors which determine the selection and use of wearable devices in a specific context (e.g., healthcare, smart home, food, agriculture, energy etc.). Also, the interdependence relationships among features, functions, and factors are not very clear.

Literature indicates that over the past two decades, multiple criteria decision-making (MCDM) has been increasingly applied in real world problems. In this study a new hybrid MCDM method was adopted, known as DANP (DEMATEL-based Analytic Network Process), to determine the key factors for decision-making (Tzeng & Shen, 2017). First, this study develops a quality model for IoT-based smart wearable devices consisting of four dimensions and thirteen criteria. Second, it uses the Decision Making Trial and Evaluation Laboratory (DEMATEL) technique (Tzeng & Shen, 2017) to determine and visualize the causal relationships between the quality factors (dimensions / criteria). Then, it uses concepts peculiar to Analytic Network Process (ANP) (Saaty, 2001) to determine the influential weights of factors. DANP was applied in various areas, such as near-field communication technology (Hu et al., 2018), RFID adoption (Lu, Lin & Tzeng, 2013), cloud provider selection (Rădulescu et al., 2016), technological innovation (Yang et al., 2018) etc. Although there is a plethora of literature using DANP (Gölcük & Baykaso, 2016; Tzeng & Shen, 2017), to the best of our knowledge, this method has not yet been applied to the wearable technology. Also, research studies dealing with the factors that affect the quality of IoT-based wearable devices are scarce. Therefore, this study attempts to fill these research gaps.

The paper is structured as follows. The next section focuses on the factors that affect the quality

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of wearable devices identified in the literature and the MCDM techniques used in various studies. The quality model and procedure applied in this study are presented in section 3. The results and findings are described in section 4. Conclusions are provided in the final section.

2. Background and related works

Existing literature has suggested several critical factors, benefits and risks derived from wearable technology, as well as antecedents of intention to use wearable technology. For instance, (Chang, Dong & Sun, 2014) proposed a model highlighting the influence of the IoT product characteristics on consumer purchase intention and defined six features, as follows: connectivity, interactivity, telepresence, intelligence, convenience, and security. (Yang et al., 2016) developed a research model for analysing the factors determining the perceived value for wearable devices. The results of their study indicated that functionality, compatibility, and visual attractiveness would enhance the perceived benefits of wearable devices. (Kalantari, 2017) reviewed literature on wearable technologies and classified factors influencing individuals' adoption decision into five categories: perceived benefits, technology characteristics, social influences, individual characteristics, and perceived risks. In the category "technology characteristics", the author included: perceived quality, aesthetics, comfort, compatibility, and visibility. (Adapa et al., 2018) explored the contributing and inhibiting factors that influence the adoption of wearable devices. For smart glasses, the "look-and-feel" was the most mentioned factor. For smartwatches, the availability of fitness applications was a key factor.

A stream of research explored antecedents of the intention to use wearable technology by using technology acceptance models and theories. For instance, (Gao, Li & Luo, 2015) used UTAUT2 for understanding the factors associated with consumer's intention to adopt wearable technology in the context of health care. Jeong et al. (2017) validated the innovation diffusion theory (IDT) within the context of wearable devices. They identified several characteristics of wearable technology based on its social, managerial, and functional aspects of wearable technology and tested its relationship with purchase intention of wearable devices. Recently, (Hsiao & Chen, 2018) developed and tested a conceptual model based on the theory of reasoned action and perceived values to investigate the antecedents of the intention to purchase a smartwatch.

Other researchers have investigated smart wearable devices as a combination of fashion and technology ("fashnology"), particularly for smart watches. For example, (Rauschnabel et al., 2016) found that the majority of the survey respondents categorized wearable technology as a "fashnology" rather than a mere technology, which suggests the need to complement technology acceptance theories with fashion-focused constructs.

Another stream of research investigated wearable technology using the multi-criteria decision-making methods. For instance, (Park & Shin, 2017) proposed a security assessment framework for IoT service based on a hybrid approach which integrates fuzzy DEMATEL and fuzzy AHP (Analytical Hierarchy Process). (Ly et al., 2018) used fuzzy theory and the AHP to evaluate the influential factors in building IoT systems. Their study found that security, value, and connectivity are more important than telepresence and intelligence. More recently, (Kao et al., 2019) defined an analytic framework consisting of DEMATEL and Partial Least Squares (PLS) approach to explore the factors that influence the adoption of IoT-based wearable fitness trackers.

Despite the numerous studies related to wearable technology, limited research has been undertaken to investigate the factors which affect the quality of IoT-based wearable devices and the causal relationship among those factors.

