processes

Article

A Multi-Criteria Decision-Making Process for the Selection of an Efficient and Reliable IoT Application

Bader Alojaiman

Applied College, Shaqra University, Shaqra 11961, Saudi Arabia; alojaiman@su.edu.sa

Abstract: Saudi Arabia initiated its much-anticipated Vision 2030 campaign, a long-term economic roadmap aimed at reducing the country's reliance on oil. The vision, which is anticipated to be accomplished in the future, underlines compliance, fiscal, and strategy adjustments that will significantly affect all the important features of Saudi economic growth. Technology will be a critical facilitator, as well as controller, of the initiative's significant transformation. Cloud computing, with the Internet of things (IoT), could make significant contributions to Saudi Vision 2030's efficient governance strategy. There are multiple IoT applications that cover every part of everyday life, as well as enabling users to use a variety of IoT applications. Choosing the best IoT applications for specific customers is a difficult task. This paper concentrates on the Kingdom's advancement towards a fresh, as well as enhanced, method of advancing the development phases pertaining to digital transformation, through implementing and adopting modern communications infrastructure and ICT technology. In addition, this study proposes a recommendation system that relies on a multi-criteria decision-making investigation focusing on the fuzzy TOPSIS method for selecting highly efficient IoT applications. The prototype, as well as the hierarchy, was created to assess and correlate critical criteria based on specialist preferences and recommendations. The T5 IoT application alternative was shown to be the most highly effective and reliable choice according to the findings of both fuzzy TOPSIS and TOPSIS.

Keywords: internet of things; Vision 2030; fuzzy logic; MCDM; recommender system

check for updates

Citation: Alojaiman, B. A Multi-Criteria Decision-Making Process for the Selection of an Efficient and Reliable IoT Application. *Processes* **2023**, *11*, 1313. https://doi.org/10.3390/pr11051313

Academic Editors: Jie Zhang and Jiaqiang E

Received: 20 February 2023
Revised: 13 March 2023
Accepted: 25 March 2023
Published: 24 April 2023

1. Introduction

For many years, a strategic primary focus has been the technological development of Saudi Arabia's healthcare delivery system, as well as the introduction of modern healthcare initiatives, resulting in hospitals and other healthcare centers functioning as advanced technological workplace environments. The development of digital workplaces is assisting in the implementation of both the Saudi Vision 2030 as well as the National Transformation Program, and participants have been kept up to date on the advancement of the digitalization of hospitals as well as primary care centers throughout the Kingdom. The development of Internet of things (IoT) solutions is being determined by a number of significant economic diversification initiatives. They are assisted by low-cost, reliable connectivity, as well as governmental policies encouraging the use of IoT. Moreover, Saudi Arabia became one of the first Gulf Cooperation Council (GCC) nations to implement a 5G network. Improved connectivity, reduced latency, and rapid connections allow more users to transfer information at the same time. Companies and future technology vendors are rapidly developing IoT solutions focused on 5G, as well as low-power wide-area network (LPWAN) innovations. These initiatives and advancements are accelerating growth in the economy [1–5].

The IoT relates to the billions of portable devices globally that are linked to the Internet to capture and share information. The sophistication of such devices ranges from simple household products to advanced industrial machinery. The IoT is a vast network of objects on which almost all individuals collect as well as communicate data relating to how they interact with the globe around them. By linking all of these different platforms and incorporating sensors into them, gadgets gain digital intellectual capacity that enables them to transfer real information without the requirement for human intervention. The IoT enables the integration of numerous machines, gadgets, and electronic devices that are linked to the Internet via various networks. An Internet of things wearable technology collaboration could allow two technology companies to combine their strengths and provide the best equipment software applications, which include advanced wearable technology for smart city architecture and enterprises such as catering and healthcare, as well as development. Smart cities in the area would then start encouraging sustainable economic growth and a high standard of living in order to confront increasing urbanization obstacles through the implementation of Information and Communication Technologies (ICTs) in a variety of capacities, such as the economy, atmosphere, transportation, well-being, living, and governance. IoT innovations, as well as their implementation, have also played a noticeable role in the Hajj and Umrah gatherings control system applications, with their consequences visible in various places throughout the two holiest sites of Makkah and Madinah, along with the two sacred mosques, sacred locations, museums, library services, and exhibitions [6–9].

According to Statista [10], the global number of IoT procedures is anticipated to nearly triple, from 9.7 billion in 2020 to over 29 billion in 2030. China will have the most IoT gadgets in 2030, with about 5 billion devices of end-user equipment. IoT equipment is used across all industries and consumers, with the customer group responsible for roughly 60% of all digital and mobile technologies in 2020. This proportion is expected to remain stable throughout the next 10 years. Power generation, gas, steam, air conditioning, water systems, discarded disposal systems, trade and wholesale, logistics and storing, as well as administration, are key industry verticals including over 100 million interconnected IoT devices. The total number of connected devices throughout all industries worldwide is expected to exceed eight billion by 2030. Customer internet and media devices, such as mobile phones, are among the most significant use examples of IoT equipment in the customer group, with the number of IoT devices expected to exceed 17 billion by 2030. Other examples, with over one billion IoT-linked devices by 2030, include linked (driverless) automobiles and IT infrastructure facilities. Figure 1 shows the number of IoT-linked devices globally from 2019 to 2021 through the predictions for 2022 to 2030, according to a report by Statista.

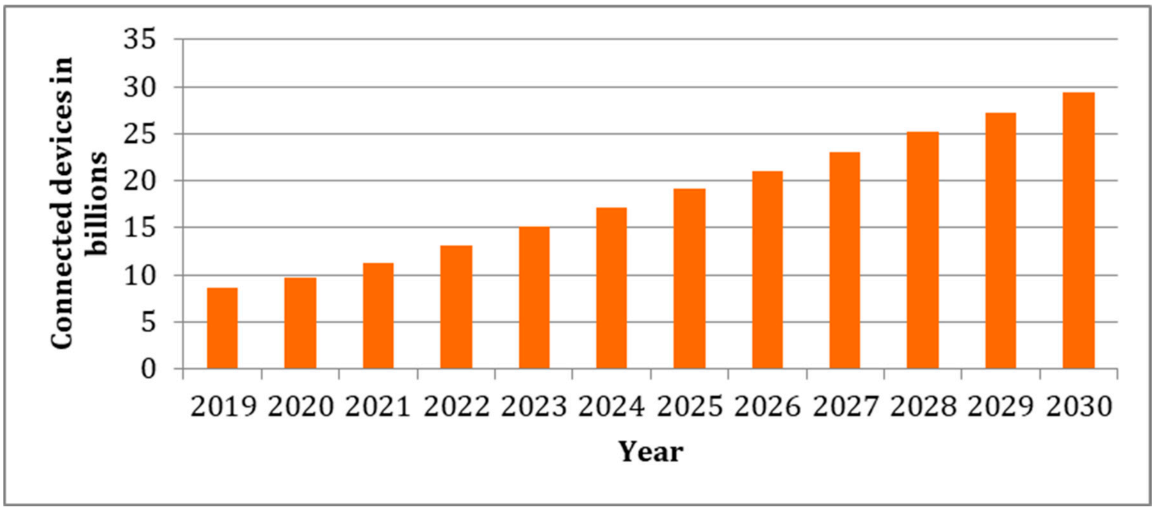

Figure 1. Number of IoT-linked devices globally from 2019 to 2021, through the predictions for 2022 to 2030 (Source: Statista).

