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A Sustainable Pattern of Waste Management and Energy Efficiency in Smart Homes Using the Internet of Things (IoT)

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Abstract: Nowadays, environmental protection involves many issues and problems, among which the waste generated by various human activities makes up a significant share, which is becoming newer day by day. Moreover, the production of normal, industrial, special, hospital, and agricultural waste and improper management of these materials has created many health, safety, and environmental problems. Based on this approach, this research study aims to determine the model of waste management and energy efficiency in smart homes using the Internet of Things (IoT). The research method used by this study is estimative-computational. For this purpose, the required data were collected using a computational approach. For this purpose, the required views and data were collected through experts in this field and calculated in MATLAB and STATA software. The data analysis tool was represented by fuzzy calculations and for this purpose MATLAB software was used. The study revealed that energy costs in smart homes using the IoT technology are impressive. The number of home residents in smart homes using the IoT is impressive. Home area in smart homes using the innovative technology of IoT is also impressive.

Keywords: smart homes; Internet of Things (IoT); energy efficiency; waste management; sustainability; environmental protection; sustainability's pillars

Citation: Ehsanifar, M.; Dekamini, F.; Spulbar, C.; Birau, R.; Khazaei, M.; Bărbăcioru, I.C. A Sustainable Pattern of Waste Management and Energy Efficiency in Smart Homes Using the Internet of Things (IoT). *Sustainability* **2023**, *15*, 5081. https://doi.org/10.3390/su15065081

Academic Editor: Mohammed Elsayed Lotfy

Received: 14 January 2023
Revised: 3 March 2023
Accepted: 11 March 2023
Published: 13 March 2023

1. Introduction

Due to the increase in waste production and the concerns related to the resulting ecological damage [1], waste management policy has become extremely important [2]. Waste is a by-product of human activities in urban areas, and residential homes are one of these areas [3]. It is noteworthy that in comprehensive waste management, waste collection and processing and disposal methods interact with each other in such a way that the three desired dimensions, respectively: environmental, social, and economic goals of the region are achieved, while those which have data Smart homes will work in this case [4]. Sustainability's three main pillars are the following: environmental, social, and economic.

On the other hand, smart home-related applications can be an effective and innovative solution for waste management, which creates higher levels of energy efficiency for them due to the improvement of recorded data [5]. Waste management using the Internet of Things (IoT) can intelligently separate waste materials from the source, in which case it can be one of the ways to increase the value of materials and find applications for them.

In general, there is an inverse relationship between the amount of waste mixing and its value. In addition, household waste usually accounts for less than ten percent of the total waste flow, but a significant part of the environmental health and cleanliness of urban management depends on it. This leads to issues such as waste management using the IoT technology as appropriate data transfer functions for energy efficiency, aspects which this research study also addressed in further sections [6].

Optimal waste management model is one of the most effective components of environmental protection that can reduce environmental pollution, and thus increase the degree of environmental health [7]. On the other hand, energy efficiency represents one of the most important indicators that are studied for explaining the structure of consumer behavior in different countries. Moreover, energy efficiency is also one of the industrial and service delivery approaches which can affect the levels of organizational costs [8]. Nowadays, one of the most important components studied in building structures is the use of tools and equipment that ultimately lead to energy efficiency. Moreover, among the engineering innovations in the structure are smart homes that are influenced by the technological process in building engineering [9]. The question is, where is the place of energy efficiency in smart homes as a new way of using technology? This is a certain issue that is considered as being one of the greatest challenges in using the smart home waste management model. In general, it can be said that small changes in energy prices, as well as the idea of stability, affect the formation of waste management so that the consumption of fossil energy reserves can be monitored [10].

In addition, the structure of structures can ultimately moderate fossil energy consumption levels and also can represent an important approach used in homes [11]. On the other hand, explaining the development of energy demand has caused engineered structures for homes to choose the best option to optimize energy consumption [12]. The question in this case is whether new technologies can be used in order to improve energy efficiency in homes? And whether this type of technology can ultimately improve waste management in homes? And whether this model can be used in smart homes? [13] From another point of view, it can be said that energy efficiency usually affects the role of energy in the structure of homes, so that the best engineering can be proven when it has the ability to build homes with energy consumption levels that can be included in the management model process. So it is important to select the best possible option, because the waste management model directly depends on the amount of energy efficiency in the structure of buildings [14]. A new great challenge in the structure of research studies and applied science is whether technologies such as the IoT can be used for engineering structures, as well as whether patterns such as building energy can be considered in order to represent the best choice for the waste management model, and whether the waste management model can use IoT technologies to moderate energy consumption and efficiency. Those are significant research questions to which we try to provide optimal and sustainable answers based on this research study. This study was conducted because the IoT technologies are used today as one of the most efficient tools in establishing intelligent communication to those various engineering structures. This makes it possible to accurately identify the components of energy distribution and production monitored and measured. Therefore, this may pose the challenge of whether the use of the IoT was ultimately able to create a waste management model for optimizing energy consumption in smart homes [1,6]. Therefore, the present study pursues objectives such as: (a) determining the pattern of waste management and energy efficiency in smart homes; (b) determining the impact of energy costs on smart homes; (c) determining the impact of the number of home residents in smart homes and determining the impact of home area on smart homes using the IoT technologies.

1. Determining the model of waste management requires structural and fuzzy calculations. Therefore it can be considered as a necessity, because ultimately waste management can create suitable conditions for urban management as well as the construction of various structures. Consequently, a research study based on this direction was really necessary.

2. Examining the waste management model usually determines the need for energy consumption, and knowing whether we can provide a waste management model that can optimally affect energy consumption is necessary. Moreover, these aspects were investigated in this research study.
3. A topic such as smart homes is an approach that can be affected by energy efficiency, and the smarter a house is, based on the results of the presented research, the higher the energy efficiency it can be expected to have. However, there is still a model that can establish a clear relationship between energy efficiency generated in smart homes with a model of waste management in structures. Nevertheless such a model it has not been presented in a codified form that specifies the necessity of its investigation.
4. On the other hand, the use of technologies such as the IoT, in smart homes is one of the common approaches, but the issue is that it has not yet been determined whether the IoT used in smart homes can affect energy efficiency. So the question is, does it provide the best and most suitable model of effective waste management or not?