3. The present research

3.1 Dimensions and criteria

This section presents a quality model which provides a set of quality characteristics relevant to a wide range of IoT-based smart wearable devices. The quality of an IoT-based wearable device in a particular context of use is determined by its inherent properties. Based on the literature review,

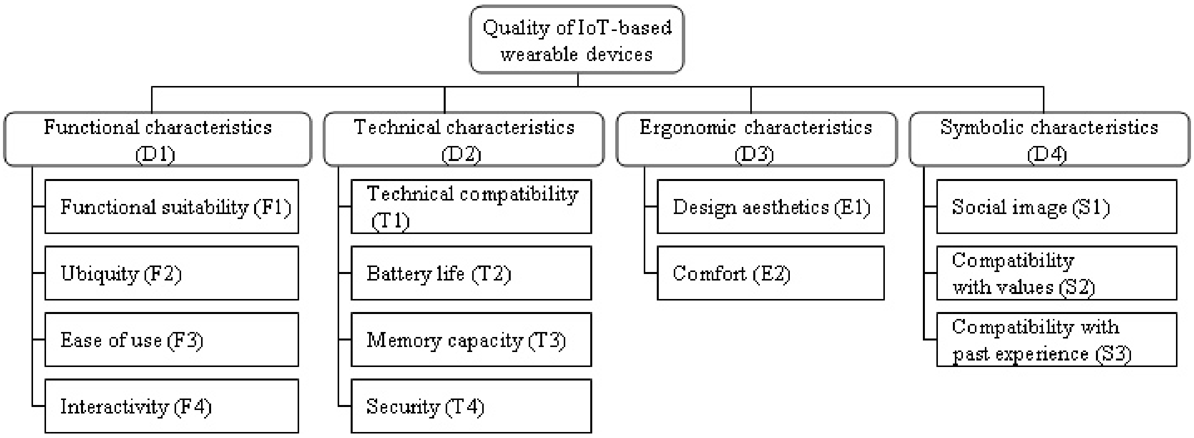


Figure 1. Quality model of IoT-based wearable devices (*source*: authors)

this study defines 13 quality criteria of the IoT-based wearable devices which are grouped into four dimensions (Figure 1).

The criteria that influence the quality of IoT-based wearable devices can vary across different devices and different user groups. It is not practically possible to specify or evaluate all criteria for all components of a IoT-based wearable device. Similarly it is not usually practical to specify or evaluate quality of IoT-based wearable devices for all possible usage scenarios. The relative importance of the respective criteria will depend on the user goals and application domain. Therefore, the model should be tailored (reduced or extended) to the particular contexts of use.

3.1.1 Functional dimension

Functional dimension refers to the degree to which an IoT-based wearable device provides functions that meet stated and implied customers' needs when used under specified conditions (ISO/IEC 25010, 2011). It consists of four criteria: functional suitability, ubiquity, ease of use, and interactivity.

Functional suitability includes functional completeness (the degree to which the set of functions covers all the specified tasks and user objectives); functional correctness (the degree to which an IoT-based wearable device provides the correct results with the needed degree of precision), and functional appropriateness (the degree to which the functions facilitate the accomplishment of specified tasks) (ISO/IEC 25010, 2011).

Ubiquity indicates the degree to which an IoT-based wearable device is operational and accessible anytime and anywhere when it is necessary to use it. Ubiquity includes mobility (the degree to which users believe they can navigate freely with their devices in different locations and during transit periods) and availability (the degree to which users believe their devices provide them real-time connectedness to information and services) (Dutot, Bhatiasevi & Bellallahom, 2019; Kim & Shin, 2015).

Ease of use underlines the capability of the IoT-based wearable device to be understood, learned and operated by users, when used under specified conditions. A better interface increases the ease of use, consumers save time and effort when using a product and this criterion plays a critical part with regard to certain wearable devices possibly due to their limited screen size and touch screen (Hsiao & Chen, 2018; Krey et al., 2016).

Interactivity is the feeling that occurs when consumers actually have their hands on a device, when information communication is bidirectional and response is timely (Chang, Dong & Sun, 2014). The level of interactivity of a device is mostly associated with its functionalities, novelty, and usefulness. A satisfactory customer interaction with the technological features leads to satisfaction in terms of user experience.

3.1.2 Technical dimension

In the context of wearable technology, several studies described the compatibility factor as "technical compatibility", which measures how well a wearable device is compatible with existing software and hardware systems (Asadi et al., 2019; Li et al., 2019; Yang et al., 2016).

In this study, *technical compatibility* is defined as the degree to which an IoT-based wearable device can exchange information with other products or systems (e.g., smart phones, tablets, other IoT devices), and/or perform its required functions, while sharing the same hardware or software environment (e.g., operating systems, networks) (ISO/IEC 25010, 2011). Technical compatibility increases usefulness and efficiency of wearable devices.

Battery life is an important criterion in the case of wearable devices because the users tend to wear them all the time for various purposes. As defined by (Pal, Funilkul & Vanijja, 2018) battery life represents the users' concern regarding the battery longevity of the wearable device when using all the features and functionalities to their full potential. Also, battery overheating is another important facet, when it is linked to health concerns and the uncomfortable effect it has on users.

Unlike the internal memory of tablets, PCs, and other devices, *memory capacity* for wearable devices is smaller. Since most wearable devices collect important data such as number of steps, sleep time, and other sensor data, they will need a bigger storage capacity. Many wearable devices rely on the connection with a more powerful device to process collected data. More sensors create a larger data volume which increases the communication network traffic between wearable devices and access points.