The Saudi Arabian IoT Market was projected to reach USD 2016.86 million in 2021 and is projected to expand at a 17.67% compounded annual growth rate from 2023 to 2027 to reach a market price of USD 5391.15 million by 2027. The exponentially growing information technology and telecoms sector, as well as the increasing penetration of worldwide web services across various end-use industries, will propel the expansion of the Kingdom's IoT marketplace over the next five years. The increasing utilization of Bluetooth and Wi-Fi services for networking purposes, as well as the increased demand for faster connectivity for connected devices, will also encourage the expansion of the Saudi Arabian IoT market over the coming five years. The increasing implementation of innovations, including cloud-oriented services, combined with an increased demand for intelligent equipment such as smart household applications, mobile phones, smart televisions, and so on, will bolster the Saudi Arabian IoT market's expansion over the next five years. Increasing investments, as well as government assistance for the nation's IT industry and its expanding desire to develop the marketplace and further transmit the nation's economic development from the petroleum industry to other industries, such as IT, will all contribute to the development of the Kingdom's IoT marketplace in the projected period between now and 2027 [11].

Several cutting-edge applications, including intelligent transportation, as well as medical and emergency management, are anticipated to be made possible by IoT. Traffic congestion could be significantly reduced by real-time information for optimal traffic routing using streaming data from highway sensors or cellphones installed on dashboards. Furthermore, a real-time IoT application could select one of several alternate routes that are open in order to transport an emergency vehicle to a patient when some of the options are closed because of renovations, a political or socioeconomic event, or a natural disaster. Other examples would be patients in the critical care unit or emergency departments with aberrant shock index readings, who have considerably greater mortality risk as well as elevated rates of developing hyperlactatemia and heart attacks. As a result, it is preferable to make treatment choices in real-time under decision constraints using an evaluation of physiological monitoring information from wearable technology. To decrease, for instance, overcrowding or fatalities in an emergency unit, a decision-maker could choose one of the available alternatives employing sensor information representing the current actual state. Moreover, to prevent potential congestion problems and excessive energy use in IoT applications from wirelessly transferring duplicate sensor data, an ultimate decision must demand only efficient and reliable IoT applications to deliver the minimum sensor data required for the outcome.

In Saudi Arabia, IoT innovation is at a tipping point, fueled by smart cities as well as currently underway megaprojects. Many IoT implementations are anticipated to be launched in the coming years, and more smart objects are anticipated to be linked together. Finding appropriate IoT applications for consumers may be a challenging assignment for a variety of reasons. First, the selection process is influenced by numerous factors, including smart object-specific requirements and application functionality, as well as cost, necessitating the comparison of a large number of criteria and alternatives that require considerable effort and time. Second, IoT companies and resources have a wide range of applications with varying requirements and specifications. Ultimately, user priorities, such as expense and ease of use, must be taken into account throughout the decision-making procedure. Consequently, selecting an IoT-based application is a complicated multicriteria decision-making (MCDM) challenge [12–14]. Moreover, because there are so many IoT applications as well as smart objects obtainable, the computational cost of choosing the most appropriate IoT-based applications is significant and must be decreased. Recommender systems are an acceptable option for choosing the most appropriate IoT-based applications for customers.

- In this research, we create efficient recommendation systems for evaluating and ranking IoT applications with the help of the MCDM framework. An MCDM strategy implementing the fuzzy TOPSIS (a technique for order performance by similarity to ideal solution) framework was used to reduce the sophistication of the envisioned solution. To the best of our experience and understanding, this is the first study to suggest a fuzzy TOPSIS for designing a recommendation method in the setting of the

IoT. It is, correspondingly, the first study to investigate as well as verify the standards utilized in the anticipated system. The results demonstrate that the suggested fuzzy TOPSIS model is reliable as well as feasible for building IoT decision-making schemes.

- From this current perspective, the study also aims to compare the outcomes with those of other MCDM approaches. It aims to investigate the outcomes of fuzzy TOPSIS and TOPSIS approaches that were used to tackle the issue of effective and trustworthy IoT application selection.

The rest of this study is structured as follows. Section 2 examines the studies published and their preliminary findings. The hierarchical structure for assessing IoT applications and the fuzzy TOPSIS approach is described in Section 3. Section 4 discusses the research study's outcomes. Section 5 deliberates the study's results. Finally, Section 6 brings the paper to a close.

2. Literature Review

When there are multiple decision factors, MCDM tackles the issue of decision-making. It chooses, examines, and ranks alternative solutions based on a variety of criteria, as well as sub-criteria, several of which are in disagreement. There are numerous MCDM methods that have been published. The TOPSIS is a commonly used MCDM strategy with a straightforward mathematical technique. The TOPSIS has been utilized in a variety of contexts. Various MCDM strategies have been used from the perspective of IoT. Guo et al. [15] presented a conceptual framework of IoT-centric smart tourist attractions and identified specific intelligent operations introduced to tourist attractions by IoT techniques. To contend with the diverse evaluations from various professionals, two fuzzy TOPSIS methodologies have been developed: a centroid-based fuzzy TOPSIS, as well as an integral-built fuzzy TOPSIS. An implementation study showed the efficacy as well as the advantages of their strategies over traditional TOPSIS. Cooperation between the fuzzy TOPSIS and the conventional TOPSIS is incapable of reflecting the decision-makers's priorities, but their evaluation results aren't completely compatible. The integral-based fuzzy TOPSIS evaluation results were also susceptible to the provided optimism point, which may affect the assessment order information. The researchers discovered some interesting observations that can be used to improve the intellectual ability of IoT-based traveler attractions.

Tariq et al. [16] studied the aspects associated with the Internet of medical things (IoMT). The goal of their research was to prioritize the degree of importance of the factors causing obstacles, which will be assessed utilizing fuzzy logic as well as MCDM strategies, such as TOPSIS and the analytic hierarchy process (AHP). According to them, this may benefit businesses by saving time as well as money. The key criteria, along with the sub-criteria, were ascertained afterward through extensive discussion with specialists on the IoMT. The objectives of their research were also to determine which criteria/factors impede the acceptance of the IoMTs. They discovered 20 criteria that should be given more significance by the sector, which is in the transformation phase of adopting the IoMTs via their investigation. The organization would be able to speed up implementation with the assistance of their research by restricting both financial and time risks.

Gupta et al. [17] used TOPSIS to figure out the kind of network that provides a tailored solution to a specific application. A generalized combination architectural style was also suggested for IoT applications.

Yadav et al. [18] created an IoT-based blueprint for supply chain performance measurements (SCPM) for agricultural production supply chains constructed on the supply chain operation reference (SCOR) prototype, and they discussed the role of IoT in data gathering as well as communication. Their research highlighted several key performance indicators (KPIs) and their roles in SCPM for achieving sustainability through the use of SCOR. Furthermore, Shannon entropy was used to quantify the basic procedures of SCPM, as well as fuzzy TOPSIS, which is used to prioritize recognized KPIs at performance measures level two. "Flexibility" as well as "responsiveness" were identified as the two highly significant KPIs in an IoT-oriented SCPM structure for ASC to achieve sustainability.

Chakraborty and Das [19] utilized three technologies to improve operational efficiency. TOPSIS was employed to deliver consumer preferences for various criteria against various attributes. The radio-frequency identification (RFID) technique may be used in SCM to gather and distribute information of occurrence(s) or 'Things' of a wide variety with the help of Internet of Things (IoT) implementation for tracking products in transportation. Ultimately, cloud computing has been suggested as a technique for managing the big data produced during the SCM process. Their work discusses in-depth the performance optimization technique of a rapid or responsive SCM predicated on TOPSIS and IoT, as well as cloud computing, to benefit companies.

