

# **Implementation and Evaluation of an IoT-Based Smart Dustbin System for Healthcare Waste Management**

**Kazi Irteza Islam**

Department of Industrial and Production Engineering  
Ahsanullah University of Science and Technology  
Department of Applied Statistics and Data Science  
Jahangirnagar University  
Dhaka, Bangladesh  
kaziirtezaislam@gmail.com

**Niloy Goswami**

Department of Electrical and Electronic Engineering  
American International University-Bangladesh  
Dhaka Bangladesh  
ngoswami@aiub.edu

## **Abstract**

Healthcare waste management (HCWM) is a growing challenge in developing countries due to inadequate infrastructure, regulatory oversight, and proper utilization of technologies. In many divisions, IoT has been a significant part of their daily operations. The primary goals of IoT are to collect, exchange, and act on data, which also contributes to automation. This study aims to implement and assess key criteria of an IoT-based Smart Dustbin system with fill level detection in HCWM through a MCDM method called the Single-Valued Neutrosophic (SVN)-DEMATEL method. In this study, the experimental setup of the smart dustbin with the results of its fill level notification and location has been presented. Additionally, the real-time update is incorporated through the Blynk application. The SVN-DEMATEL method is applied to evaluate a total of nine criteria, where three of each are technical, environmental, and economic criteria, respectively. The results of this study showed that one of the criteria, “Carbon footprint (C5)”, is the strongest driver among the identified factors. The criterion named “Real-time monitoring, (C2)” is the strongest effect among others. These findings can guide future practitioners to decide which of these criteria are most impactful, as well as how to design a system similar to this with possible efficient outcomes. Lastly, a more dynamic application of the methods and findings can be achieved based on this study.

## **Keywords**

IoT, MCDM, SVN-DEMATEL, HCWM, ROI, KPI.

## **1. Introduction**

Healthcare waste management is often considered a crucial challenge to overcome, as it involves numerous criteria to address, including understanding and characterizing waste types, differentiating methods for segregation, and efficiently disposing of or recycling waste to minimize hazardous events and mitigate environmental effects. A recent study highlights the growing global challenge of managing medical waste, revealing that only 38.9% is being properly sorted and handled. Furthermore, 41% of employees have received training on medical waste disposal (Singh et al., 2022). As this study encompasses both developed and developing countries, such as Bangladesh, the issue of waste management is particularly significant in that country. Another alarming consequence of this mismanagement, lack of knowledge, and technologies is that practitioners who are directly involved and have frequent exposure are adopting

the unsafe alternatives (Minoglou et al., 2017). Furthermore, a recent research study took place in the capital of Bangladesh (Dhaka) where the researchers built a sample from participants for different levels and categorized the waste categories through a simple random sampling method (SRS). In this research, among four types of waste (Clinical waste - Yellow container, Sharp waste - Red container, Reusable waste - Black container, General waste - Green container), statistically, clinical waste is found to weigh out compared to all other types. The study also shows that individuals with higher education levels and those who acknowledged their participation were more likely to participate simultaneously than others (Alzoubi et al., 2025). Overall, the optimized use of technology has become a problem in HWM. Tracking that problem and observing the general practice, especially in a developing country like Bangladesh, is crucial to be familiar with technologies and standardize modern Industry 4.0-associated practices, such as implementing IoT for waste management in any industry (Singh et al., 2025). In this study, an I-4 practice by incorporating IoT in it has been introduced to the healthcare practitioners, which is IoT-based smart dustbin on which the authority do real-time monitoring of the waste level overall. To conduct this research, a prototype of the setup is first conducted, then this model was presented to the respected authorities. The authorities' selected member then took part in this survey. After that, the survey is analyzed with an MCDM method named SVN-DEMATEL.

To initiate that, the potential adopters of IoT and other related technologies' verdicts are very important for future enhancement. Through their participation, along with the implementation of a decision-making methodology such as Multi-Criteria Decision-Making (MCDM), can help future adopters and ease out the operations of this system (Dhukari et al., 2025). In addition, this research identified the crucial criteria for IoT-based applications of the system, which will not only be an efficient process but also enable the practical understanding of the return on investment (ROI) benefits through experts' opinions.

### **1.1 Objectives**

The research objectives of this study are:

- To fabricate and present the experimental setup of an IoT-based Smart Dustbin.
- To assess the key criteria in the relevant context.
- To provide a scientific result from the perspective of field application.
- To help understand the general outcome of this advancement.
- To provide a general idea of the impact of different criteria for future KPI.