This issue shows that the present study is important and necessary. Moreover, the need to examine and to determine the hypotheses based on it seems to be a challenge that was addressed in this study. Therefore, according to the objectives of the research and what has been also mentioned above, the research hypotheses are as follows:

1. The model of waste management and energy efficiency in smart homes using the IoT is effective.
2. The cost of energy in smart homes using the IoT is impressive.
3. The number of home occupants in smart homes using the IoT is impressive.
4. Home area in smart homes using the IoT is impressive.

2. Conceptual Model of Research

The conceptual model of this research was taken from the studies of certain researchers [15,16]. Phonphoton and Pharino [15] revealed that energy costs as well as the number of household inhabitants usually affect the level of energy efficiency. When smart homes are examined, it can be seen that in addition to energy costs and the number of inhabitants, the criteria of home area will be critical. This is especially important when a waste transfer station can be added to the study complex. Based on this approach, it can be said that energy efficiency in smart homes using the IoT is usually affected by some important components. The following conceptual model shows that in general, six scales can be emphasized as important factors affecting energy efficiency in smart homes when the IoT technologies are used. Based on Figure 1, the following concept model can be displayed, and through the further sections, the research will delve into the most outstanding parts of this conceptual model.

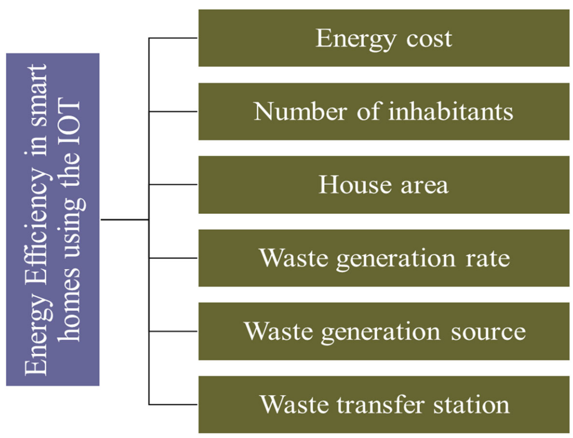

Figure 1. Conceptual model of research based on the studies of [15,16].

3. Literature Review

3.1. IoT

The increasing use of the IoT, smart devices, sensors, and device-to-device connectivity, has the potential to reduce unnecessary costs due to operational inefficiencies in waste management processes. The IoT-based intelligent (smart) waste management solutions have focused on improving the overall efficiency of waste management and waste recycling. The most common use of the IoT technologies in waste management is optimization, which also reduces energy consumption while disposing of waste in the city [12].

IoT applications effectively improve performance in waste management. Predefined paths and obsolete methods of waste collection are increasingly being replaced by smart objects with sensors and sophisticated waste management applications [17]. The IoT helps to collect the waste in order to reduce operating costs by eliminating unnecessary functions, providing dynamic collection routes, and programs to fully optimize operations [18].

In this regard, He, Yang [19] introduced an IoT theory based on the dimensions of privacy. Their views were based on two dimensions including: blockchain and things management. This theory proved that each component affects the IoT.

Moreover, Dizdarević, Carpio [20] discussed the IoT based on the dimensions of cloud services. Their views were based on two dimensions. These dimensions include the computing model and the communication protocols. This theory proved that each component of the Internet of Things (IoT) would have a tier.

Arithmetic Optimization Algorithm (AOA), a recently introduced metaheuristic, is presented in the study of Bahmanyar, Razmjooy [21] in a multi-objective form, under the name Multi-Objective Arithmetic Optimization Algorithm (MOAOA), to determine the best scheduling of household appliances. The signals for real-time pricing (RTP) and critical peak pricing (CPP) are considered to be energy tariffs. In two alternative situations, simulations are running, such as: (I) a standard appliance scheduling method, and (II) a standard appliance scheduling system with the addition of renewable energy sources (RES).

The advantages of modern cutting-edge technologies, including the IoT (IoT), 5G, and cloud computing, were used in the work of Humayun, Alsaqer [22] in order to improve energy efficiency in smart cities. They have designed a model that can be utilized to optimize energy use in both smart homes and smart cities using this cutting-edge technology. The proposed concept would result in energy savings for four key components of smart cities, such as: street lighting, building and street billboards, smart houses, and smart parking. The proposed model was put through a mathematical evaluation, and the results revealed that it could help smart cities in order to use energy more efficiently.

3.2. Energy Efficiency

Energy efficiency goals can be classified into several main categories. Energy intensity targets are used in order to reduce the total final energy consumption set for each unit of economic activity. As part of the Energy Efficiency Guidelines, major energy consuming countries have committed to a 20% improvement in energy efficiency by 2020 and a 32.5% reduction in energy consumption by 2030 [23]. Physical indicators of total energy consumption in home consumption activities are generally more related to energy efficiency improvements than economic indicators of energy efficiency, which are affected by additional effects such as changes in product value [16]. Proper use and efficiency of global energy resources are of particular importance for both the world (or globally) and each country in terms of sustainable development, economic management, and social welfare. Therefore, the continuous use of fresh energy was possible when attention was paid to energy sustainability and efficiency [24].

Firstly, Sovacool and Del Rio [25] have provided a theory of energy efficiency based on the dimensions of smart home technology. Their ideas were based on four dimensions. These dimensions include concepts, benefits, risks and policies. This theory proved that each component had an effect on energy efficiency.

Jurenoks and Jokić [26] introduced the theory of energy efficiency based on the dimensions of human-computer interaction. Their views were based on three dimensions. These dimensions include improving sustainability and lifestyle. This theory proved that each component had an effect on energy efficiency.

Iqbal and Kim [27] have suggested a predictive optimization-based IoT activity management system for minimizing energy usage in smart residential buildings. The suggested activity management system includes an optimization module for reducing energy usage and a predictive optimization module based on prediction. The suggested anticipatory optimization approach is evaluated using energy data from several appliances. Results of the suggested approach are contrasted with modules for prediction and optimization. Regression performance measures are used to assess the performance.

A unique solar-powered smart inverter that automatically transfers the power source from the grid to the inverter during peak hours is described in Madhu, Padunnavalappil [28]. It features an all-encompassing design and is designed in order to accommodate smart home needs up to 1 kW. However, in order to demonstrate the improvements, the performance of the circuit is examined and is contrasted and compared with research studies with a similar nature from the existing literature. The suggested system ensures an uninterrupted power supply for smart homes, according to simulations and systems.