Singla [20] presents an assessment methodology predicated on the fuzzy AHP and the fuzzy TOPSIS that assists users in selecting an optimal cloud, where ambiguity and subjective experience were modeled utilizing triangular fuzzy members and treated utilizing linguistic values. Their suggested computational decision-making prototype assists decision-makers in effectively understanding the entire evaluation process, resulting in a more accurate, systematic, as well as productive decision-support tool.

Qahtan et al. [21] created an MCDM Model for measuring the security and privacy of blockchain-oriented IoT healthcare Industry 4.0 processes. The technique begins with the creation of a decision matrix predicated on the connection of "blockchain-based Internet of Things healthcare Industry 4.0 systems" as well as "security and privacy characteristics" (e.g., authentication methods, authentication protocols, personal privacy, accessibility, as well as confidentiality). The weight values of every security and private property were also determined by calculating using the S-FWZIC technique in the second stage. The consolidated grey relational analysis-TOPSIS, as well as the bald eagle search (BES)-based optimization technique, is then used to measure the performance of blockchain-centric IoT medical Industry 4.0 processes. Their findings are summarized below. Firstly, the S-FWZIC simple procedure weighs security as well as privacy characteristics, implying that access control seems to have the greatest importance weight, of 0.2070, whereas integrity takes the smallest weight (0.0646); subsequently, the grey relational analysis-TOPSIS, as well as the BES optimization methods, successfully rank.

Wibowo and Grandhi [22] created a fresh fuzzy multicriteria group decision-making algorithm predicated on the TOPSIS technique, and the idea of comparison metrics was established to determine every alternative's overall effectiveness. Their proposed multicriteria analysis model has the benefit of being able to conquer the shortcomings of existing strategies in intuitionistic fuzzy surroundings. The fuzzy-based multicriteria team decision-making prototype enables organizations to assess the effectiveness of their IoT-centric supply chains in order to improve their competitive strength. An example is provided to determine the utility of the planned prototype in addressing a real-world IoT measuring performance issue.

Gardas et al. [23] proposed a fresh node search technique for blockchain-oriented edge IoT which is both fast and highly reliable. In addition, fuzzy judgment to estimation logic was employed to handle mathematical as well as semantic figures at the same time. Furthermore, the TOPSIS, a strong tool for investigating MCDM issues, was employed. In IoT-edge situations, the proposed fuzzy-centric procedure uses three response requirements to choose the appropriate IoT nodule for a given assignment. The experimental findings demonstrated that their proposed framework improves the variables under evaluation.

There are further approaches, such as the novel multiple attribute decision-making (MADM) approach known as the ordinal priority approach (OPA), which was recently introduced. The OPA offers numerous advantages over older approaches, such as the analytical hierarchy process (AHP) as well as the TOPSIS. Unfortunately, this strategy does not allow for the decision-making procedure to take into account different ranks or adopt an ambiguity strategy [24]. The aforementioned related works demonstrate a range of innovative efforts made to effectively assist real-time IoT decision-making employing recent sensor data. More precisely, they strive to conveniently organize decision-making operations and assess logic queries that model different scenarios. Although strongly linked fields that serve as a foundation for real-time strategic planning, which include sensor predictive analytics through machine learning, as well as wireless communication for IoT, have already been explored thoroughly, the subject of study on decision-making in the selection of an efficient and reliable IoT application is still in its initial stages. In the interest of bridging the gap, we examine the most advanced factors for decision-making in IoT application selection and other closely connected fields in this study, outlining their advantages and disadvantages. Selecting an efficient and reliable IoT-based application, therefore, presents a challenging MCDM problem [25–27]. The computational cost of selecting the most suitable IoT-based apps is also substantial and needs to be reduced due to the numerous IoT applications and smart gadgets available. Decision support systems are a viable choice for helping clients select the best IoT-based apps. In this study, we use the MCDM model to create effective decision support systems for assessing and ranking IoT applications.

3. Materials and Methods

This section outlines the hierarchy's development, the criteria's recognition, and the research methods employed in the assessment process.

3.1. Fuzzy TOPSIS Approach

A framework for assessing and selecting IoT applications is described in this paper. The prototype is predicated on the idea that preference for an IoT application should be based on its benefits, both tangible and intangible uncertainties, as well as its costs. The selection of IoT applications is a complicated situation with several subjective attributes to take into account. These characteristics make the assessment process difficult and ambiguous. A hierarchical structure is an effective way to describe a complex system. Expert opinions are always imprecise rather than precise numbers. It is more appropriate and expandable to express experienced professional decisions in fuzzy numbers rather than crisp numbers. Fuzzy TOPSIS can use a hierarchical structure to make comparative studies of such characteristics into consideration. By now, numerous fuzzy TOPSIS techniques have been proposed that do not take into account these comparative studies among attributes, or provide a hierarchical structure. A fuzzy TOPSIS strategy must take this hierarchical system into account in order to distinguish between these techniques [28–30]. This capability is provided by the hierarchical fuzzy TOPSIS procedure created in this research, without the use of correlation coefficients. It is obvious that selecting an IoT application is a challenging and delicate issue with both statistical and qualitative aspects, as well as sophistication and inaccuracies. Even so, the advanced fuzzy method appears to be suitable for solving this problem. For our challenge, which was to select an efficient IoT application, we used the hierarchical fuzzy TOPSIS framework. The factors were based on previous research, as well as validated through interviews with independent scholars. Table 1 provides a brief overview of the various factors utilized during the IoT application assessment process. Figure 2 shows the hierarchical structure for the evaluation of different IoT applications.

Table 1. Different criteria with descriptions.

Criteria	Description
Ease of Use (R1)	Ease of use is a fundamental term that refers to how simple it is for users to use a product. Design professionals identify particular metrics for each project, such as "Users should be allowed to tap Find within three seconds of attempting to access the interface." The goal is to optimize ease of use while providing maximum features and functions and upholding business constraints [30].
Energy Consumption (R2)	All of the energy utilized to execute an action, manufacture something, or merely inhabit a construction is referred to as energy consumption. Power factor, energy consumption, peak voltage, as well as power consumption are all factors that influence energy consumption. Meters' functionality enables them to be used for a variety of monitoring purposes [31].

Table 1. *Cont.*

Criteria	Description
Interoperability (R3)	Interoperability is the characteristic that allows uncontrolled resource-sharing among various systems. This could be described as the capacity to share data among distinct elements or machines, via both hardware and software, or as the transfer of information and infrastructure between multiple machines through local area networks (LANs) or wide area networks (WANs). The term interoperability is widely defined as the capacity of two or more elements or systems to share information and utilize that information [32].
Privacy (R4)	When it comes to the Internet, privacy refers to an individual's personal or a group's command over their preferential anonymity, and also how secure they feel about sharing and storing information. One important objective of data privacy is to guarantee that data in transport and at rest has always been shielded while enabling information to flow [33].
Availability (R5)	One of the three basic features of security management prevalent in all systems is availability. The assumption that a computer is accessible or available to an authorized user whenever they are required is known as availability. System availability must be high to guarantee that the system works as expected when required. The availability of the products allows for the development of fault detection systems. In addition, it guarantees backup computation by incorporating hot and cold sites into planning for disaster recovery [34].
Interface (R6)	An interface in computer technology is a shared boundary that allows three or more distinct elements of a computer system to exchange information. Applications, computer hardware, passive components, humans, and combinations of these, can all be exchanged [35].
Customer Service(R7)	Customer service refers to a variety of services that help customers make the most cost-effective and appropriate use of a good or service. It includes help with production planning, installation, mentoring, troubleshooting, servicing, upgrading, and decommissioning. Technical support is also used to refer to IoT technology items such as portable phones, sensors, computer systems, software platforms, or other mechanical and electronic products [36].

