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Attract Human Loyalty: Revealing Innovative Recommender System using Nebulous and Intelligent Techniques in Virtual Business Realm

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Abstract

Lately, third-party businesses have been offering a variety of Internet apps due to innovations in digital technologies. One technological innovation whose use has gained importance is the Internet of Things (IoT) which touches on several facets of everyday living. Due to its ability to track and surveillance human behavior through smart devices. As a result, this technology has data from gathering smart devices data on people and their preferences. Accordingly, it has become easy to predict people's needs and tendencies and recommend them. Herein, we are leveraging IoT applications in the recommender system (RS). Wherein, one of the key components of efficient IoT-based smart commerce systems is locating products and services that consumers would find interesting and persuading them to purchase them. Hence, harnessing effective IoT application-based RS is a crucial matter. This matter is a catalyst for constructing a robust intelligent decision-support model for selecting optimal RS-IoT for serving human needs. We are leveraging multi-criteria decision making (MCDM) techniques such as MEthod based on the Removal Effects of Criteria (MEREC) Method to determine the weights of criteria utilized in Multi-Attributive Border Approximation Area Comparison (MABAC) to evaluate and rank a set of RSs-IoT. These alternatives have been evaluated by using triangular fuzzy number (TFN) with its scale.

Keywords: Internet of Things, Recommender System, Multi-Criteria Decision Making, Fuzzy Set.

1 | Introduction

1.1 | Context

Internet of Things (IoT) is a novel concept that has emerged as a result of the revolution in information and communication technologies (ICT) [1]. Wherein [2] described the paradigm of IoT as a conglomeration of communication and technology that encompasses everything that happens in the surrounding environment. Due to the ability of IoT in [3] to create a vast network based on the communication between objects, or smart things, including phones, smart TVs, tablets, and watches. Without human intervention, IoT connects smart items and allows for data transmission between them. As a result, IoT [4] has made it possible to

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strongly address the interests of the user by bridging the gap between the physical and virtual worlds. Owing to embracing automation and intelligence of contemporary technologies in human beings' daily practices, their lives of more convenient. Confirmation of that [2] stated that almost every business uses the Internet of Things, including smart homes and workplaces, healthcare, and transportation. IoT applications are becoming more and more inventive and competitive with one another. They will probably continue to spread. As in [5] by employing IoT technology, businesses may ascertain which goods captured consumers' hearts by applying Barcode and Radio Frequency identifying (RFID), which scan product identifying codes. As shown in Figure 1 using wireless technologies to establish a connection between the business and its merchants. It enables the business management to track and keep an eye on product demand. Any business may decide which product to produce with the help of IoT. The business may provide clients with product recommendations based on new items by using these monitoring and scanning technologies. From the perspective of [6] constructing a recommendation system (RS) based on IoT is the optimal supplier for customer demand. Accordingly, it was quickly realized that IoT devices needed to be customized according to customer preferences; as a result, stakeholders began utilizing recommender systems (RSs) [7].