The study of Philip, Islam [29] addresses the issue of user-defined indoor thermal while investigating the optimal pre-cooling problem for air conditioners (AC) utilized in IoT (IoT)-enabled smart homes. The suggested approach makes use of the times when renewable energy was generated and shifts some of the air conditioning loads to these times in order to lower the demand for electricity. They specifically suggest a multi-step approach that, in the first stage, maximizes the use of renewable energy to meet air conditioning loads and, in the second stage, schedules the residual energy consumption of these loads to times when prices were low. It has been demonstrated that the strategy put forward can greatly cut the amount of energy and money needed to run an air conditioner practically every day of the summer when cooling is necessary.

3.3. Smart Homes

Smart home is a term used to refer to modern homes that have appliances, lighting, or electronics that can be controlled by a remote control, often through a mobile application [26]. Some home automation systems warn homeowners if they notice any movement in the home, and some can call the fire department in the event of an impending situation. Once these smart devices are connected, an example of what we call IoT technology becomes important [30]. In this regard, the fundamental aspects, relationships, and conditions that should be considered in smart homes such as ecological design principles, social characteristics, environmental functions, cycle effects, cultural accountability parameters, welfare criteria, and economic concerns should be discussed and examined [30].

Accordingly, the creation of an intelligent environment in order to ensure the well-being of users based on the values of specific information technology is promoted worldwide. This research study shows that achieving the health of users requires the anomaly of environmental and socio-cultural values in the functional spaces of a home along with the integration of automated technologies. Moreover, it investigates the nature of smart homes and identifies appropriate amounts of technology, which can undermine the quality of living environments [26].

In Taiwan, Sung and Hsiao [31] have conducted a smart home theory based on the dimensions of thermal comfort. Their views were based on three dimensions. These dimensions included the IoT and fuzzy controls. This theory proved that each component will affect smart homes.

In another research study, Sovacool and Del Rio [25] have provided a smart home theory based on the dimensions of smart home technology. Their ideas were based on four dimensions. These dimensions include the following: concepts, benefits, risks, and policies. This theory proved that each component had an effect on smart homes.

Rajesh et al., [32] have suggested a hybrid approach for an IoT-based energy management system (EMS) for smart homes (IoT). Adaptive Neuro-Fuzzy Interference System (ANFIS) and Sailfish Optimizer (SFO) are both hybridized in the suggested hybrid approach (ANFIS), or usually referred to as the SFOANFIS technique. The suggested approach controls the distribution system's resources and electricity in the best possible way (DS). Every home device is connected to the IoT cloud using an unique internet protocol (IP) addresses according to the suggested approach, which uses a DS-based IoT-based communication system to reduce the rise of demand response (DR) in home EMS (HEMS). The centralized server gathers the obtained demand response data from every home appliance.

3.4. Energy Cost

Energy saving is the first priority of every home. Various methods have been adopted by various researchers to reduce fossil fuel consumption and improve system performance. Hence, the need for smart devices, distribution network optimization methods, and intelligent building management systems to meet the growing demand for electricity has increased [33]. Energy costs change daily, but there is no reason to believe that they will decline significantly in the near future, and the belief that they are predictable for the future was also unstable [34]. With the increasing popularity of smart devices, smart energy cost reduction applications are emerging in the IoT. In the meantime, the IoT can help to reduce energy costs in smart homes in the areas of e-commerce, advanced manufacturing, automation, etc. However, the way the IoT works and the costs involved are still there. This needs to be studied and optimized, so studying this field is very important [12].

In this regard, Wen, Hu [12] discussed their energy cost theory based on the dimensions of conscious energy planning. Their views were based on two dimensions. These dimensions include energy efficiency and cost reduction. This theory proved that each component affects the cost of energy.

Also, Xu, He [35] highlighted a relevant approach regarding energy costs based on energy forecast dimensions. Their views were based on three dimensions. These dimensions include the IoT, improving lifestyle, and resident support. This theory proved that each of the components will have an energy cost.

Using the IoT (IoT), demand monitoring, green energy conservation, energy conservation, and microgrids, the research study of Alowaidi [36] provides a fuzzy framework for smart home monitoring systems (FF-SHMS). The creation of sustainable, resource-controlled loads, intelligent microgrids with storage networks, and other objectives is optimized using the proposed fuzzy architecture. The fuzzy framework enhances electricity and storage to employ renewable sources while maximizing the microgrid's financial return. Sun power, wind speed, and power load are used as input factors in the fuzzy framework to enable both regulated and uncontrolled power efficiency.

Khan, Sajjad [37] introduces an IoT-based energy management strategy to track and manage certain loads in buildings. An additional web-server-based monitoring strategy is also pursued by the IoT scheme for the online visualization, monitoring, and control of financial parameters.

3.5. Number of Inhabitants

Today, new technologies such as the IoT can communicate well with different tastes and interests of a larger number of residents and adjust and control their type and amount of energy consumption, as well as massive energy loss due to uniform energy consumption at home [38].

Increasing the number of residents of a house means that the number of exit consumers from the building increases and as a result energy consumption also increases. Moreover, the number of residents can have a side effect on energy consumption, while, of course, new technology can be a way use a solution for this purpose. In addition, the length of the shower and the frequency of the shower are related to the number of residents. Therefore, domestic water heating increasingly contributes to the energy consumption loads in the sample. Using appliances such as dishwashers, washing machines, and dryers as a routine task at home can be monitored and managed by smart devices. In addition, by educating the residents, the necessary foundations can be made to improve energy efficiency [39].

Based on this, Yang, Zhao [38] introduced a theory of population size based on the dimensions of multilevel pollutants. Their views were based on two dimensions. These dimensions include human health and residents' waste. This theory proved that each component affects the number of inhabitants.

Furthermore, Cabral, Cunha [40] discussed their resident number theory based on the frequency of consumption. Their views were based on two dimensions: the amount of consumption and choice of materials. This theory proved that each component will affect the number of inhabitants.