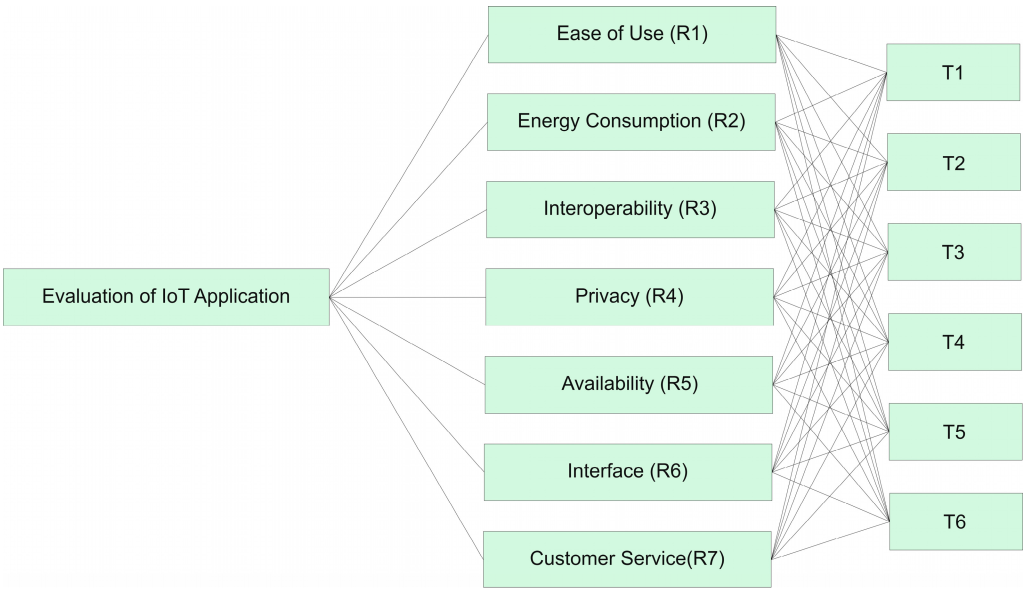

Figure 2. Hierarchical model for the evaluation of IoT applications.

3.2. Fuzzy TOPSIS Approach

The fuzzy TOPSIS approach is the simplest and most straightforward method in MCDM. In the TOPSIS approach, the notion of range tactics was introduced by Hwang and Yoon [4], including alternatives from the positive ideal solution (PIS) as well as the negative ideal solution (NIS). TOPSIS is a multi-criteria decision analytical procedure that ranks various possibilities based on a variety of criteria. It is contended that if a fuzzy MCDM challenge is first defuzzified into a crisp one, the benefit of accumulating fuzzy data disappears. TOPSIS is a significant decision branch; it is a useful and practical strategy for ranking and selecting a set of externally calculated alternatives according to their distance. Based on this essence, we created a fuzzy TOPSIS problem-solving method in which the criteria attributes are linguistic fuzzy figures. The rating was investigated, as well as the outcomes gathered, at the end of the process of decision analysis. Hwang and Yoon introduced TOPSIS for determining PIS- and NIS-utilizing linguistic terms to analyze the ranking [34–37]. Saraswathi et al. proposed the fuzzy TOPSIS approach for resolving MCDM complications where the effectiveness-ranking standards and criteria weights are lingual conditions that can be demonstrated in the form of triangular fuzzy numbers [38]. The simple steps of the TOPSIS method are presented in Figure 3.

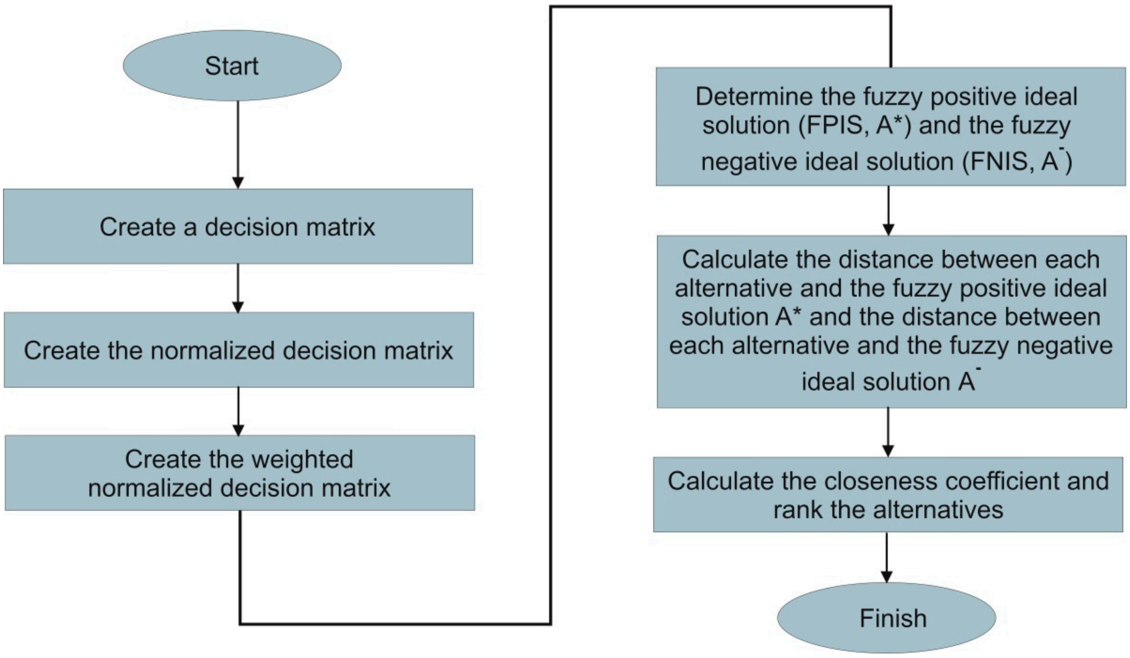

Figure 3. Flow diagram of fuzzy TOPSIS approach.

Step 1: Generate a decision model.

The fuzzy TOPSIS tactic is used in this investigation to assess seven characteristics (R1, R2, R3, R4, R5, R6, and R7) as well as six alternatives (T1, T2, T3, T4, T5, and T6). The categorization depicts the various types of factors. Assume the decision-making unit has K members. If the fuzzy numerical value and priority weight of the k^{th} judgment consultant for the i^{th} alternative upon that j^{th} criterion are as follows:

$$\check{x}_{ij}^{k} = \left(a_{ij}^{k}, b_{ij}^{k}, c_{ij}^{k}\right) \text{and } \check{w}_{j}^{k} = \left(w_{j1}^{k}, w_{j2}^{k}, w_{j3}^{k}\right), \text{ respectively,}$$

where $i = 1, 2, \ldots, m$, and $j = 1, 2, \ldots, n$, now the combined fuzzy rankings $\check{x}_{ij}$ of alternatives (i) with respect to each standard (j) are indicated with the help of $\check{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$. Table 2 displays the category of standards as well as the weight applied to every criterion.

The triangular fuzzy number (TFN) is designated as (L, M, or U). The specifications L, M, and U represent the least effective, most expected, and absolute highest value systems, in that order. The fuzzy measurement used in the prototype is illustrated in Table 3.

Table 2. Features of Different Criteria.

	Criteria	Category	Weight
1	R1	+	(0.143,0.143,0.143)
2	R2	+	(0.143,0.143,0.143)
3	R3	+	(0.143,0.143,0.143)
4	R4	+	(0.143,0.143,0.143)
5	R5	+	(0.143,0.143,0.143)
6	R6	+	(0.143,0.143,0.143)
7	R7	+	(0.143,0.143,0.143)

Table 3. Fuzzy-based measuring scale.