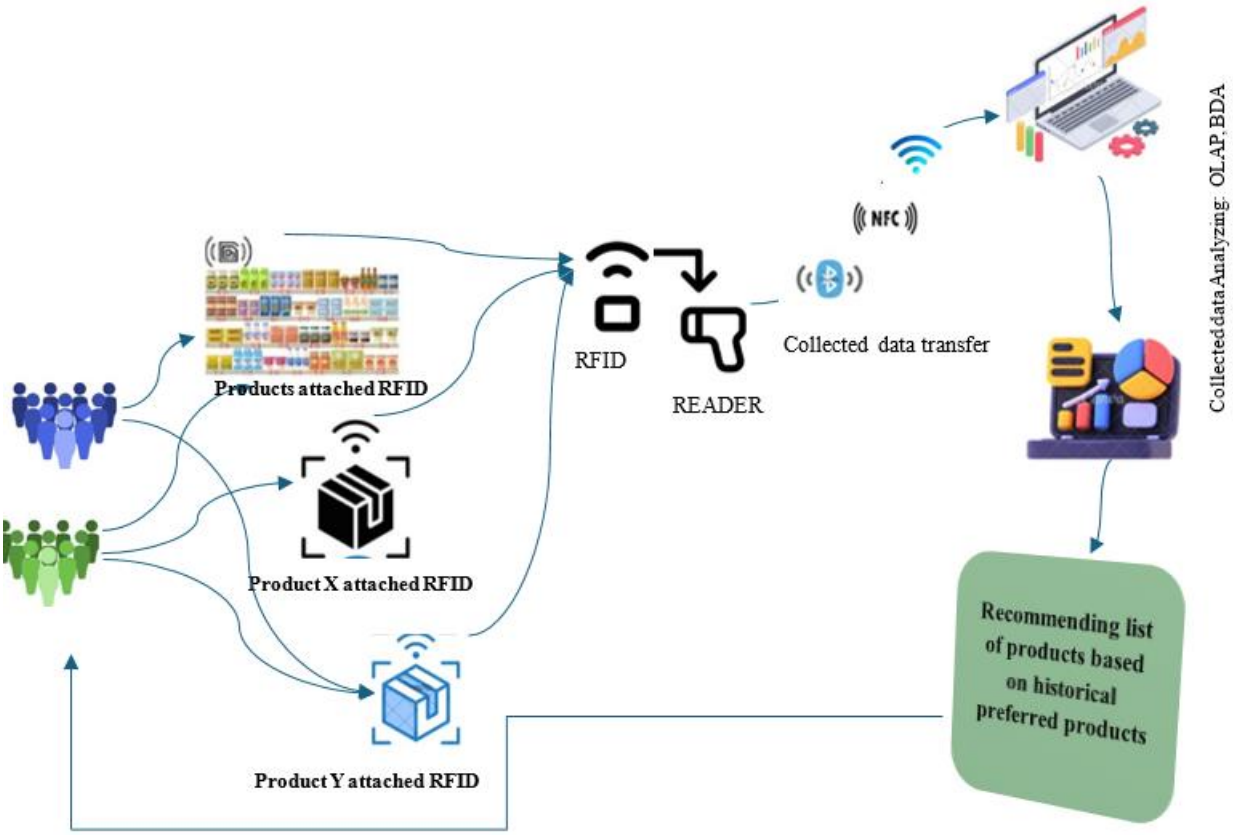

Figure 1. Role of IoT for recommending products.

1.2 | About Recommender System

RSs are software programs that examine data about items, users, and their interactions to forecast a user's interest in a certain item and then recommend the best items for that user [8]. Depending on the suggestion strategy employed, recommendation systems are typically divided into four categories:

Content-based: make recommendations for new products based on past ratings from the user for items that are comparable to those that the user has already evaluated [9]. Crucially, the recommendation mixes the item's properties with the users. Thus, the outcomes simply show how interested the user was in this particular item [10].

Collaborative filtering: usually relies on the resemblance between users who have rated the same objects implicitly or explicitly, having engaged with the system in comparable ways. As a result, anything pertaining to these users ought to apply to the current user and be on the list of suggestions [11].

A knowledge-based: is dependent on knowledge engineering. To describe all of the knowledge needed in the system, knowledge engineering is essential in knowledge-based techniques like ontologies in recommender systems [12].

Hybrid techniques: are mostly employed to produce more accurate recommendations [13].

Any recommender system's foundation is knowledge about user preferences. The capacity of such a recommender system for IoT to leverage additional IoT data and human behavior to generate precise recommendations is its most significant feature [14]. RSs are quite useful in a variety of contexts, including artificial intelligence and information filtering. The recent move to the Internet of Things is no exception. Recommender systems have been used by IoT to provide users with more optimum choices based on their interests and habits. Additionally, recommender systems and the Internet of Things both benefit from this partnership. Personalized suggestions for the IoT based on user behavior and preferences are a blessing, while real-time, context-aware recommendations for recommender systems can be produced utilizing IoT devices. Over the past 20 years, researchers have been researching in both fields. They are now interested in fusing recommender systems with IoT to get the best of both worlds [7]. A crucial concern is: How can IoT data be efficiently utilized as a source to develop recommendation systems, given that billions of IoT resources are connected to and available over the Internet? [14].