3.6. Waste Generation Rate

Waste management methods may vary between developed countries, between an urban and rural environment, or between an industrial and residential area. Waste management in metropolitan and rural areas is the overall responsibility of a municipality, while waste generated by industries is their responsibility and is self-managed [34]. Major advances have led to the development of technology in waste management. Undoubtedly, the development of the IoT has transformed the world and made global communication even wider. Likewise, the IoT is fundamentally changing the amount of waste generated in the home [41].

Human activities always produce waste. This is important when we know that the human population has increased and the amount of waste production has also increased. Increasing the problems of solid waste and its disposal lead to environmental and health risks [41]. Integrated waste management in a sustainable approach is essential as a response to the needs of waste management strategy. In minimizing waste, in the form of waste separation and proper use, separation from the waste source is very appropriate, and also produces products such as compost and renewable energy [42].

In line with the mentioned issues, Kumar, Samadder [43] conducted a study on waste generation based on the dimensions of recycling. Their views were based on two dimensions. These dimensions include plastic waste and economic groups. This theory proved that each component will affect the amount of waste production.

In other research, Ding, Gong [41] studied waste generation based on the dimensions of modernized waste management. Their views were based on one dimension. This dimension is waste generation rates. This theory proved that each of the components affects the amount of waste production.

Also, a cheap, secure, and waste-efficient WiFi-based smart house or intelligent home system is described in Omran, Hamza [44], which enables homeowners to keep an eye on their home appliances from nearby and far away using a mobile phone or computer. Additionally, various sensors that are connected to a controller have been successfully used to control home appliances (lights, fans, reverse fans, water pumps, etc.) automatically or via relays, as well as to monitor current, voltage, power, energy, frequency, humidity, temperature, motion, flame, smoke, and other household conditions.

3.7. Waste Generation Source

The issue of waste management is the biggest challenge for small and large enterprises. This is mainly due to the increasing production of such waste from home consumption. In addition to high costs, waste management does not work well due to a lack of understanding of the various factors that lead to waste generation [45].

Engineers and scientists can decide on their potential as a fuel based on the source of waste, the calorific value, and the main position of the household waste. Meanwhile, such information helped predict the composition of greenhouse gas emissions. This waste is connected to energy conversion technologies such as degassing, incineration, and so on. In this regard, the composition and sources of waste provide valuable information to managers to improve energy efficiency [46]. Therefore, waste production and compounds affected by economic factors such as average family population, number of rooms, monthly income, and employment status are considered as effective factors in waste production in homes. It has also been reported that there is a direct relationship between waste and social activities in society [45,46].

First, de la Rosa, Flores-Gallegos [47] studied waste source theory based on the dimensions of food waste. Their views were based on one dimension. These dimensions include advances in production reduction. This theory proved that each component affects the source of waste generation.

In line with the previous research, Qi, Wang [48] provides waste source generation theory based on the dimensions of waste disposal. Their views were based on two dimensions. These dimensions are the source of carbon and food waste. This theory proved that each component will affect the source of waste generation.

New tactics are being developed on Alzoubi [49] to keep up with the demand for energy through the lens of waste. Residential energy use ranges from 30 to 40 percent in several places. The emergence and growth of smart homes has increased the demand for intelligence in fields such as asset management, energy-efficient automating, safety, and healthcare monitoring. In this study, energy management is being used to address the optimization of energy use. The proposed study's data fusion technique was used to calculate the accuracy and miss rate of energy consumption estimates.

3.8. Waste Transfer Station

A transfer station is a construction or processing site for the temporary disposal of waste, often referred to as waste transfer stations or recycling facilities. Typical activities at a landfill include dumping garbage, screening previews and removing unsuitable items such as car batteries, compressing and then reloading on larger vehicles such as trucks, trains and loading to their final destination. In urban areas, the location of landfills can be very controversial [50].

Waste transportation can save fuel, reduce road wear, and reduce air pollution due to the lack of vehicles on the road, and provides a disposal site for waste and recyclable materials for citizens. By moving it to larger vehicles, the overall traffic density in the community is reduced [51]. Many communities are raising the cost of upgrading existing facilities or creating new landfills and want to increase existing facilities. For these communities, the transfer of waste leads to a large landfill in the area that replaces invisibility [52].

Based on this, Kostowski, Pajączek [53] conducted a deep study on waste transfer station theory according to the dimensions of recovery methods. Their views were based on three dimensions including heat recovery, compression station, and energy storage. This theory proved that each component affects the waste transfer station.

Kavvadias and Quoilin [54] also conducted research according to the dimensions of technical and economic evaluation. Their views were based on two dimensions: waste heat and energy system efficiency. This theory proved that each component will affect the waste transfer station.

4. Research Background

In this section, some of the prominent researches summarized in Table 1, according to their titles and key findings.

Table 1. Research background.

Row	Researcher	Research Title	Research Findings
1	[27]	IoT Task Management Mechanism Based on Predictive Optimization	Modules for prediction and optimization are compared to the results of the suggested approach. Performance is evaluated using regression performance metrics.
2	[21]	Multi-objective scheduling of IoT-enabled smart homes for energy management	The findings show that using the proposed plan significantly lowers the price of power usage as well as PAR, in addition to integrating MOAOA with RES, which significantly improves user comfort.
3	[36]	Fuzzy efficient energy algorithm in smart home environment using IoT	The result illustrates how manufacturing can be done for consumer usage. It has been examined to use the expert method of hourly parameter entry.
4	[32]	Energy Optimization for Smart Cities Using IoT	The developed model was put through a mathematical evaluation, and the results show that it could help smart cities use energy more efficiently.
5	[55]	Energy-efficient IoT service composition for concurrent timed applications	The IoT can provide services that overcome time and space constraints and consume energy in a way that helps extend the life of the network.
6	[56]	An Augmented Reality Prototype for supporting IoT-based Educational Activities for Energy-efficient School Buildings	The use of augmented reality technologies leads to better use and efficiency of the IoT in schools as well as the efficient use of energy.
7	[57]	Energy Autonomy in IoT Technologies	There is a strong interdependence between energy and the IoT. It should be noted that the future of energy depends on the activities of the IoT.
8	[8]	Energy efficient offloading strategy in fog-cloud environment for IoT applications	Various performance measures such as computational time, energy consumption, CO_2 emissions, and temperature emissions work better than other methods.
9	[58]	An IoT-based smart cities infrastructure architecture applied to a waste management scenario	Manage a large number of trash cans at the same time and show little response time, which leads to the quality of a good work experience in this field.
10	[7]	Energy efficient communication based on self-organisation of IoT devices for material flow tracking	Active devices capable of wireless communication are observed. However, the dependence of IoT devices on battery energy indicates a maintenance dependence.
11	[12]	Design, implementation, and evaluation of an IoT network system for restaurant food waste management	Using the IoT network, we can manage waste and see its positive effects on waste management.
12	[59]	Wireless powered Public Safety IoT	Increasing the integration of IoT architecture can support key information flows.