Code	Linguistic terms	L	M	U
1	Very low	1	1	3
2	Low	1	3	5
3	Medium	3	5	7
4	High	5	7	9
5	Very high	7	9	9

Step 2: Render the normalized decision model.

Normalized decision matrices can be created by applying the following relation to both positive and negative ideal possibilities:

$$\widetilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right);\ c_j^* = \max_i c_{ij};\ \text{Positive ideal solution} \tag{1}$$

$$\widetilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right);\ a_j^- = \min_i a_{ij};\ \text{Negative ideal solution} \tag{2}$$

Step 3: Render a weighted normalized decision model.

The weighted standardized decision matrix can be created by multiplying the weight assigned to each criterion in the standardized fuzzy decision matrices through the following equation, taking into consideration the highly variable weight of each characteristic.

$$\widetilde{v}_{ij} = \widetilde{r}_{ij}.\widetilde{w}_{ij} \tag{3}$$

where $\widetilde{w}_{ij}$ designates the weight of criterion c_j.

Step 4: Ascertain both the fuzzy positive ideal solution (FPIS, A*) and the fuzzy negative ideal alternative (FNIS, A^-)

The FPIS, in addition to the FNIS of the alternative solution, might be definite, as the following calculations 4 and 5 demonstrate:

$$A^* = \left\{\widetilde{v}_1^*, \widetilde{v}_2^*, \ldots, \widetilde{v}_n^*\right\} = \left\{\left(\max_j v_{ij} | i \in B\right), \left(\min_j v_{ij} | i \in C\right)\right\} \tag{4}$$

$$A^- = \left\{\widetilde{v}_1^-, \widetilde{v}_2^-, \ldots, \widetilde{v}_n^-\right\} = \left\{\left(\min_j v_{ij} | i \in B\right), \left(\max_j v_{ij} | i \in C\right)\right\} \tag{5}$$

where $\widetilde{v}_i^*$ is the extreme quantity of i for all the alternatives, and $\widetilde{v}_1^-$ is the minimum quantity of i for all the alternative solutions. B and C indicate the positive and negative ideal resolutions, respectively.

Step 5: Determine the separation between each alternative and also the fuzzy positive ideal solution, A*, in addition to the range between each immediate solution and also the fuzzy negative ideal alternative, A^-.

The discrepancy between each potential substitute and the FPIS, in addition to between every alternative and the FNIS, is determined with the help of Equations (6) and (7), respectively:

$$S_i^* = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^*) \quad i = 1,2,\ldots,m \tag{6}$$

$$S_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-) \quad i = 1,2,\ldots,m \tag{7}$$

Once two triangular fuzzy figures (a_1, b_1, c_1) and (a_2, b_2, c_2) are anticipated, the range between the two can be estimated by employing formula (8):

$$d_v(\tilde{M}_1, \tilde{M}_2) = \sqrt{\frac{1}{3}\left[(a_1 - a_2)^2 + (b_1 - b_2)^2 + (c_1 - c_2)^2\right]} \tag{8}$$

taking into account $d(\tilde{v}_{ij}, \tilde{v}_j^*)$ and $d(\tilde{v}_{ij}, \tilde{v}_j^-)$ are crisp figures.

Step 6: Quantify the closeness coefficient and position the choices available.

The following expression could be employed to evaluate the similarity coefficient of each potential substitute:

$$CC_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{9}$$

For quality assurance, as well as to prioritize the alternatives based on a variety of factors, there are many multiple approaches available. The pros and cons of each strategy are generally comparable. One of the extensively used fuzzy TOPSIS MCDM methods has the benefit of actual, mathematical, and simple-to-illustrate human preferences, as well as permitting straightforward and transparent trade-offs between many different constraints [39–43]. Besides this, the pattern is classified as a revealing notion, with the idea that even if no finest condition exists, a resolution with optimized principles for all the requirements is possible. As a consequence, in this research study, fuzzy TOPSIS through a triangular association valuation is used to analyze different IoT applications.

4. Results

4.1. Statistical Findings

Six different IoT applications were assessed by using the above-mentioned multi-attribute decision-making strategy. Using the hierarchy shown in Figure 2, a survey form for fuzzy TOPSIS was created to collect the participants' weights of essential characteristics and was delivered to a total of 110 academics investigating IoT technology research and specialists employed in the field. The percentage of responses was 83%, or 92 out of 110 participants. Tables 4–9 show the findings of this research study.

Table 4. Decision-makers's judgment matrix.

	R1	R2	R3	R4	R5	R6	R7
T1	(4.275,6.275,8.231)	(4.319,6.319,8.011)	(4.099,6.099,7.989)	(4.385,6.385,7.989)	(4.187,6.187,8.077)	(4.341,6.341,8.143)	(4.319,6.319,8.121)
T2	(4.385,6.385,8.165)	(4.319,6.319,8.099)	(4.341,6.341,8.055)	(4.297,6.297,8.121)	(4.209,6.209,7.901)	(4.209,6.209,8.033)	(4.363,6.363,8.011)
T3	(4.297,6.297,8.143)	(4.604,6.604,8.253)	(4.187,6.187,7.989)	(4.451,6.451,8.099)	(4.165,6.165,7.923)	(4.275,6.275,8.033)	(4.209,6.209,7.945)
T4	(4.385,6.385,8.187)	(4.385,6.385,8.077)	(4.363,6.363,8.099)	(4.099,6.099,7.967)	(4.033,6.033,7.879)	(4.143,6.143,7.967)	(4.209,6.209,7.967)
T5	(4.143,6.143,8.033)	(4.473,6.473,8.209)	(4.451,6.451,8.209)	(4.275,6.275,8.121)	(4.297,6.297,8.121)	(4.253,6.253,8.209)	(4.209,6.209,8.011)
T6	(4.451,6.451,8.275)	(4.341,6.341,8.165)	(4.143,6.143,8.033)	(4.319,6.319,8.143)	(4.187,6.187,8.099)	(4.143,6.143,7.989)	(4.275,6.275,8.143)

Table 5. The normalized decision matrix.

	R1	R2	R3	R4	R5	R6	R7
T1	(0.517,0.758,0.995)	(0.523,0.766,0.971)	(0.499,0.743,0.973)	(0.538,0.784,0.981)	(0.516,0.762,0.995)	(0.529,0.772,0.992)	(0.530,0.776,0.997)
T2	(0.530,0.772,0.987)	(0.523,0.766,0.981)	(0.529,0.772,0.981)	(0.528,0.773,0.997)	(0.518,0.765,0.973)	(0.513,0.756,0.979)	(0.536,0.781,0.984)
T3	(0.519,0.761,0.984)	(0.558,0.800,1.000)	(0.510,0.754,0.973)	(0.547,0.792,0.995)	(0.513,0.759,0.976)	(0.521,0.764,0.979)	(0.517,0.762,0.976)
T4	(0.530,0.772,0.989)	(0.531,0.774,0.979)	(0.531,0.775,0.987)	(0.503,0.749,0.978)	(0.497,0.743,0.970)	(0.505,0.748,0.971)	(0.517,0.762,0.978)
T5	(0.501,0.742,0.971)	(0.542,0.784,0.995)	(0.542,0.786,1.000)	(0.525,0.771,0.997)	(0.529,0.775,1.000)	(0.518,0.762,1.000)	(0.517,0.762,0.984)
T6	(0.538,0.780,1.000)	(0.526,0.768,0.989)	(0.505,0.748,0.979)	(0.530,0.776,1.000)	(0.516,0.762,0.997)	(0.505,0.748,0.973)	(0.525,0.771,1.000)

Table 6. The weighted normalized decision matrix.