But there are still some new issues that can be found with RSIoT, and these are, for the most part, more complicated than the traditional recommender systems for three key reasons [4]:

- To provide appropriate suggestions, handling and analyzing a vast volume of extremely heterogeneous data necessitates thorough analysis and identification.
- Resource limitations could impede the process of providing recommendations that align with user preferences, as it is necessary to leverage extensive contextual information.
- To be interpreted and provide recommendations to the end user, IoT data must travel through multiple levels of intensive processing throughout their entire life cycle. As a result, securing the Internet of Things typically calls for extra security layers and degrades system performance.

Because of the different needs of the organizations using the system, it can be challenging to evaluate recommender systems and apply the most effective RS. Client satisfaction and repeat business are the most valuable metrics. While a heuristic equation cannot measure user satisfaction, recommender systems can be assessed according to how successfully they address common problems [15].

1.3 | Driving Forces for Research

To optimize recommender systems and produce more useful recommendations, it is imperative to analyze the various factors influencing users' opinions. Hence, [16] indicated that various criteria must be used to compare various suppliers and apps. There is no denying the complexity and length of this procedure. In addition, businesses and internet service providers provide several extremely laborious and intricate services. Additionally, several apps with varying features and requirements are offered by organizations and internet providers. The last thing to keep in mind is the needs of the consumer, such as affordability and ease. As a result [17] treats such problems by deploying MCDM techniques for recommending the best IoT application. Wherein [18] demonstrated that MCDM techniques can help with the recommendation creation process, even if recommender systems have already been using several characteristics for the development of recommendations.

Nevertheless Altulyan et al. [14] had a point of view that designing and evaluating an RS based on IoT is far more complicated than designing a traditional RS because of the multi-criteria limitations that are associated with the use of IoT.

This research bolstered MCDM techniques by collaborating with uncertainty techniques of Triangular Fuzzy Numbers (TFN) to overcome the obstacles of uncertain and incomplete information also, a volatile environment.

2 | Related Work

In many domains, recommendation systems are vital, and IOT is no exception. Recommender systems have been employed by IoT technology in recent years to analyze device data and user behavior and optimize the alternatives shown to IoT users [1]. IoT accelerates the amount of data that is available online, impeding the capacity of traditional research paradigms to obtain knowledge through methodical, in-depth analysis to satisfy end-user needs. For Internet of Things (IoT) consumers to profit from the communication and relevant data generated by items from smart spaces, intelligence mechanisms must be able to advise or promote appropriate products based on the available data [8]. The potential of recommendation algorithms in the context of the IoT and vice versa has recently been the subject of investigation. Combining two smart systems into one seems more promising in terms of customer satisfaction because millennial customers frequently seek out rapid services. Scholars worldwide have taken notice of this research, which goes beyond simply suggesting items to users via the Internet of Things to suggesting services to them. world has become interested in this research, which has drawn attention to anything from IoT-based product recommendations to IoT-based service recommendations [7]. The authors of [19] investigated the extent of IoT product recommendations. The authors suggested utilizing a unified probabilistic-based framework to combine user and object data to produce better suggestions. In [20], the authors investigated how recommendation algorithms might be used to create suggestion services for the Internet of Things. IoT-based applications allow for a greater understanding of user preferences and behaviors when compared to conventional recommendation systems. This is mainly due to the availability of heterogeneous information sources. One important component of IoT-based retail environments, for example, is personalized shopping. As customers approach a store, they are given recommendations for things and corresponding pricing offers; these recommendations are based on the condition of the items that are being provided. For instance, special discounts can be made known to the consumer if the RFID (radio frequency identification) tags on some of the supplied items indicate that their expiration date is drawing near [21]. In addition, a different study created a recommender system that gives users of smartphones recommendations based on IoT. The suggested method is to make product recommendations for smartphone purchases. The findings of this study may enhance e-commerce to increase sales of IoT devices. Additionally, researchers examined and assessed a few recommendation systems for IoT users [1].