Security indicates the degree to which a wearable device protects information and data, so that persons, other products or systems have an appropriate level of access to their types and levels of authorization (ISO/IEC 25010, 2011). IoT devices have limited capabilities in terms of computational, storage, and network capacity which makes them more vulnerable to security threats. Security includes confidentiality, integrity, and authenticity. According to (ISO/IEC 25010, 2011) confidentiality is the degree to which an IoT-based wearable device ensures that data are accessible only to those who have authorized access to data. Integrity refers to the degree to which an IoT-based wearable device prevents unauthorized access to data. Also, authenticity is defined as the degree to which the identity of a subject or resource can be proved to be the one claimed.

3.1.3 Ergonomic dimension

Design aesthetics refers to the beauty of a product's appearance (Hsiao & Chen, 2018) and it involves a visual representation of a wearable device. As noted by (Liu, 2003), aesthetics is related to ergonomic and usability features. Thus, (Liu, 2003) proposed the concept of ergo-aesthetics to refer to the integrated design approach that is aimed at meeting both ergonomic and aesthetics design objectives. Some wearable devices, such as smartwatches, are viewed as aesthetic items that express users' values and norms, being a mixture of technology and fashion (Choi & Kim, 2016; Rauschnabel et al., 2016). In this study, design aesthetics is defined as the way in which the colour, shape, screen size, texture, and appearance of a device provide a certain aesthetics, create a sense of balance, or appeal to emotions (Cyr, Head & Ivanov, 2006; Hsiao & Chen, 2018; Kim, 2017). The "look" aspect of the IoT wearable devices is consistent with the "fashnology" perspective on the importance of wearable technology as a statement on fashion (Rauschnabel et al., 2016).

Comfort in usage underlines the physical and sensorial aspects of wearable devices, such as weight, bulk, the quality of material used, texture, elasticity etc. These attributes can affect the usage of wearable devices, since users need to wear them for a long period of time (Pal, Funilkul & Vanijja, 2018). This criteria affects the consumer's satisfaction with the physical attributes of the IoT-based wearable devices and their physical well-being.

3.1.4 Symbolic dimension

Social image points out the extent to which the use of an innovation is perceived as enhancing one's image or status. In particular, the wearable nature of smart devices has a symbolic function that influences the way others think about the wearer (Choi & Kim, 2016; Chuah et al., 2016; Jeong et al., 2017). This study defines social image as the extent to which users may attract respect and admiration from peers in their social communities through wearable device usage (Yang et al., 2016. This criterion is particularly important for wearable technology because the IoT devices are worn on the body and can be seen and recognized by others (Chuah et al., 2016; Krey et al., 2019).

(Rogers, 2003) defined compatibility as the degree to which an innovation is perceived as being consistent with the existing values, past experience, and needs of potential users. As stated by (Karahanna, Agarwal & Angst, 2006), *compatibility with values* refers to the match between the possibilities offered by the technology and the user's dominant value system. Furthermore, the authors argued that values and norms are persistent and less likely to change in the short-term.

Compatibility with past experience reflects a fit between the target technology (in this study, wearable technology) and a variety of users' past encounters with technology (Karahanna, Agarwal & Angst, 2006).

3.2 Analytical procedures

This study defines a quality assessment framework for smart wearable devices based on a hybrid approach which integrates DEMATEL and ANP, namely DANP.

In order to collect data, a questionnaire was developed. Five experts were asked to complete the questionnaire. Two of the experts hold the title of Associate Professor and they carry out academic research in higher education institutions. Three of the experts are currently carrying out research on how to sustain healthcare by using IoT technology. They have at least five years of work experience and a doctorate degree. Each expert evaluated the degree of direct influence between any two criteria by an integer score from 0 to 4, with 0 as 'no influence' and 4 as 'very high influence'. After receiving the filled-in questionnaires forms from experts, the DEMATEL technique was used to identify the most influential factors and to determine and visualize the causal relationships between the quality factors. Then, DEMATEL-based ANP technique was used for weighting each criterion by combining the DEMATEL and ANP methods.

The DANP steps adapted in this study are briefly presented in Figure 2 based on the calculation processes found in (Chen & Lin, 2018; Hu, Lu & Tzeng, 2014). Due to space limitations, full details of the specific formulas of the DANP are not presented.

The results of analytical procedures are shown in the next section. The computation steps were performed using the MATRIX procedure in IBM SPSS 23.