## **2. Literature Review**

The MCDM decision-making tool has come a long way and has efficiently proven methodology. While IoT is a relatively nascent idea that has changed the perspective of data, automation, and efficiency. With the use of MCDM methods such as SVN-DEMATEL, an insightful picture can be presented of the major criteria of IoT-enabled waste management system such as Smart IoT Dustbin in a relevant context for practitioners and future adopters. This literature review shows very recent studies that are addressing the use of IoT in HCWM and MCDM methods in various areas.

A study of (Mirchandani et al., 2017) has rigorously explained the primary benefits of real-time monitoring with IoT enabled dustbin in waste management. This paper address key challenges of public garbage bins overflow before scheduled cleaning. (Jayashree et al., 2021) provided a scientific study of IoT-enabled smart dustbin which primarily focused toward enhancing hygiene, reduced labor, and enabling data-driven collection for sustainable and efficient urban environments. (Ishaq et al., 2025) demonstrates how IoT sensor technology in Kaduna hospitals improves biomedical waste management by enabling real-time monitoring, prompt collection alerts, and data-driven insights, highlighting the need for specialized approaches to hazardous waste due to variability in waste types and volumes across facilities. (Shah et al., 2025) presented an IoT-enabled smart bin leveraging Raspberry Pi 5 and deep learning automates waste segregation across sectors, especially medical waste classification, while enabling real-time monitoring through a mobile app for efficient, accurate, and adaptable waste management. (Kittappa et al., 2025) presented an IoT-based biomedical waste management system enables multi-level monitoring—including transport, treatment facilities, and hospitals—using GPS tracking and real-time bin status updates to promote safe disposal. Establishing a broad network of healthcare facilities can reduce medical waste, lower costs, and enhance sustainability, but success requires collaboration among healthcare providers, waste managers, financiers, and regulators. This system addresses the critical risks posed by improperly handled medical waste from hospitals. A recent study of (Billah et al., 2025) an IoT-based intelligent waste management system uses sensors and GPS-enabled vehicles to monitor

bin fill levels, categorize waste, and optimize collection routes, improving efficiency, reducing costs, and supporting sustainability goals while advancing smart city infrastructure and community engagement.

A recent study by (Koochkan et al., 2025) focused on the significant gaps in the integration of emerging technologies and a holistic management framework that configures a healthcare waste chain that takes into account the variability dimension and application of the Internet of Things (IoT). The study focused on a comprehensive decision-making framework to configure viable healthcare waste management. The framework incorporates sustainability, digitization, agility, and resilience through a multi-objective, scenario-based paradigm. Another prominent study on improving healthcare waste management was provided by (Beheshtinia et al., 2025). This study uses a unique multi-criteria decision-making process called the ELECTOR method to choose the optimal healthcare waste disposal option based on a long list of factors (Abdullah et al., 2025) research work has the application theory of DEMATEL with Single-Valued Neutrosophic Hypersoft sets, which is the most relevant to this study because this study is focusing especially on uncertainty and ambiguity, where Single-Valued Neutrosophic DEMATEL will be one of the most efficient ones. A study of (Liu et al., 2025) has utilized the SVN-DEMATEL method for the selection of the transport service provider. Another study of (Adouhawwash et al., 2025) has used this method to develop a methodology for wind turbine development. A recent study of (Islam et al., 2024) presents a smart billing meter integrating Arduino, sensors, and GSM technology to optimize energy consumption through real-time load control, data display, and tampering detection. Simulation and hardware tests demonstrate its effectiveness in enhancing energy management and consumer safety, highlighting its innovation compared to existing solutions.

In this study, it is not only limited with one particular aspect but it is presentation of both the prototype of the intended setup and the prominent factors during field applications. Through a scientific procedure of decision making methodology SVN-DEMATEL, a solid conclusion can be drawn from it.

### **3. Methodology**

#### **3.1 Implementation and experimental setup of smart dustbin system**

To implement the smart IoT-based dustbin system, a sustainable and cost-effective prototype is presented to the relevant experts. This IoT-based smart dustbin model is fabricated with ESP8266 Nodemcu Wifi module, GSM/GPRS sim800A module, GPS module, 16x2 I2C LCD, Ultrasonic sensor (Field level detector), 3.7 volt Li-Po battery

**Algorithm 1:** IoT based smart dustbin with fill level detection

BEGIN

#### **1. Initialize system**

- **Define** Blynk credentials and include libraries
- Set pin modes for trigPin, echoPin, and led
- Start Serial and LCD display
- Show welcome message on LCD

#### **2. Connect to WiFi**

- Attempt connection until successful
- **Print** IP address and start server

#### **3. LOOP FOREVER**

- Trigger ultrasonic sensor
- Measure duration and calculate distance
- Compute fill level:  $((25 - \text{distance}) / 25) \times 100$
- Display level on LCD
- **Turn off** LED

**IF** level  $\geq$  threshold **THEN**

- Send SMS alert
- Turn on LED
- Trigger IFTTT event

**END IF**

**END LOOP**

In Figure 1, it shows the workflow diagram of the smart IoT bin. The diagram has following three actions: measuring the fill level, real-time monitoring and transmission of the information when fill level is full. Figure 2 shows the circuit diagram for the experimental setup. In Figure 3, the following setup is completed with circuit diagram of Figure 2. The ultrasonic sensor is placed facing downward to the bean.