3 | Research Methodology

The advantage of the MEREC Method has been leveraged to determine the weights of criteria utilized in MABAC to evaluate and rank the set of Recommender Systems based on IoT. These techniques and TFN are integrated to construct a robust decision-making model. Wherein this model proceeds a set of steps for recommending optimal RS based on IoT as follows:

3.1 | Figuring out the Basic Pillars

First Pillar: determining the alternatives of RSs-IoT to be candidates in the evaluation process as $RS_n = \{RS_1, RS_2 \dots RS_n\}$.

Second Pillar: determining the influenced criteria which candidates are evaluated based as $C_n = \{C_1, C_2 \dots C_n\}$.

Third Pillar: Communicating with decision makers who are related to our scope to form the panel of DMs to rate the RSs-IoT based on determined criteria. $DM_n = \{DM_1, DM_2, DM_3\}$.

3.2 | Contemplating and Valuating Criteria Weights

Constructing TFN decision matrices owing to each DM for evaluating RS_n based on C_n as seen in Eq. (1). DMs utilized the scale in Table 1 to rate the alternatives of RS_n.

$$\widetilde{\wp} = \begin{array}{c} \\ RS_1 \\ RS_2 \\ \vdots \\ RS_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \dots & C_n \end{array} \\ \begin{bmatrix} \widetilde{g_{11}}^z & \widetilde{g_{12}}^z & \dots & \widetilde{g_{1n}}^z \\ \widetilde{g_{21}}^z & \widetilde{g_{22}}^z & \dots & \widetilde{g_{2n}}^z \\ \vdots & \vdots & & \vdots \\ \widetilde{g_{m1}}^z & \widetilde{g_{m2}}^z & & \widetilde{g_{mn}}^z \end{bmatrix} \end{array} \tag{1}$$

Integrating TNF matrices into an aggregated matrix based on Eq. (2) [22].

$$\widetilde{g}_{ij=}(x_{ij}, y_{ij}, f_{ij}) \tag{2}$$

Where:

$$x_{ij} = \min\{x_{ijk1},\}, y_{ij}, = \frac{1}{s}\sum y_{ij\,k2}, , f_{ij} = \max\{f_{ijk3}\}$$

Table 1. TFN scale [23].

Linguistic terms	TFN
Least preferable (LP)	(1,3,5)
Moderately preferable (MP)	(3,5,7)
Preferable (P)	(5,7,9)
Fairly preferable (FP)	(7,9,10)
Highly preferable (HP)	(9,10,10)

Convert the TFN aggregated matrix into the crisp matrix through Eq. (3) for Best Nonfuzzy Performance Value (BNP) [22].

$$BNP = \frac{(u-l)+(m-l)}{3} + l \tag{3}$$

Normalizing the aggregated matrix through deploying Eq. (4) to generate the normalized matrix.

$$\tilde{r}_{ij} = \begin{cases} \frac{\min_a g_{aj}}{g_{ij}} & \text{if} \quad j \in B_c \\ \frac{g_{ij}}{\max_a g_{aj}} & \text{if} \quad j \in C_c \end{cases} \tag{4}$$

Calculate the overall performance of the alternatives (s_i) based on Eq. (5).

$$S_i = ln\left(1 + \left(\frac{1}{m}\sum_j \left|ln(\tilde{r}_{ij})\right|\right)\right) \tag{5}$$

Calculate the performance of the alternatives by removing each criterion via Eq. (6).