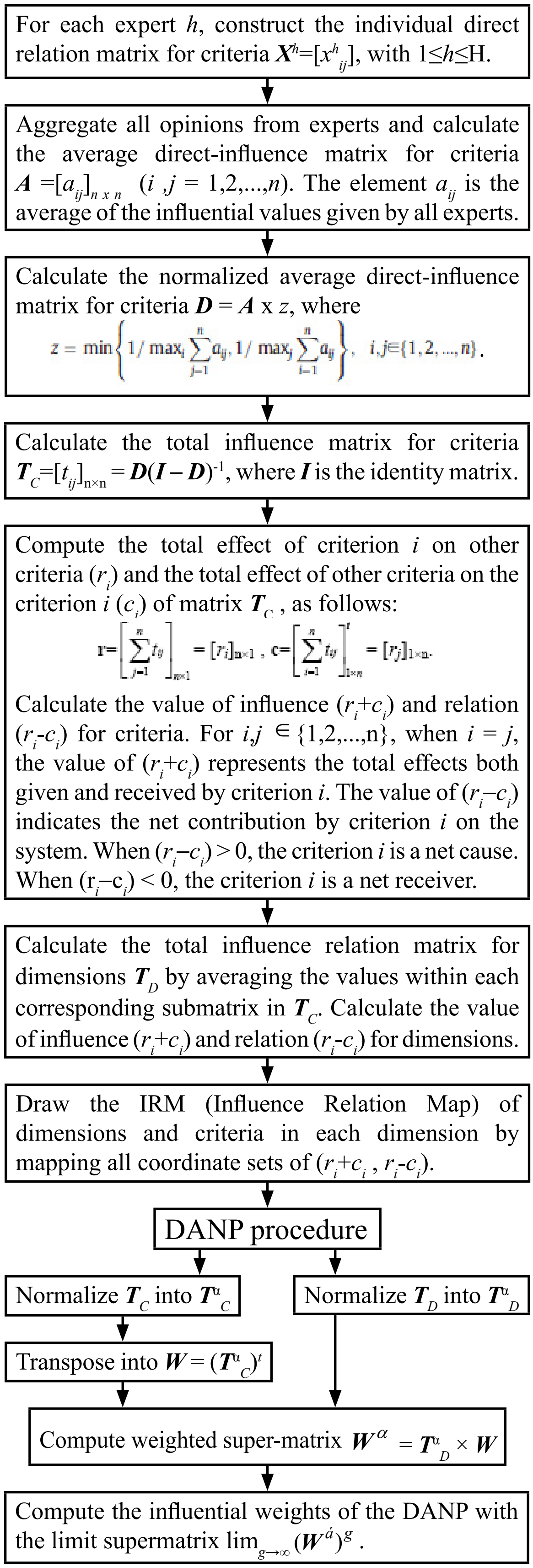


Figure 2. The DANP procedure (drawn by authors)

4. Results and discussion

4.1 Measuring relationships among dimensions / criteria using DEMATEL

Table 1 shows the average direct-influence relation matrix $\boldsymbol{A}$ for criteria obtained by aggregating the opinions of the five experts mentioned above. The average sample gap of the evaluation results from all experts was 4.91%, which is less than 5%. This result implied that the inclusion of an additional expert in this study would not influence the findings and that the significant confidence level was 95.09% (greater than 95%).

Table 1. The average direct-influence relation matrix $\boldsymbol{A}$ for the criteria presented above

	F1	F2	F3	F4	T1	T2	T3	T4	E1	E2	S1	S2	S3
F1	0.00	1.80	2.00	2.40	0.60	0.60	2.20	2.20	2.40	1.80	3.00	3.60	2.20
F2	3.40	0.00	1.60	2.20	2.20	1.60	3.20	3.20	1.00	1.00	3.00	3.00	2.40
F3	3.40	1.40	0.00	3.40	0.60	1.00	1.60	2.20	2.60	1.00	3.00	3.00	2.20
F4	2.60	1.00	2.00	0.00	1.00	1.00	2.00	2.20	2.20	1.00	2.80	3.00	2.20
T1	3.60	3.80	2.00	2.80	0.00	0.20	3.60	4.00	1.60	4.00	1.00	0.20	1.80
T2	3.80	2.80	2.00	2.00	3.00	0.00	2.60	3.60	0.00	1.20	1.00	0.20	1.80
T3	3.20	3.60	2.00	2.00	2.60	2.60	0.00	3.60	0.20	0.40	1.20	1.00	2.00
T4	4.00	2.80	2.60	2.60	4.00	3.60	4.00	0.00	0.00	0.40	1.00	1.80	1.60
E1	3.00	2.00	2.40	3.00	3.40	2.60	2.80	1.00	0.00	2.00	2.00	2.20	2.00
E2	2.60	3.00	3.60	3.00	1.00	1.00	0.80	0.80	1.00	0.00	1.80	1.80	1.80
S1	2.00	2.00	3.00	1.40	0.40	0.40	0.00	1.00	0.00	1.00	0.00	2.80	1.80
S2	2.80	2.60	3.00	2.40	0.40	0.40	2.00	1.00	2.60	2.00	2.00	0.00	3.20
S3	2.80	2.80	4.00	3.40	0.40	0.40	2.80	2.80	2.40	2.00	1.00	1.80	0.00

Matrix $\boldsymbol{A}$ was further normalized (Table 2). Subsequently, through matrix operation, a total influence relation matrix $\boldsymbol{T}_C$ of criteria was obtained (Table 3). In Table 4, all criteria were further classified into the corresponding dimensions, and each dimension was averaged to obtain matrix $\boldsymbol{T}_D$.