	R1	R2	R3	R4	R5	R6	R7
T1	(0.074,0.108,0.142)	(0.075,0.109,0.139)	(0.071,0.106,0.139)	(0.077,0.112,0.140)	(0.074,0.109,0.142)	(0.076,0.110,0.142)	(0.076,0.111,0.143)
T2	(0.076,0.110,0.141)	(0.075,0.109,0.140)	(0.076,0.110,0.140)	(0.075,0.111,0.143)	(0.074,0.109,0.139)	(0.073,0.108,0.140)	(0.077,0.112,0.141)
T3	(0.074,0.109,0.141)	(0.080,0.114,0.143)	(0.073,0.108,0.139)	(0.078,0.113,0.142)	(0.073,0.109,0.140)	(0.074,0.109,0.140)	(0.074,0.109,0.140)
T4	(0.076,0.110,0.141)	(0.076,0.111,0.140)	(0.076,0.111,0.141)	(0.072,0.107,0.140)	(0.071,0.106,0.139)	(0.072,0.107,0.139)	(0.074,0.109,0.140)
T5	(0.072,0.106,0.139)	(0.078,0.112,0.142)	(0.078,0.112,0.143)	(0.075,0.110,0.143)	(0.076,0.111,0.143)	(0.074,0.109,0.143)	(0.074,0.109,0.141)
T6	(0.077,0.111,0.143)	(0.075,0.110,0.141)	(0.072,0.107,0.140)	(0.076,0.111,0.143)	(0.074,0.109,0.143)	(0.072,0.107,0.139)	(0.075,0.110,0.143)

Table 7. The positive and negative ideal solutions.

	Positive Ideal	Negative Ideal
R1	(0.077,0.111,0.143)	(0.072,0.106,0.139)
R2	(0.080,0.114,0.143)	(0.075,0.109,0.139)
R3	(0.078,0.112,0.143)	(0.071,0.106,0.139)
R4	(0.078,0.113,0.143)	(0.072,0.107,0.140)
R5	(0.076,0.111,0.143)	(0.071,0.106,0.139)
R6	(0.076,0.110,0.143)	(0.072,0.107,0.139)
R7	(0.077,0.112,0.143)	(0.074,0.109,0.140)

Table 8. The range of positive and negative ideal solutions.

	Distance from Positive Ideal	Distance from Negative Ideal
T1	0.018	0.016
T2	0.017	0.017
T3	0.015	0.018
T4	0.023	0.009
T5	0.013	0.019
T6	0.017	0.017

Table 9. Closeness coefficient (Ci) value and ranking.

	Ci	Rank
T1	0.47	5
T2	0.509	3
T3	0.538	2
T4	0.282	6
T5	0.595	1
T6	0.495	4

We discovered the relevance of the closeness coefficient (Ci) in our objective assessment of the effectiveness of the best IoT application, T5 > T3 > T2 > T6 > T1 > T4, where ">" actually implies "recommendable over". As a consequence, T5 is widely regarded as the most efficient and effective IoT application, as shown in Figure 4.

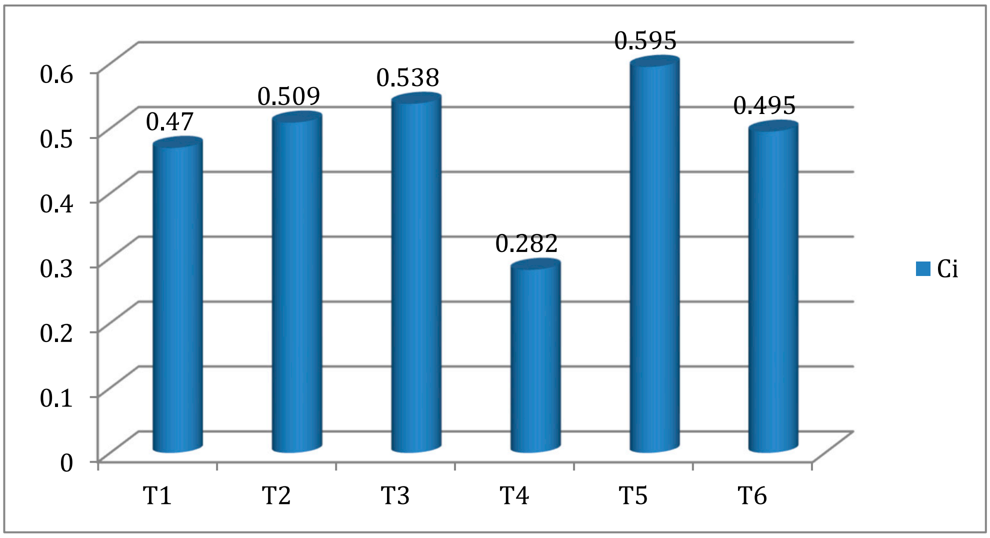

Figure 4. Closeness coefficient graph.

4.2. Comparative Findings of the Fuzzy TOPSIS and TOPSIS Analysis

The selection order of the different alternatives is compiled in Table 10 using the TOPSIS and fuzzy TOPSIS approaches. It is clear that both approaches result in the selection of T5; therefore, the IoT application T5 exhibits the highest efficiency and reliability. Except for T5, each approach has a different preference. The fuzzy TOPSIS results in the rankings T5 > T3 > T2 > T6 > T1 > T4, whereas the TOPSIS technique results in T5 > T2 > T6 > T1 > T3 > T4. Given the MCDM characteristics of the suggested problem, an ideal solution might not be available; however, a systematic analysis of the MCDM challenge can lessen the likelihood of making a quality service pick that is unsatisfactory. The TOPSIS technique is accepted as a satisfactory solution for the selection of an effective and trustworthy IoT application challenge when accurate performance ratings are given. When using fuzzy TOPSIS to address the intended service quality issue, imprecise or hazy performance evaluations are acceptable.

Table 10. Comparison table.

Ranking Order	1	2	3	4	5	6
TOPSIS	T5	T2	T6	T1	T3	T4
Fuzzy TOPSIS	T5	T3	T2	T6	T1	T4

The suggested research aims to present a methodical evaluation strategy for choosing the most effective and trustworthy IoT application, comparing both TOPSIS and fuzzy TOPSIS. The suggested methodology offers a way to reduce the number of options and ease the decision-making procedure. Ultimately, the fuzzy TOPSIS technique has some drawbacks. The managerial perspective of the decision-maker affects the membership degree of natural language representation. In order to assess the significance and patterns of all the different facets, including ease of use, energy consumption, interoperability, privacy, availability, interface, and customer service, to analyze different IoT applications as alternatives, the decision-maker needs to be at a tactical rank in the organization.

5. Discussion

Organizations are currently experimenting with different data sources, and it has been widely anticipated that IoT will significantly improve asset management decision-making. Companies can efficiently and comprehensively embrace such new sources of information in their decision-making if the information that is assessed can provide an overview of the asset's significant aspects. This has practical consequences for companies and demonstrates how IoT implementations can result in far-reaching modifications. Implementation of IoT enables more comprehensive and precise predictive analysis, expanding confidence in the process of asset management, as well as enhancing the predictive ability in risk-based judgments. Because of the increased certainty about when and how to take appropriate action, decision-making is becoming slightly automated. Business operations for decision-making must be rearranged to include IoT-generated information and ensure traceability so that decision-makers can perceive the data's constraints as well as potential, while also guaranteeing security and privacy [44–48]. Moreover, people who participate in business processes must learn new skills in order to comprehend and interpret data. Decision-makers must become more comfortable with data as well as data analysis tools. To transition from physical to data-based asset checking, the culture must change. To embrace IoT, asset management organizations must change their cultural identities so that data-based asset-checking is deeply engrained throughout the organization instead of being lost in individual departments' warehouses. The adoption of IoT necessitates an IT infrastructure capable of accommodating new data sources, as well as a thorough knowledge of the information gathered and its overall quality. The adoption of IoT necessitates proper data management to guarantee compliance with laws and regulations. To make sure that IoT can provide trustable data for decision-making, good data governance is essential. The findings indicate that decision procedures must be altered to accommodate the real-time characteristics of the data, and that managers must adapt and acquire new abilities and skills in order to understand the information.