$$S'_{ij} = ln\left(1 + \left(\frac{1}{m}\sum_{k,k\neq j} \left|ln(n^x_{ij})\right|\right)\right) \tag{6}$$

Compute the removal effect of the jth criterion by using Eq. (7).

$$E_j = \sum\left|S'_{ij} - S_i\right| \tag{7}$$

Determine the final weights of the criteria based on Eq. (8).

$$w_j = \frac{E_i}{\sum_k E_k} \tag{8}$$

3.3 | Ranking RSs-IoT using the TFN-MABAC Method

Eq. (9) utilized for Normalizing the aggregate decision matrix.

$$r_{ij} = \begin{cases} \frac{g_{ij} - g_i^m}{g_i^M - g_i^m} & \text{if} \quad j \in B_c \\ \frac{g_{ij} - g_i^M}{g_i^M - g_i^m} & \text{if} \quad j \in C_c \end{cases} \tag{9}$$

Determine the weighted normalized decision matrix.

$$b = [b_{ij}]_{n \times m}\,;\; b_{ij} = w_j.(r_{ij}^x + 1) \tag{10}$$

Determine the border approximation area matrix, (BAA) for each criterion using the following formula:

$$\mathfrak{H} = \left[\left(\prod_{j=1}^{n} b_{ij}\right)^{1/n}\right]_{1 \times m} \tag{11}$$

The distances matrix of the alternatives from the border approximation area as in Eq. (12).

$$Q = b - \mathfrak{H} \tag{12}$$

Ranking all alternatives based on Eq. (13).

$$S_i = \sum_{j=1}^{n} q_{ij} \quad (j=1,2,\ldots n;\;\; i=1,2,\ldots\ldots m) \tag{13}$$

4 | Illustrative Case Study

Herein, five RSs-IoT are volunteered as alternatives in our case study to validate our proposed model. The evaluation for RSs-IoT is conducted based on ten criteria as mentioned in Figure 2 where criteria from C1 to C8 are beneficial whilst C9 and C10 are non-beneficial. Three DMs are rating the volunteered RSs-IoT. As a result, three TFN decision matrices are constructed and MEREC is utilized in these matrices as the following:

- Eq. (2) is employed for aggregating these matrices into an aggregated matrix.
- The aggregated matrix converts to a crisp matrix through Eq. (3).
- Eq. (4) is applied in the aggregated matrix for generating the normalized matrix as in Table 2.
- The overall performance of the alternatives is calculated based on Eq. (5).
- The performance of the alternatives by removing each criterion is based on Eq. (6) and listed in Table 3.
- The removal effect is computed using Eq. (7) and obtained in Table 4.
- Figure 3 represents the final criteria weights.

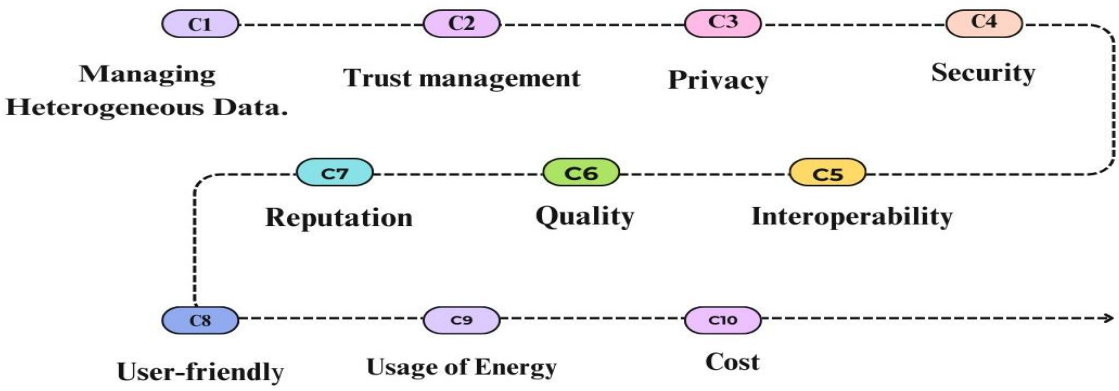

Figure 2. Determined criteria.