Table 2. The normalized average direct-influence relation matrix $\boldsymbol{D}$ for the criteria presented above

	F1	F2	F3	F4	T1	T2	T3	T4	E1	E2	S1	S2	S3
F1	0.000	0.048	0.054	0.065	0.016	0.016	0.059	0.059	0.065	0.048	0.081	0.097	0.059
F2	0.091	0.000	0.043	0.059	0.059	0.043	0.086	0.086	0.027	0.027	0.081	0.081	0.065
F3	0.091	0.038	0.000	0.091	0.016	0.027	0.043	0.059	0.070	0.027	0.081	0.081	0.059
F4	0.070	0.027	0.054	0.000	0.027	0.027	0.054	0.059	0.059	0.027	0.075	0.081	0.059
T1	0.097	0.102	0.054	0.075	0.000	0.005	0.097	0.108	0.043	0.108	0.027	0.005	0.048
T2	0.102	0.075	0.054	0.054	0.081	0.000	0.070	0.097	0.000	0.032	0.027	0.005	0.048
T3	0.086	0.097	0.054	0.054	0.070	0.070	0.000	0.097	0.005	0.011	0.032	0.027	0.054
T4	0.108	0.075	0.070	0.070	0.108	0.097	0.108	0.000	0.000	0.011	0.027	0.048	0.043
E1	0.081	0.054	0.065	0.081	0.091	0.070	0.075	0.027	0.000	0.054	0.054	0.059	0.054
E2	0.070	0.081	0.097	0.081	0.027	0.027	0.022	0.022	0.027	0.000	0.048	0.048	0.048
S1	0.054	0.054	0.081	0.038	0.011	0.011	0.000	0.027	0.000	0.027	0.000	0.075	0.048
S2	0.075	0.070	0.081	0.065	0.011	0.011	0.054	0.027	0.070	0.054	0.054	0.000	0.086
S3	0.075	0.075	0.108	0.091	0.011	0.011	0.075	0.075	0.065	0.054	0.027	0.048	0.000

Table 4. The total influence matrix $\boldsymbol{T}_D$ for the dimensions presented above

	D1	D2	D3	D4	r_i
D1	0.176	0.139	0.116	0.179	0.610
D2	0.215	0.166	0.104	0.147	0.632
D3	0.205	0.138	0.096	0.160	0.599
D4	0.187	0.110	0.111	0.136	0.544
c_i	0.783	0.553	0.427	0.622	

Table 5 shows the degree of importance (r_i+c_i) and the degree of relation (r_i–c_i) for the above-mentioned dimensions and the related criteria. Figures 3 and 4 illustrate the influential relation map (IRM) of the respective dimensions and the IRMs of the related criteria under each dimension.

Table 5. The sum of influences given and received on dimensions and criteria

Dimension / criteria	r_i+c_i	r_i–c_i
Functional dimension	1.393	–0.173
Functional suitability	4.939	–0.955
Ubiquity	4.568	–0.090
Ease of use	4.438	–0.372
Interactivity	4.314	–0.598
Technical dimension	1.185	0.079
Technical compatibility	3.883	0.789
Battery life	3.266	0.716
Memory capacity	4.260	–0.210
Security	4.565	0.083
Ergonomic dimension	1.026	0.172
Design aesthetics	3.686	0.902
Comfort	3.217	0.379
Symbolic dimension	1.166	–0.078
Image	3.236	–0.640
Compatibility with values	4.078	–0.122
Compatibility with past experience	4.226	0.118

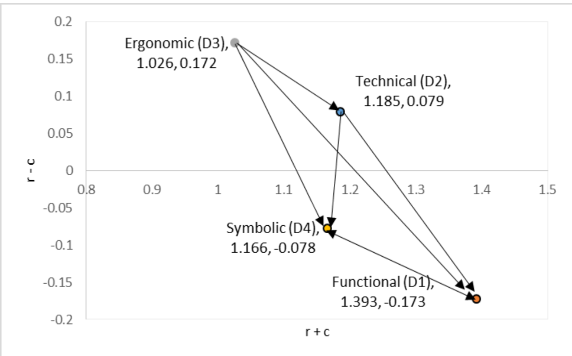
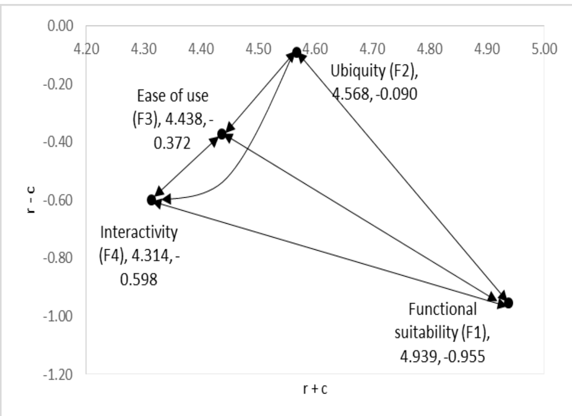
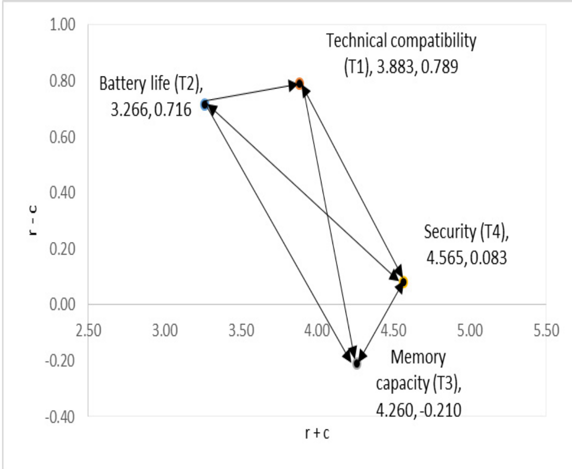