6. Conclusions

Using a fuzzy TOPSIS MCDM strategy, this research presents the issue of choosing the most highly appropriate IoT-based application, an MCDM challenge. We demonstrated an issue hierarchy as well as performed pair-wise comparability of standards predicated on experienced professional choices. In the final instance, a systematic approach was looked at to show how to use MCDM within the IoT platform. The research findings may help the distributors and builders of IoT development tools to make better judgments. There were some limitations to this research. First, it was conducted in a small geographical region. Some considerations, such as local cultures and individuals, as well as geographical differences, may have influenced the results, which may not be generally applicable to other regions of the world. It is recommended that the present prototype be considered in other areas and that a cross-cultural contrast be conducted. Second, because this is survey-based research, it is susceptible to experimental error, including the number of participants, the type of survey questions used, and the capturing of personal views. Third, the standards utilized in this research were chosen and constructed on professional sentiments. Even though the specialists' decisions were well-founded, many other factors could have been taken into account. For instance, it is essential to investigate customer characteristics. Fourth, the article's small number of participants might contribute to inadequate assessments. To avoid such situations, future studies should include a greater number of specialists. Finally, expert evaluations and comparisons can be inaccurate and incompatible. Furthermore, the standards investigated in the current research were not mutually exclusive. The ANP would be an efficacious solution to this problem. As a result, we plan to look into IoT service selection using several frameworks in the future.

Future research possibilities in this conventional but significant field of study include the above. This study's primary limitation is the sampling. Because the assessment was conducted on a sample from Middle Eastern countries, a careful thinker may want to approach the study's conclusions with care, especially when applying generalizations of the findings to IoT application service providers throughout the world.

Funding: This research received no specific grant from any funding agency.

Data Availability Statement: Not applicable.

Acknowledgments: The authors extend their appreciation to the Shaqra University, Saudi Arabia.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Alfayad, F.S. Huawei and the Gulf region: Market opportunities despite the ongoing US-China trade war. *Int. Rev. Manag. Mark.* **2019**, *9*, 47–53. [CrossRef]
2. Albreem, M.A.; Sheikh, A.M.; Bashir, M.J.; El-Saleh, A.A. Towards green Internet of Things (IoT) for a sustainable future in Gulf Cooperation Council countries: Current practices, challenges and future prospective. *Wirel. Netw.* **2022**, *29*, 539–567. [CrossRef]
3. Ansari, M.T.J.; Baz, A.; Alhakami, H.; Alhakami, W.; Kumar, R.; Khan, R.A. P-STORE: Extension of STORE methodology to elicit privacy requirements. *Arab. J. Sci. Eng.* **2021**, *46*, 8287–8310. [CrossRef]
4. Ansari, M.T.J.; Al-Zahrani, F.A.; Pandey, D.; Agrawal, A. A fuzzy TOPSIS based analysis toward selection of effective security requirements engineering approach for trustworthy healthcare software development. *BMC Med. Inform. Decis. Mak.* **2020**, *20*, 236. [CrossRef]
5. Habibi, N. The Persian Gulf and China: The Growth and Limits of Economic Ties. In *Middle East Briefs*; Crown Center for Middle East Studies: Waltham, MA, USA, 2020; p. 34201.
6. Shambour, M.K.; Gutub, A. Progress of IoT research technologies and applications serving Hajj and Umrah. *Arab. J. Sci. Eng.* **2022**, *47*, 1253–1273.
7. Brdesee, H. Exploring Factors Impacting E-Commerce Adoption in Tourism Industry in Saudi Arabia. Ph.D. Thesis, RMIT University, Melbourne, VIC, Australia, 2013.
8. Othman, F.M. A System of Mobile Service Units for the Large-Scale Event Industry: An Implementation for the Hajj, the Pilgrimage to Makkah, Saudi Arabia. Ph.D. Thesis, Loughborough University, Loughborough, UK, 2003.
9. Ansari, M.T.J.; Pandey, D.; Alenezi, M. STORE: Security threat oriented requirements engineering methodology. *J. King Saud Univ.-Comput. Inf. Sci.* **2018**, *34*, 191–203.
10. Vailshery, L.S. IOT Connected Devices Worldwide 2019–2030. Statista. Available online: https://www.statista.com/statistics/1183457/iot-connected-devices-worldwide/ (accessed on 25 September 2022).
11. Saudi Arabia Internet of Things (IOT) Market, by Component (Software, Hardware, Services), by Connectivity, by End Use, by Region, by Top 5 Cities, Competition, Opportunity, and Forecast, 2017–2027. Research and Markets-Market Research Reports-Welcome. Available online: https://www.researchandmarkets.com/reports/5562151/saudi-arabia-internet-of-things-iot-market-by (accessed on 25 September 2022).
12. Nabeeh, N.A.; Abdel-Basset, M.; El-Ghareeb, H.A.; Aboelfetouh, A. Neutrosophic multi-criteria decision making approach for iot-based enterprises. *IEEE Access* **2019**, *7*, 59559–59574. [CrossRef]
13. Abdel-Basset, M.; Gamal, A.; Son, L.H.; Smarandache, F. A bipolar neutrosophic multi criteria decision making framework for professional selection. *Appl. Sci.* **2020**, *10*, 1202.
14. Ansari, M.T.J.; Agrawal, A.; Khan, R.A. DURASec: Durable Security Blueprints for Web-Applications Empowering Digital India Initiative. *ICST Trans. Scalable Inf. Syst.* **2022**, *9*, e7. [CrossRef]
15. Guo, X.; Zeng, T.; Wang, Y.; Zhang, J. Fuzzy TOPSIS approaches for assessing the intelligence level of IoT-based tourist attractions. *IEEE Access* **2018**, *7*, 1195–1207. [CrossRef]
16. Tariq, M.I.; Mian, N.A.; Sohail, A.; Alyas, T.; Ahmad, R. Evaluation of the challenges in the Internet of medical things with multicriteria decision making (AHP and TOPSIS) to overcome its obstruction under fuzzy environment. *Mob. Inf. Syst.* **2020**, *2020*, 8815651. [CrossRef]