Table 2. Normalized matrix.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
RS-IoT1	0.755102	0.8113	0.96	0.80357	0.5211	0.9811	0.9615	1	0.6667	0.68254
RS-IoT2	0.685185	0.8113	0.9	1	1	0.8125	0.9615	0.493	0.6522	1
RS-IoT3	0.521127	1	1	0.5625	0.7255	0.9811	1	0.6034	0.6667	0.87302
RS-IoT4	0.513889	0.8431	0.75789	0.84906	0.6727	0.8254	1	0.6604	0.7681	0.84127
RS-IoT5	1	0.7818	0.91139	0.9	0.7255	1	0.9434	0.6863	1	0.77778

Table 3. Performance of the alternatives by removing each criterion.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
RS-IoT1	0.17948	0.185470	0.199351	0.184672	0.148003	0.201134	0.199483	0.202690	0.169022	0.171007
RS-IoT2	0.15666	0.171013	0.179717	0.188482	0.188482	0.171135	0.185228	0.128113	0.152438	0.188482
RS-IoT3	0.17912	0.232178	0.232178	0.185489	0.206407	0.230666	0.232178	0.191310	0.199504	0.221353
RS-IoT4	0.18659	0.226856	0.218324	0.227413	0.208696	0.225159	0.240364	0.207191	0.219401	0.226679
RS-IoT5	0.13553	0.11378	0.127377	0.126269	0.107089	0.135513	0.130411	0.102084	0.135513	0.113322

Table 4. Removable effect.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
RS-IoT1	0.0232	0.01722	0.00333	0.018018	0.054686	0.0015565	0.003207	0	0.03366	0.031686
RS-IoT2	0.0318	0.01746	0.008764	0	0	0.017346	0.003253	0.060368	0.036043	0
RS-IoT3	0.05305	0	0	0.046688	0.025770	0.001511	0	0.040868	0.032673	0.01082
RS-IoT4	0.05377	0.01350	0.02203	0.012950	0.031667	0.015204	0	0.033172	0.020963	0.013685
RS-IoT5	0	0.02172	0.0081	0.009243	0.028423	0	0.005101	0.033429	0	0.02219088

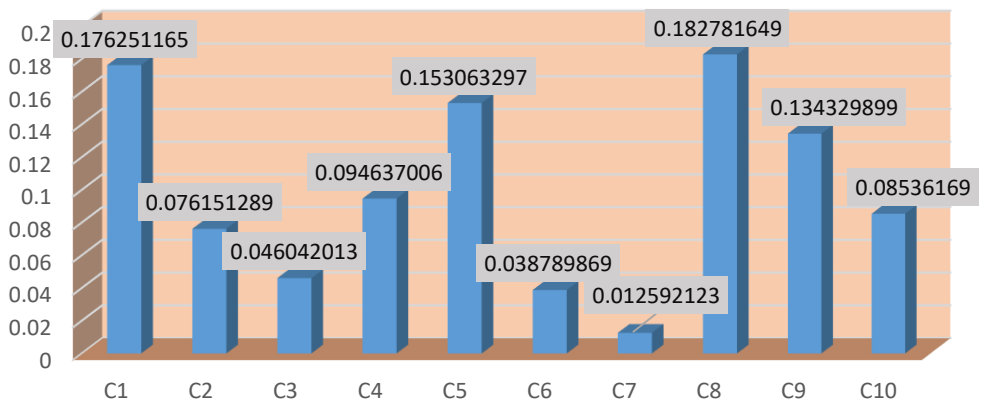

Figure 3. Final criteria weights.