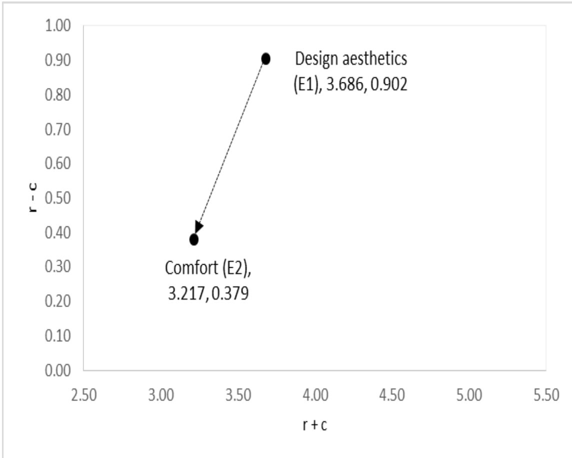
Figure 3. The IRM of the four dimensions



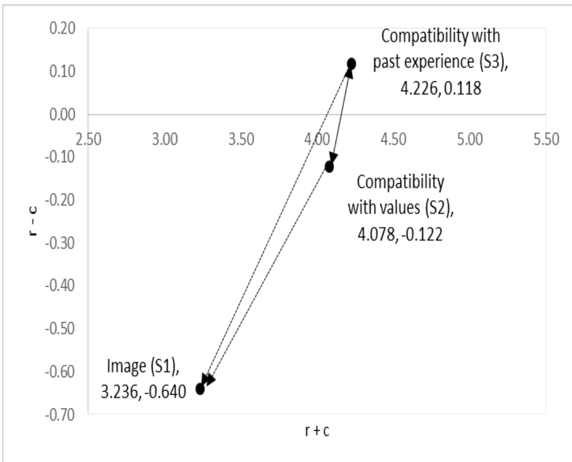
a. The IRM of the criteria under functional dimension (D1)



b. The IRM of the criteria under technical dimension (D2)



c. The IRM of the criteria under ergonomic dimension (D3)



d. The IRM of the criteria under symbolic dimension (D4)

Figure 4. The IRM of the criteria under each dimension

From Figure 3 and Table 5 it can be noted that the importance of the four dimensions can be prioritized as D1>D2>D4>D3. The functional dimension (D1) has the highest (r_i+c_i) value (1.393) indicating that this dimension is the most important factor. The ergonomic dimension (D3) is the least important factor with a value of 1.026.

Analysing the causal diagram in Figure 3, it can be noticed that the four dimensions are divided into cause and effect groups. The causal group contains the technical dimension (D2) and the ergonomic dimension (D3). These have positive values for (r_i–c_i), 0.079 and 0.172, respectively. The effect group includes functional (D1) and symbolic (D4) dimensions. These have negative values for (r_i–c_i), –0.173 and –0.078, respectively. These last two dimensions influence each other, as both values from the matrix $\boldsymbol{T}_D$ (0.179 and 0.187, respectively) were greater than the threshold value α (0.149). All other relationships are unidirectional ones. Of the four dimensions, the ergonomic dimension (D3) is the most influential driving factor, as it has the highest degree of relationship (r_i–c_i), has influenced all other dimensions and was not significantly influenced by other dimensions. The functional dimension (D1) is the most important core problem to be solved, followed by the symbolic dimension (D4).

Although the technical dimension (D2), as a net cause, is less important than the net receiver D1, it must be improved, as it is the second influential factor and the origin of problems and has a significant effect on the functional dimension (D1) and on the symbolic dimension (D4). Therefore, all the net causes (D3 and D2) need to be improved to enhance the quality of wearable devices, while functional dimension (D1) should be given higher priority in this matter as well.

From Table 5 it can be noticed that the functional suitability (F1) is considered by experts the most important criterion and has the most significant relationship to other criteria (4.939). By contrast, comfort (E2) relates the least to other attributes. By analysing the degree of relation (r_i–c_i), it can be stated that the criterion with the maximum relation degree is design aesthetics (E1) which most influences other criteria. The criterion with the minimum relation degree (r_i–c_i) is functional suitability (F1) which is the most influenced by other criteria.

4.2 Weighting of each criterion by combining DEMATEL with ANP methods (DANP technique)

This study used DANP to compute the influential weights for the above-mentioned dimensions and criteria. The matrices $\boldsymbol{T}_D$ and $\boldsymbol{T}_C$ obtained through DEMATEL were normalized as $\boldsymbol{T}^{\alpha}_D$ (Table 6) and $\boldsymbol{T}^{\alpha}_C$ (Table 7).

Table 6. The matrix $\boldsymbol{T}^{\alpha}_D$ obtained by normalizing matrix $\boldsymbol{T}_D$

	D1	D2	D3	D4
Functional (D1)	0.289	0.227	0.191	0.294
Technical (D2)	0.340	0.262	0.165	0.232
Ergonomic (D3)	0.342	0.231	0.160	0.267
Symbolic (D4)	0.344	0.203	0.204	0.250

Then, matrix $\boldsymbol{T}^{\alpha}_C$ was transposed into an unweighted supermatrix $\boldsymbol{W}$=($\boldsymbol{T}^{\alpha}_C$)' (Table 8). Subsequently, $\boldsymbol{T}^{\alpha}_D$ was multiplied by $\boldsymbol{W}$ to obtain a weighted supermatrix $\boldsymbol{W}^{\alpha}$ (Table 9). Finally, $\boldsymbol{W}^{\alpha}$ was multiplied by itself several times to obtain the stable matrix. That is, the global influential weights were obtained by limiting the power of the weighted super matrix $\boldsymbol{W}^{\alpha}$. The local weights were calculated from the global weights (Table 10).