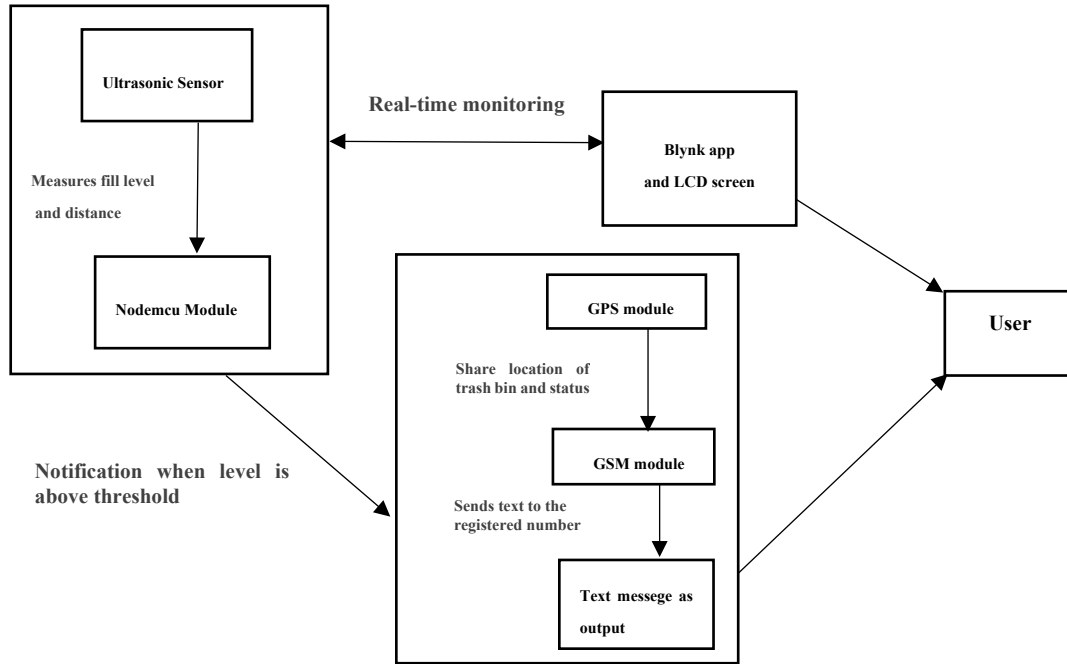


Figure 1. Workflow diagram of IoT bin

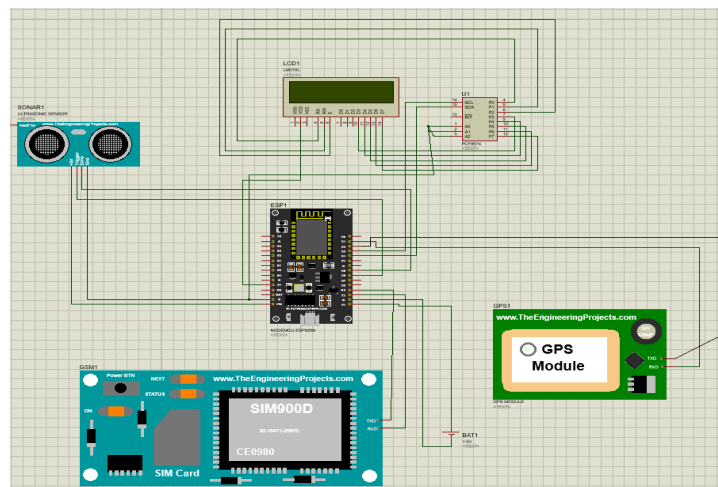


Figure 2. Circuit diagram of an IoT-based smart dustbin system for waste management.