5. Research Methodology

The method of this research was estimative-computational. For this purpose, the required data were collected using a computational approach in the form of data information. For this purpose, the required views and data were collected through experts in this field and calculated in MATLAB and STATA software.

To prove the research hypotheses as well as analyze the results and identify the best model for optimization to build it in this study, the fuzzy computing approach was used. This computational approach to building an optimal model has many advantages, because the existence of fuzzy computations can simultaneously rank the effects of the main variables and determine the strength and weakness.

In this research method, the fuzzy method will be used. Fuzzy set theory provides a way to compute uncertain and ambiguous data and information, while providing an inference mechanism for reasoning based on a set of if-then rules. These rules are defined by fuzzy sets in which each member of the set is rated between zero and one. A real example of the uncertainty of the existence of ambiguity in the natural language of human beings. Fuzzy systems combine the concepts of fuzzy set theory and fuzzy logic to provide a framework for presenting linguistic knowledge with uncertainty, and have two main characteristics that have increased their popularity: one is that they are used for approximate reasoning, especially for systems. Those from which it is difficult to derive a mathematical model are suitable, and the other is that fuzzy logic allows decisions to be made using incomplete and uncertain information with the help of linguistic variables, which are easily understood by humans. In this regard, according to TOPSIS approach [60], it can be said that: each data set is selected and each goal is analyzed in order. Some researchers [61] suggested that Internet of Things (IoT) represents an optimization tool which generates cost optimization and increase the life of some equipments. Other researchers [62] argued that the technologies supporting Industry 5.0, include the following categories: the Internet of Things (IoT), but also edge computing, digital twins, participatory robots, blockchain, and 6G networks.

The statistical population of the study is all companies active in the field of production of intelligent equipment and virtual data transmission networks, which have the ability to connect to spatial servers, cloud servers, as well as the IoT in various ways. The statistical sample includes 25 experts and specialists active in the field of energy efficiency in smart homes and intelligence under the IoT, who filled in a symmetric fuzzy matrix with a computational checklist.

Based on the computational checklist obtained, it can be said that the fuzzy values of the data are eventually filled in by the experts and this data will be provided to the software. After initialization and normalization, the initial fuzzy matrix will be provided to MATLAB software for final calculations. In the next step, MATLAB software will provide tables of fuzzy weight values as well as fuzzy rankings related to each of the components.

Step (1) The first step of the fuzzy hierarchical analysis process method, such as the deterministic AHP method, is drawing the hierarchical structure or hierarchical state of the research problem. It should be noted that this issue has only two levels of goals and main indicators.

Step (2) The second step of the fuzzy hierarchical analysis process is the design of the paired comparison questionnaire and data collection. After collecting the required data in the conversion tables, it is converted into fuzzy numbers, and then the inconsistency rate of each of the paired comparison questionnaires is calculated based on the Gogos and Boucher method. After determining that the inconsistency rate of the questionnaires is acceptable (less than 0.1), the matrix of integrated fuzzy pairwise comparisons is calculated.

Step (3) In this step, based on the stated relations, the fuzzy sum of each line and the fuzzy compound expansion are calculated.

Step (4) In this step, based on the stated relationships, the degree of possibility of magnitude, the degree of preference and the normalization of preference are calculated.

Step (5) In this step, the weight of indicators related to the pairwise comparison questionnaire was calculated.

Step (6) Draw a graph of research indicators based on their weight.

Validity of the research questionnaire based on the study of [15,16] confirmed the face and content validity associated with the computational checklist. These studies showed in their findings that the use of computational factors in the research design has sufficient face and content validity and can therefore be generalized to other studies. Regarding the reliability of the questionnaire, it should be said that the type of computational checklist in this study is fuzzy with fuzzy numbers from 1 to 9 and therefore does not require reliability calculations to build a sample questionnaire, due to its computational nature. To provide reliability based on the proposed and uncommon indicators, an important issue in this type of computation is the ability to construct a weighted normalized fuzzy matrix. If the studied factor in studies with fuzzy nature and fuzzy TOPSIS have a normal weight matrix, the results of the study can be cited in the final steps and they can be considered valid for testing and evaluation.

6. Empirical Results

6.1. Check the Normality of Data Distribution

To use fuzzy computational data, it is necessary to check the distribution of normality. For normality, the Anderson-Darling test is used in the symmetric matrix computing environment, which has the ability to calculate the perturbation and residuals due to the components of the symmetric matrices. If the significance level of this test statistic is more than 0.05, it means that the distribution of those variable data is normal.

According to Figure 2, it can be said that the data distribution is due to the energy cost variable and the Anderson-Darling test is equal to 0.388 and is at a level higher than 0.05.

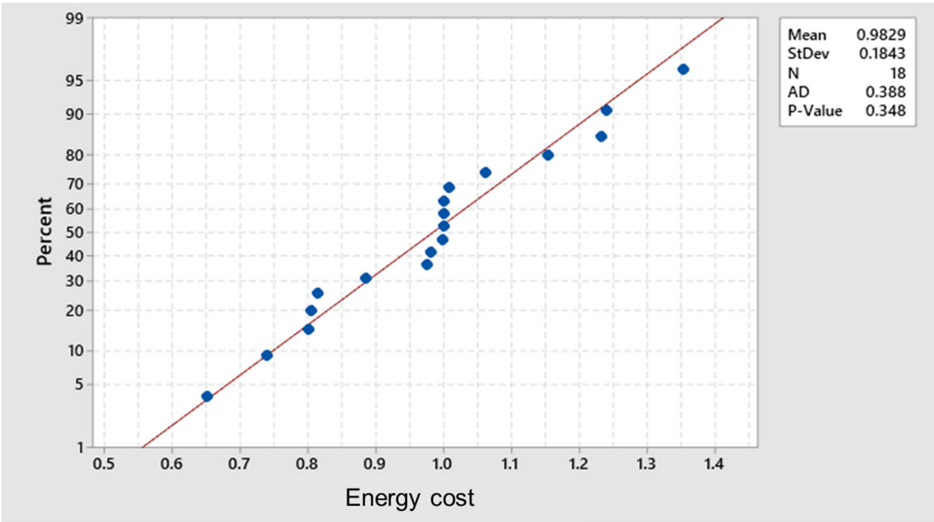

Figure 2. Normal distribution of data related to energy costs.