Table 7. The matrix $\boldsymbol{T}^{\alpha}_C$ obtained by normalizing matrix $\boldsymbol{T}_C$

	F1	F2	F3	F4	T1	T2	T3	T4	E1	E2	S1	S2	S3
F1	0.221	0.242	0.261	0.276	0.184	0.161	0.329	0.326	0.534	0.466	0.326	0.372	0.301
F2	0.332	0.177	0.235	0.256	0.212	0.169	0.309	0.310	0.498	0.502	0.331	0.350	0.319
F3	0.323	0.212	0.174	0.291	0.185	0.180	0.305	0.330	0.587	0.413	0.335	0.356	0.308
F4	0.327	0.218	0.267	0.188	0.196	0.174	0.312	0.319	0.570	0.430	0.329	0.359	0.312
T1	0.292	0.257	0.213	0.239	0.149	0.137	0.350	0.364	0.404	0.596	0.322	0.304	0.374
T2	0.315	0.243	0.218	0.224	0.253	0.109	0.298	0.340	0.410	0.590	0.322	0.294	0.384
T3	0.295	0.265	0.217	0.223	0.241	0.216	0.198	0.344	0.479	0.521	0.311	0.320	0.369
T4	0.307	0.234	0.226	0.233	0.261	0.224	0.320	0.195	0.466	0.534	0.299	0.355	0.345
E1	0.290	0.220	0.235	0.256	0.258	0.205	0.298	0.239	0.381	0.619	0.321	0.346	0.333
E2	0.261	0.232	0.261	0.246	0.219	0.195	0.291	0.294	0.596	0.404	0.325	0.345	0.329
S1	0.269	0.228	0.285	0.217	0.202	0.180	0.267	0.352	0.423	0.577	0.208	0.440	0.352
S2	0.278	0.230	0.254	0.238	0.187	0.163	0.351	0.298	0.536	0.464	0.339	0.251	0.410
S3	0.265	0.222	0.262	0.252	0.171	0.150	0.340	0.338	0.529	0.471	0.328	0.399	0.274

Table 8. The unweighted supermatrix W

	F1	F2	F3	F4	T1	T2	T3	T4	E1	E2	S1	S2	S3
F1	0.221	0.332	0.323	0.327	0.292	0.315	0.295	0.307	0.290	0.261	0.269	0.278	0.265
F2	0.242	0.177	0.212	0.218	0.257	0.243	0.265	0.234	0.220	0.232	0.228	0.230	0.222
F3	0.261	0.235	0.174	0.267	0.213	0.218	0.217	0.226	0.235	0.261	0.285	0.254	0.262
F4	0.276	0.256	0.291	0.188	0.239	0.224	0.223	0.233	0.256	0.246	0.217	0.238	0.252
T1	0.184	0.212	0.185	0.196	0.149	0.253	0.241	0.261	0.258	0.219	0.202	0.187	0.171
T2	0.161	0.169	0.180	0.174	0.137	0.109	0.216	0.224	0.205	0.195	0.180	0.163	0.150
T3	0.329	0.309	0.305	0.312	0.350	0.298	0.198	0.320	0.298	0.291	0.267	0.351	0.340
T4	0.326	0.310	0.330	0.319	0.364	0.340	0.344	0.195	0.239	0.294	0.352	0.298	0.338
E1	0.534	0.498	0.587	0.570	0.404	0.410	0.479	0.466	0.381	0.596	0.423	0.536	0.529
E2	0.466	0.502	0.413	0.430	0.596	0.590	0.521	0.534	0.619	0.404	0.577	0.464	0.471
S1	0.326	0.331	0.335	0.329	0.322	0.322	0.311	0.299	0.321	0.325	0.208	0.339	0.328
S2	0.372	0.350	0.356	0.359	0.304	0.294	0.320	0.355	0.346	0.345	0.440	0.251	0.399
S3	0.301	0.319	0.308	0.312	0.374	0.384	0.369	0.345	0.333	0.329	0.352	0.410	0.274