17. Gupta, N.; Sharma, V.; Kashyap, M. A critical analysis of sensor based IoT architectures using fuzzy TOPSIS. In Proceedings of the 2018 International Conference on Advances in Computing, Communication Control and Networking (ICACCCN), Greater Noida, India, 12–13 October 2018; pp. 21–27.
18. Yadav, S.; Garg, D.; Luthra, S. Development of IoT based data-driven agriculture supply chain performance measurement framework. *J. Enterp. Inf. Manag.* **2020**, *34*, 292–327. [CrossRef]
19. Chakraborty, B.; Das, S. Introducing a new supply chain management concept by hybridizing topsis, IoT and cloud computing. *J. Inst. Eng. (India) Ser. C* **2021**, *102*, 109–119. [CrossRef]
20. Singla, C.; Mahajan, N.; Kaushal, S.; Verma, A.; Sangaiah, A.K. Modelling and analysis of multi-objective service selection scheme in IoT-cloud environment. In *Cognitive Computing for Big Data Systems over IoT*; Springer: Cham, Switzerland, 2018; pp. 63–77.
21. Qahtan, S.; Sharif, K.Y.; Zaidan, A.A.; Alsattar, H.A.; Albahri, O.S.; Zaidan, B.B.; Zulzalil, H.; Osman, M.H.; Alamoodi, A.H.; Mohammed, R.T. Novel multi security and privacy benchmarking framework for blockchain-based IoT healthcare industry 4.0 systems. *IEEE Trans. Ind. Inform.* **2022**, *18*, 6415–6423. [CrossRef]
22. Wibowo, S.; Grandhi, S. Fuzzy multicriteria analysis for performance evaluation of internet-of-things-based supply chains. *Symmetry* **2018**, *10*, 603. [CrossRef]
23. Gardas, B.B.; Heidari, A.; Navimipour, N.J.; Unal, M. A Fuzzy-Based Method for Objects Selection in Blockchain-Enabled Edge-IoT Platforms Using a Hybrid Multi-Criteria Decision-Making Model. *Appl. Sci.* **2022**, *12*, 8906. [CrossRef]
24. Mahmoudi, A.; Deng, X.; Javed, S.A.; Zhang, N. Sustainable supplier selection in megaprojects: Grey ordinal priority approach. *Bus. Strategy Environ.* **2021**, *30*, 318–339. [CrossRef]
25. Ijemaru, G.K.; Ang, L.M.; Seng, K.P. Transformation from IoT to IoV for waste management in smart cities. *J. Netw. Comput. Appl.* **2022**, *204*, 103393. [CrossRef]
26. Krishankumar, R.; Ecer, F. Selection of IoT service provider for sustainable transport using q-rung orthopair fuzzy CRADIS and unknown weights. *Appl. Soft Comput.* **2023**, *132*, 109870. [CrossRef]
27. Ahmed, U.; Carpitella, S.; Certa, A.; Izquierdo, J. A Feasible Framework for Maintenance Digitalization. *Processes* **2023**, *11*, 558. [CrossRef]
28. Deveci, M.; Gokasar, I.; Pamucar, D.; Chen, Y.; Coffman, D.M. Sustainable E-scooter parking operation in urban areas using fuzzy Dombi based RAFSI model. *Sustain. Cities Soc.* **2023**, *91*, 104426. [CrossRef]
29. Alyami, H.; Nadeem, M.; Alharbi, A.; Alosaimi, W.; Ansari, T.J.; Pandey, D.; Kumar, R.; Khan, R.A. The Evaluation of Software Security through Quantum Computing Techniques: A Durability Perspective. *Appl. Sci.* **2021**, *11*, 11784. [CrossRef]
30. Kan, S.H. *Metrics and Models in Software Quality Engineering*; Addison-Wesley Professional: Boston, MA, USA, 2003.
31. Tribus, M.; McIrvine, E.C. Energy and information. *Sci. Am.* **1971**, *225*, 179–190. [CrossRef]
32. Zeng, M.L.; Chan, L.M. Trends and issues in establishing interoperability among knowledge organization systems. *J. Am. Soc. Inf. Sci. Technol.* **2004**, *55*, 377–395. [CrossRef]
33. Ansari, M.T.J.; Pandey, D. Risks, security, and privacy for HIV/AIDS data: Big data perspective. In *Big Data Analytics in HIV/AIDS Research*; IGI Global: Hershey, PA, USA, 2018; pp. 117–139.
34. Ansari, T.J.; Pandey, D. An Integration of Threat Modeling with Attack Pattern and Misuse Case for Effective Security Requirement Elicitation. *Int. J. Adv. Res. Comput. Sci.* **2017**, *8*, 16–20.
35. Benford, S.; Greenhalgh, C.; Reynard, G.; Brown, C.; Koleva, B. Understanding and constructing shared spaces with mixed-reality boundaries. *ACM Trans. Comput. Interact.* **1998**, *5*, 185–223. [CrossRef]
36. Winer, R.S. A framework for customer relationship management. *Calif. Manag. Rev.* **2001**, *43*, 89–105. [CrossRef]
37. Yoon, K.P.; Hwang, C.L. *Multiple Attribute Decision Making: An Introduction*; Sage Publications: Thousand Oaks, CA, USA, 1995.
38. Alyami, H.; Ansari MT, J.; Alharbi, A.; Alosaimi, W.; Alshammari, M.; Pandey, D.; Agrawal, A.; Kumar, R.; Khan, R.A. Effectiveness Evaluation of Different IDSs Using Integrated Fuzzy MCDM Model. *Electronics* **2022**, *11*, 859. [CrossRef]
39. Alzahrani, F.A.; Ahmad, M.; Ansari, M.T.J. Towards Design and Development of Security Assessment Framework for Internet of Medical Things. *Appl. Sci.* **2022**, *12*, 8148. [CrossRef]
40. Alharbi, A.; Ansari, T.J.; Alosaimi, W.; Alyami, H.; Alshammari, M.; Agrawal, A.; Kumar, R.; Pandey, D.; Khan, R.A. An Empirical Investigation to Understand the Issues of Distributed Software Testing amid COVID-19 Pandemic. *Processes* **2022**, *10*, 838. [CrossRef]
41. Alassery, F.; Alzahrani, A.; Khan, A.I.; Khan, A.; Nadeem, M.; Ansari, T.J. Quantitative Evaluation of Mental-Health in Type-2 Diabetes Patients Through Computational Model. *Intell. Autom. Soft Comput.* **2022**, *32*, 1701–1715. [CrossRef]
42. Braglia, M.; Frosolini, M.; Montanari, R. Fuzzy TOPSIS approach for failure mode, effects and criticality analysis. *Qual. Reliab. Eng. Int.* **2003**, *19*, 425–443. [CrossRef]
43. Agrawal, A.; Khan, R.A.; Ansari, M.T.J. Empowering Indian Citizens through the Secure E-Governance: The Digital India Initiative Context. In *Emerging Technologies in Data Mining and Information Security*; Springer: Singapore, 2023; pp. 3–11.
44. Ansari, M.T.J.; Khan, N.A. Worldwide COVID-19 Vaccines Sentiment Analysis Through Twitter Content. *Electron. J. Gen. Med.* **2021**, *18*, em329. [CrossRef]
45. Khan, A.I.; Alsolami, F.; Alqurashi, F.; Abushark, Y.B.; Sarker, I.H. Novel energy management scheme in IoT enabled smart irrigation system using optimized intelligence methods. *Eng. Appl. Artif. Intell.* **2022**, *114*, 104996. [CrossRef]
46. Almalawi, A.; Khan, A.I.; Alqurashi, F.; Abushark, Y.B.; Alam, M.M.; Qaiyum, S. Modeling of Remora Optimization with Deep Learning Enabled Heavy Metal Sorption Efficiency Prediction onto Biochar. *Chemosphere* **2022**, *303*, 135065. [CrossRef] [PubMed]

47. Khan, A.I.; Alghamdi, A.S.A.; Abushark, Y.B.; Alsolami, F.; Almalawi, A.; Ali, A.M. Recycling waste classification using emperor penguin optimizer with deep learning model for bioenergy production. *Chemosphere* **2022**, *307*, 136044. [CrossRef] [PubMed]
48. Alassery, F.; Alzahrani, A.; Khan, A.I.; Irshad, K.; Kshirsagar, S.R. An artificial intelligence-based solar radiation prophesy model for green energy utilization in energy management system. *Sustain. Energy Technol. Assess.* **2022**, *52*, 102060. [CrossRef]