- The aggregated matrix from the previous steps is employed for obtaining a normalized matrix by using Eq. (9). As in Table 5.
- The weighted normalized decision matrix is computed through Eq. (10) as in Table 6.
- The final rank for alternatives of RSs-IoT is illustrated in Figure 4 where RS- IoT 4 is the optimal whilst RS- IoT 1 is the worst.

Table 5. Normalized matrix based on MABAC-TFN.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
RS-IoT1	0.343	0.833	0.130	0.314	1.000	0.083	0.667	0.000	-0.958	-1.000
RS-IoT2	0.486	0.833	0.348	0.000	0.000	1.000	0.667	1.000	-1.000	0.000
RS-IoT3	0.971	0.000	0.000	1.000	0.412	0.083	0.000	0.639	-0.958	-0.400
RS-IoT4	1.000	0.667	1.000	0.229	0.529	0.917	0.000	0.500	-0.667	-0.500
RS-IoT5	0.000	1.000	0.304	0.143	0.412	0.000	1.000	0.444	0.000	-0.700

Table 6. Weighted decision matrix.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
RS-IoT1	0.2367	0.1396	0.0520	0.1244	0.3061	0.0420	0.0210	0.1828	0.0056	0.0000
RS-IoT2	0.2619	0.1396	0.0621	0.0946	0.1531	0.0776	0.0210	0.3656	0.0000	0.0854
RS-IoT3	0.3475	0.0762	0.0460	0.1893	0.2161	0.0420	0.0126	0.2996	0.0056	0.0512
RS-IoT4	0.3525	0.1269	0.0921	0.1163	0.2341	0.0743	0.0126	0.2742	0.0448	0.0427
RS-IoT5	0.1763	0.1523	0.0601	0.1082	0.2161	0.0388	0.0252	0.2640	0.1343	0.0256

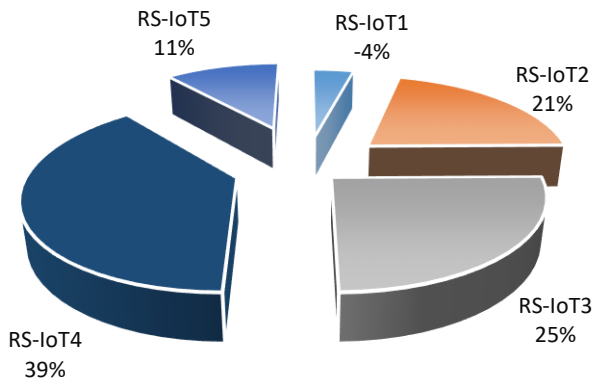

Figure 4. Final ranking for RS-IoT alternatives.

5 | Conclusion

IoT and RSs have become increasingly popular over the last 20 years, both in the research and industrial domains. The reasons for this are numerous and include the capacity to connect multiple devices concurrently, share data via the Internet, offer services to users based on real-time requirements, and make intelligent decisions. In their respective fields, both research areas are equally helpful. In contrast, integrating the two is more likely to result in improved services in a variety of application areas, such as smart healthcare, smart transportation, or smart education.

However, designing and evaluating an RS based on IoT is far more complicated than designing a traditional RS because of IoT limitations. For this reason, a framework and debate for the ranking and selection of

optimal RSs based on IoT. Plenty of relevant prior studies are analyzed through a set of criteria. The problem of selecting optimal RSs is represented in IoT criteria that fall under managing heterogeneous collected data, Trust management, Privacy, Security, Interoperability, Quality, Cost…etc. Also, MCDM techniques are employed in RSs to analyze criteria among a set of candidates. These alternatives are {RS-IoT1, RS-IoT 2, RS-IoT 3, RS-IoT 4, RS-IoT 5}.

multi-criteria analysis was carried out to determine which RS options were most and least favored, based on data provided by the experts regarding the IoT multi-criteria and the related features. In this study, the advantage of the MEREC Method to determine the weights of criteria in MCDM problems is combined with MABAC to evaluate and rank a set of RSs using TFN.

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Author Contributions

All authors contributed equally to this work.

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Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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