Table 9. The weighted supermatrix W^{α}

	F1	F2	F3	F4	T1	T2	T3	T4	E1	E2	S1	S2	S3
F1	0.064	0.096	0.093	0.094	0.099	0.107	0.100	0.104	0.099	0.089	0.093	0.095	0.091
F2	0.070	0.051	0.061	0.063	0.087	0.083	0.090	0.080	0.075	0.079	0.078	0.079	0.076
F3	0.075	0.068	0.050	0.077	0.072	0.074	0.074	0.077	0.080	0.089	0.098	0.087	0.090
F4	0.080	0.074	0.084	0.054	0.081	0.076	0.076	0.079	0.088	0.084	0.075	0.082	0.086
T1	0.042	0.048	0.042	0.044	0.039	0.067	0.063	0.069	0.060	0.051	0.041	0.038	0.035
T2	0.036	0.038	0.041	0.039	0.036	0.029	0.057	0.059	0.047	0.045	0.037	0.033	0.030
T3	0.075	0.070	0.069	0.071	0.092	0.078	0.052	0.084	0.069	0.067	0.054	0.071	0.069
T4	0.074	0.070	0.075	0.072	0.096	0.089	0.090	0.051	0.055	0.068	0.072	0.061	0.069
E1	0.102	0.095	0.112	0.109	0.067	0.068	0.079	0.077	0.061	0.096	0.086	0.109	0.108
E2	0.089	0.096	0.079	0.082	0.098	0.097	0.086	0.088	0.099	0.065	0.117	0.094	0.096
S1	0.096	0.097	0.099	0.097	0.075	0.075	0.072	0.070	0.086	0.087	0.052	0.085	0.082
S2	0.109	0.103	0.105	0.105	0.071	0.068	0.074	0.083	0.092	0.092	0.110	0.063	0.100
S3	0.089	0.094	0.091	0.092	0.087	0.089	0.086	0.080	0.089	0.088	0.088	0.102	0.068

Table 10. The weights of criteria and dimensions

Dimension / criteria	Weighting by ANP	
	Local weight	Global weights
Functional dimension	**0.316**	
Functional suitability	0.294	0.093
Ubiquity	0.234	0.074
Ease of use	0.222	0.070
Interactivity	0.250	0.079
Technical dimension	**0.230**	
Technical compatibility	0.209	0.048
Battery life	0.178	0.041
Memory capacity	0.304	0.070
Security	0.309	0.071
Ergonomic dimension	**0.183**	
Design aesthetics	0.503	0.092
Comfort	0.497	0.091
Symbolic dimension	**0.263**	
Image	0.316	0.083
Compatibility with values	0.350	0.092
Compatibility with past experience	0.335	0.088

First, the results show that functional suitability is the most important criterion for evaluating IoT-based wearable devices with an influential weight of 0.093. Experts considered that the functional attributes (completeness, accuracy and appropriateness) of wearable devices are the most important for facilitating the accomplishment of tasks and user needs. Functional capabilities claimed by manufacturers should be present in the wearable device. The measurement accuracy is one of the key attributes for IoT-based smart wearable devices.

Second, design aesthetics and compatibility with values are the following important criteria, each having an influential weight of 0.092. Experts concluded that the "look" aspects (i.e., shape, colour, size etc.) are the important attributes of wearable devices. This is consistent with some studies from literature (e.g., Choi & Kim, 2016; Jeong et al., 2017; Jung, Kim & Choi, 2016). Also, technologies that are consistent with one's system of value are likely to be perceived as helping to foster and promote such values (Karahanna Agarwal & Angst, 2006).

Third, the results show that functional dimension is the most important dimension. This is coherent with the IRM (Figure 3). Experts assumed that functional features could not be overlooked by manufacturers when developing IoT-based wearable devices.

5. Conclusion

This study applied the DANP method to identify and visualize the causal relationships between the quality factors of the IoT-based wearable devices and to determine the influential weights of the respective dimensions / criteria. Through the research carried out, this paper provided a number of contributions to the existing literature.

First, as a theoretical contribution of this study, one proposed a quality model for IoT-based smart wearable devices consisting of four dimensions and thirteen criteria. To the best of our knowledge, this is one of the first studies that defined and applied a quality model to the wearable technology. Second, the applicability and utility of DANP method was demonstrated in a numerical example. Identifying the cause-effect relationship among the factors involved and the mutual influences provides evidence that cannot be obtained based on other traditional methods (e.g., structural equation modelling). As far as it is known, this method has not yet been applied to the wearable technology.

From the point of view of the dimensions, experts considered that the functional dimension is the most important, has the highest degree of centrality and the stronger influential relationship. From the point of view of the criteria involved, functional suitability is the most important criterion for the evaluation of wearable devices, followed by the design aesthetics and the compatibility with users' system of values.

To conclude, this study contributes to a better understanding of the quality of IoT-based wearable devices. The results of this study provide valuable information for developers and specialists by defining the factors that influence quality of IoT-based wearable devices and the relations between them. Manufacturers can develop and provide strategies for improving quality of wearable devices for each of the above-mentioned dimensions / criteria, according to a certain order of priorities.

This study has several limitations, which can be addressed through future research. First, data are collected in a Romanian context and from a small number of experts, which may limit the possibility of generalizing the findings of this study. In this regard, in the future, more empirical studies could be conducted with a more diversified group of respondents (users, professionals, etc.). Second, the criteria that influence the quality of IoT-based wearable devices can vary across different devices and different user groups. Also, there might be other important factors that affect the quality of IoT-based wearable devices. While DANP method could be used for most of the IoT-based smart wearable devices, the relative importance of the criteria involved may vary according to the particularities of each wearable device. Therefore, future research is required to include other factors and to examine the influence relationships. Also, DANP method could be combined with other methods (e.g., PROMETHEE, VIKOR) in order to further improve or validate the findings of this study.

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