According to Figure 3, it can be said that the data distribution due to the number of residents variable is normal and the Anderson-Darling test is equal to 0.282 and is at a level higher than 0.05.

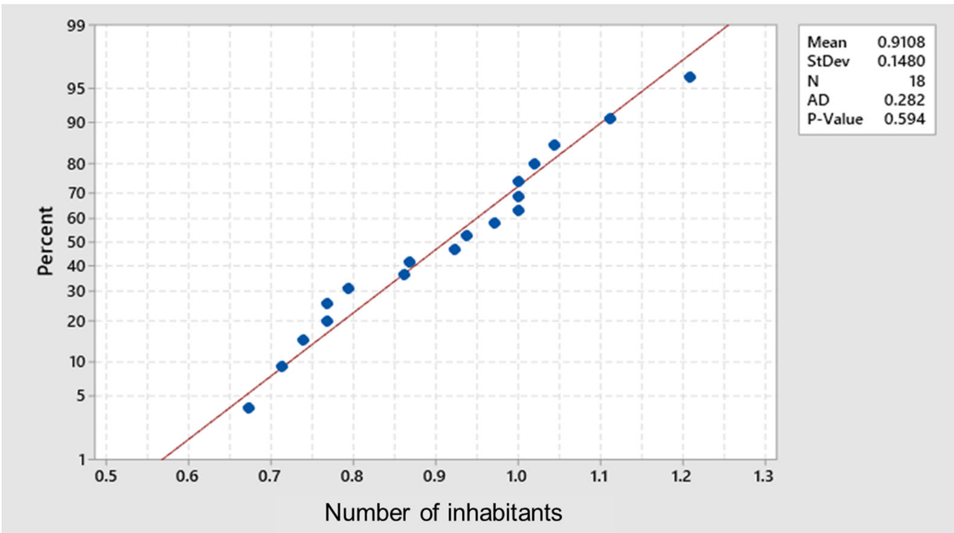

Figure 3. Normal distribution of data related to the number of inhabitants.

According to Figure 4, it can be said that the data distribution due to the house area variable is normal and the Anderson-Darling test is equal to 0.398 and is at a level higher than 0.05.

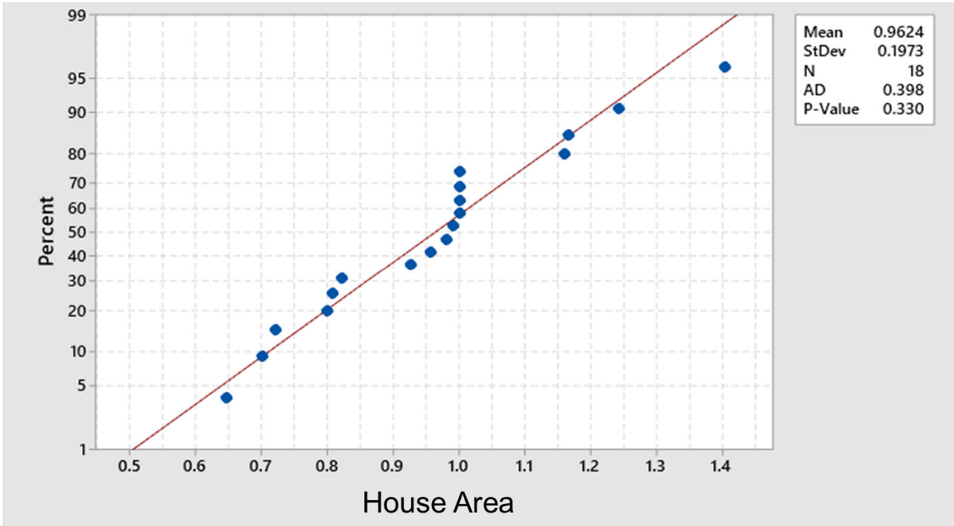

Figure 4. Normal distribution of data related to the area of the house.

6.2. Estimation of Fuzzy Calculations

The first step for estimating fuzzy calculations is to compute the fuzzy comparison matrix. This matrix is used to create a pairwise comparison scale, and a pairwise comparison matrix is constructed for each level in the hierarchy. Then, the subsets of each row in the matrix are calculated to have a new set. Triangular fuzzy general values (mi, ui) for the Mi criterion are obtained by calculating Li/Σ li, mi/Σ mi, ui/Σ ui, (i = 1,2, . . . , n) membership functions, which means the average corresponding weight of the options in the corresponding matrix, are calculated using these values for each criterion. Then they are normalized, and the final weight of the significance of each criterion is obtained, which is shown in Table 2 as the merged comparison matrix.

Table 2. Integrated comparison matrix.

Variables	Energy Cost			Number of Inhabitants			House Area			Waste Generation Rate			Waste Generation Source			Waste Transfer Station		
Energy cost	1	1	1	0/98	1/153	1/353	0/805	0/999	1/24	0/738	0/884	1/062	0/649	0/799	0/975	0/814	1/008	1/232
Number of inhabitants	0/73	0/867	1/02	1	1	1	0/712	0/862	1/045	0/767	0/922	1/112	0/767	0/971	1/208	0/672	0/793	0/938
House area	0/807	1/001	1/243	0/957	1/161	1/404	1	1	1	0/72	0/926	1/167	0/7	0/821	0/981	0/646	0/799	0/991
Waste generation rate	0/941	1/131	1/355	0/9	1/084	1/304	0/857	1/079	1/389	1	1	1	0/978	1/196	1/448	0/901	1/098	1/37
Waste generation source	1/026	1/251	1/54	0/828	1/03	1/304	1/02	1/219	1/429	0/737	0/896	1/1	1	1	1	0/901	1/117	1/407
Waste transfer station	0/812	0/992	1/229	1/066	1/261	1/487	1/009	1/251	1/548	0/73	0/911	1/11	0/711	0/895	1/11	1	1	1

According to Table 2, the degree of preference of Si over Sk can be calculated for the matrix relationship between the research variables. These calculations make it possible to finally make a fuzzy prioritization of the research results in a fuzzy approach using a high matrix in the MATLAB space.

According to Table 3, it can be said that the degree of preference determined for the connection between the fuzzy matrix devices has finally been confirmed and the values of these data show the number of inhabitants with energy cost, waste generation rate, waste generation source, and transfer station. Waste had an equal relationship.

Table 3. Degree of preference of Si over Sk.

Variables	Number of Inhabitants			House Area			Waste Generation Rate			Waste Generation Source			Waste Transfer Station		
Energy cost	1	1	0/819	0/837	0/885	1	1	0/819	0/837	0/885	1	1	0/819	0/837	0/885
Number of inhabitants	0/883	0/92	0/7	0/718	0/767	0/883	0/92	0/7	0/718	0/767	0/883	0/92	0/7	0/718	0/767
House area	0/966	1	0/789	0/806	0/853	0/966	1	0/789	0/806	0/853	0/966	1	0/789	0/806	0/853
Waste generation rate	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Waste generation source	1	1	1	0/983	1	1	1	1	0/983	1	1	1	1	0/983	1
Waste transfer station	1	1	1	0/936	0/954	1	1	1	0/936	0/954	1	1	1	0/936	0/954

After the matrix calculations due to the preference of Si over Sk, the research variables can be shown in a calculation column (Table 4). Based on the calculation derived from FAHP, it can be said that the degree of preference of the energy cost variable is 0.157, 0.134, while the degree of preference of the variable house area is equal to 0.151, the degree of preference of the variable amount of waste production is equal to 0.191, the degree of preference of the variable source of waste production is equal to 0.188 and the degree of preference of the waste transfer station is equal to 0.179.

Table 4. Degree of preference of research variables.

Row	The Symbol Used in the Checklist	Examined Variables	Degree of Preference
1	A	Energy cost	0/157
2	B	Number of inhabitants	0/134
3	C	House area	0/151
4	D	Waste generation rate	0/191
5	E	Waste generation source	0/188
6	F	Waste transfer station	0/179

6.3. Fuzzy TOPSIS Estimation

To approach TOPSIS Fuzzy, the approach used in FAHP calculations and symmetric matrices in MATLAB software will be used. The results of calculations in the software are as follows (Tables 5 and 6):

Table 5. Weighting matrix in TOPSIS Fuzzy calculations.

Variables	Energy Cost			Number of Inhabitants			House Area			Waste Generation Rate			Waste Generation Source			Waste Transfer Station		
Energy cost	0/649	0/649	0/649	0/659	0/776	0/91	0/52	0/645	0/801	0/633	0/758	0/91	0/449	0/552	0/673	0/578	0/716	0/876
Number of inhabitants	0/48	0/563	0/663	0/672	0/672	0/672	0/46	0/557	0/675	0/657	0/79	0/953	0/53	0/671	0/834	0/478	0/564	0/667
House area	0/524	0/65	0/807	0/644	0/78	0/944	0/646	0/646	0/646	0/617	0/794	1	0/483	0/567	0/677	0/459	0/568	0/705
Waste generation rate	0/611	0/735	0/88	0/605	0/729	0/877	0/554	0/697	0/897	0/857	0/857	0/857	0/675	0/826	1	0/64	0/78	0/974
Waste generation source	0/666	0/812	1	0/557	0/692	0/876	0/659	0/787	0/924	0/632	0/768	0/943	0/691	0/691	0/691	0/64	0/794	1
Waste transfer station	0/527	0/644	0/798	0/717	0/848	1	0/652	0/808	1	0/626	0/781	0/951	0/491	0/618	0/767	0/711	0/711	0/711

Table 6. Normalized matrix in TOPSIS Fuzzy environment.

Variables	Energy Cost			Number of Inhabitants			House Area			Waste Generation Rate			Waste Generation Source			Waste Transfer Station		
Energy cost	0/144	0/203	0/274	0/469	0/219	0/375	0/153	0/21	0/365	0/206	0/167	0/284	0/186	0/179	0/238	0/244	0/367	0/388
Number of inhabitants	0/107	0/176	0/28	0/479	0/19	0/277	0/136	0/181	0/307	0/214	0/175	0/297	0/219	0/218	0/295	0/202	0/289	0/295
House area	0/116	0/203	0/341	0/458	0/22	0/389	0/191	0/21	0/294	0/201	0/175	0/312	0/2	0/184	0/239	0/194	0/291	0/312
Waste generation rate	0/136	0/229	0/371	0/431	0/206	0/361	0/163	0/227	0/408	0/279	0/189	0/267	0/28	0/269	0/353	0/27	0/399	0/431
Waste generation source	0/148	0/253	0/422	0/396	0/195	0/361	0/194	0/256	0/42	0/206	0/17	0/294	0/286	0/225	0/244	0/27	0/407	0/443
Waste transfer station	0/117	0/201	0/337	0/51	0/239	0/412	0/192	0/263	0/455	0/204	0/173	0/297	0/203	0/201	0/271	0/3	0/364	0/315

6.4. Prioritize to Select A Template

To prioritize pattern selection using TOPSIS Fuzzy calculations, we came to the following table in the MATLAB computing environment (Table 7):

Table 7. Fuzzy prioritization for security against the protection of identity information for the Internet system.

Priority	Main Variables	TOPSIS Fuzzy Prioritization
1	Waste generation rate	0/201
2	Waste generation source	0/198
3	Waste transfer station	0/174
4	Energy cost	0/152
5	House area	0/139
6	Number of inhabitants	0/137

6.5. Waste Management Model and Energy Efficiency in Smart Homes in TOPSIS Fuzzy Model

Figure 5 shows the Waste management model and energy efficiency in smart homes using the IoT.

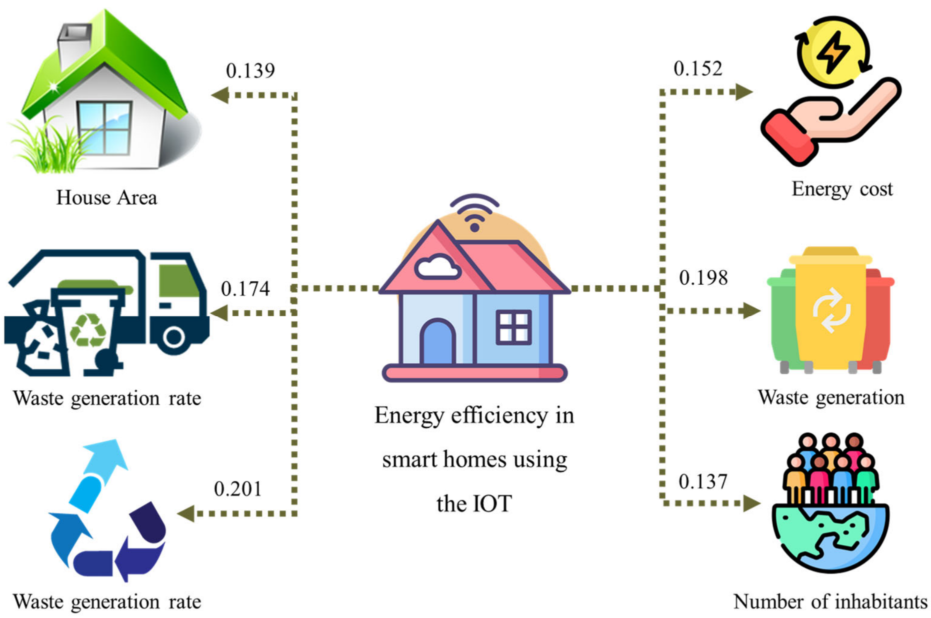

Figure 5. Waste management model and energy efficiency in smart homes using the IoT.

6.6. Answer to Research Hypotheses

Fuzzy TOPSIS outputs were used to test the hypotheses [60]. It can be stated that in the absence of appropriate data, or the inability of the data to matrix overlap, the possibility that a variable under study has a weighted coefficient is almost impossible. Therefore, when the variables under study have measurable coefficients, and in the next step the outputs are related to ranking. It can be said that the variables studied in the research showed that there was a set of rankable components that have the ability to create an optimal analysis for determining the pattern of waste management and energy efficiency in smart homes using the IoT with efficiency. Based on this we can say that:

In response to the main hypothesis of the research which states that the model of waste management and energy efficiency in smart homes using the IoT is effective, findings of the study show that the pattern of waste management and energy efficiency in smart homes using the IoT is effective, because all the studied variables had estimated coefficients. This issue was extracted based on F-TOPSIS estimates and the priorities related to the variables studied in the study were identified. In response to the other three sub-hypotheses, it can be said that the findings of the study show that these hypotheses also had a positive effect.

7. Discussions and Conclusions

Based on the findings of this research study, it can be concluded that the waste management model will improve energy efficiency in smart homes, while ultimately leading to energy efficiency in these homes. The goal of energy costs in smart homes using the IoT technologies is to reduce the impact on the environment, which also reduces municipal landfills. This method minimizes the risks of traditional burial and it can eliminate the effects of land scarcity, because land scarcity has caused the need for a waste management system to be urgently felt.

In this case, the cost of energy in smart homes using the IoT is essential to environmental, economic, and social relations. In addition, the number of home residents in smart homes and the ability to use new technologies to reduce the negative effects of municipal solid waste will be effective, and the IoT will provide a low-cost solution with the power of energy efficiency in this case. It will make its use for smart homes a necessity. The area of the house is essential in determining the amount of waste production. In this case, smart homes using the Internet can monitor waste management methods and multi-criteria decision-making methods and optimize its levels. Moreover, according to the number of inhabitants, the IoT technologies can more easily optimize material consumption.

Using smart homes and connecting to the IoT can ultimately reduce waste generation by optimizing and planning. Moreover, to dispose of it will be an essential element in this case. The IoT technologies can usually provide the right options. For this purpose, the source of waste generation in smart homes using the IoT is effective.

The source of waste generation in smart homes is the ability to estimate the most likely landfill area to improve knowledge of the decision-making process using the IoT. In which case, it can be expected that landfill location is improved using the IoT technologies, and that more opportunities for collaboration and use are created. Waste transfer stations from smart homes using the IoT are also effective. Waste transfer stations from smart homes in most developing countries such as Iran will be essential in the case of efficiency and productivity of other energy inputs. In this case, waste disposal will be in good condition due to sufficient knowledge and equipment for waste management based on the IoT.

In comparison to the previous papers, firstly, the results of this study were consistent with the studies conducted by Gawali and Deshmukh [57] and Adhikari and Gianey [8]. In their results, these studies showed that waste management and energy efficiency represent an important element that is affected by the IoT. In addition, usually by using the IoT, it can be made smarter in different places, which is one of the components and places for smart homes.

Secondly, the findings of this research study suggested that the cost of energy in smart homes using the IoT is effective. The results of this study are consistent with the studies conducted by Azar, Makhoul [10]; Lee, Cho [30]; Škulj, Sluga [7]. In their results, these studies showed that the IoT can optimize the cost of energy and this work will ultimately lead to the improvement of energy use in smart places.

Finally, the results of this study are consistent with the research studies conducted by Esmaeilian, Wang [13]; Casado-Vara, Chamoso [9] and Bhadbhade, Yilmaz [23]. These studies showed in their results that with the IoT, it is possible to carry out the correct implementation of energy management, which will be effective with the use of smart sensors on the level of the investigated place, such as the area of the house. In this case, waste management in smart and sustainable cities takes the form of sensor-based infrastructure for timely separation and collection, while the IoT technologies will play a fundamental role.

Future researchers, according to the results of this research, can pursue the following components in the continuation of this research. These include:

1. Assessing the stability of the supply chain of waste recycling plants to use the intelligence of the waste transmission line to the plant based on the IoT.
2. Modeling related to the stability of waste management and waste management in relation to the reduction in environmental pollution using the transfer of environmental data in the IoT.
3. Investigation of the life cycle of destruction and fermentation of different types of waste using sensors to estimate the acidity and energy efficiency based on the IoT.

Author Contributions: All authors contributed equally to this research. All authors discussed the results and contributed to the final manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

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

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