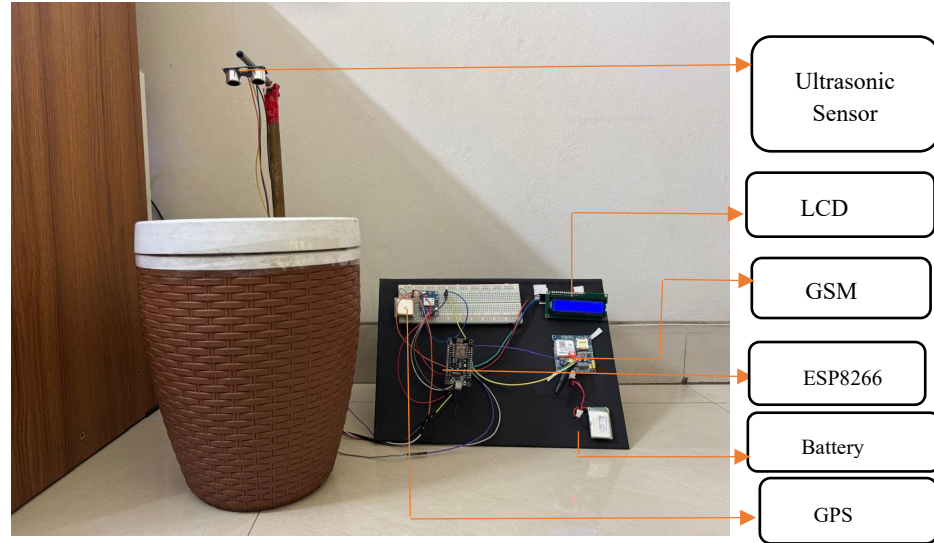


Figure 3. Experimental setup of IoT-based smart dustbin.

### 1.2 MCDM methodology

In this study, the SVN-DEMATEL MCDM method will be utilized for the evaluation of IoT-based system criteria. SVN-DEMATEL is a hybrid decision-making method that stands for Single-Valued Neutrosophic Decision Making Trial and Evaluation Laboratory. This decision-making tool will be used for handling uncertainty, ambiguity, and inconsistency in information.

### 1.3 Evaluation Criteria

In this study, a total of nine criteria are selected for evaluation of IoT based smart-dustbin system. Among them, three are based on technical context, three are environmental context, and the last three are based on economic context. Here is the table of these criteria. Table 1 contains the code, context and name of the criteria.

Table 1. Description of Criteria

Code	Context	Criteria
C1	Technical	Accuracy of waste tracking
C2	Technical	Real-time monitoring
C3	Technical	Scalability
C4	Environmental	Waste reduction efficiency
C5	Environmental	Carbon footprint
C6	Environmental	Recycling rate
C7	Economic	Operational cost
C8	Economic	Return on investment (ROI)
C9	Economic	Cost savings

### 1.4 Sampling Method

In this study, the purpose sampling method is utilized to select experts' opinions. Purpose Sampling is a non-probability sampling method used where samples are selected based on characteristics of a population and the objective of the study. Researchers rely on their judgment when choosing samples. Ten experts have been selected at the end where fifteen experts were initially shortlisted by this method.

### 1.5 Single-Valued Neutrosophic DEMATEL Theory

Single-Valued Neutrosophic DEMATEL Theory:

The Decision-Making Trial and Evaluation Laboratory (DEMATEL) is a well-established technique within the realm of Multi-Criteria Decision-Making (MCDM), widely recognized for its ability to explore and interpret complex causal

relationships among various criteria in a system. By incorporating Single-Valued Neutrosophic Sets (SVNS) into the DEMATEL framework, the method becomes more effective in handling the uncertainties and imprecision commonly found in group decision-making scenarios. The following steps outline the SVN-DEMATEL procedure (Abdullah et al., 2021).

**Step 1:** Each decision-maker's judgment is gathered and compiled into a direct-relation matrix  $X_{n \times n}$ , where  $n$  represents the total number of criteria. This matrix captures the perceived influence or interrelationship among the elements, based on a 5-point linguistic rating scale. Here is the decision matrix of the first expert.

**Step 2:** The relative importance (or weight) of each expert is determined using the following equation: Let  $\lambda_k = (T_k, I_k, F_k)$  be representing the Single-Valued Neutrosophic Number (SVNN) indicating the relative importance of the  $k$ th expert. The corresponding value for the  $k$ th expert can be calculated using the following equation:

$$\lambda_k = \frac{T_k(X) + I_k(X) \left( \frac{T_k(X)}{T_k(X) + F_k(X)} \right)}{\sum_{k=1}^l T_k(X) + I_k(X) \left( \frac{T_k(X)}{T_k(X) + F_k(X)} \right)}, \quad (1)$$

Table 2 shows the conversion of linguistic term to SVNS value of decision makers.

Table 2. Linguistic terms representing the relative importance weights of decision-makers

Linguistic terms	SVNS (T, I, F)
Very Influencing	(0.90, 0.10, 0.10)
Influencing	(0.80, 0.20, 0.15)
Medium Level Influence	(0.50, 0.40, 0.45)
Low Influencing	(0.35, 0.60, 0.70)
Not Influencing	(0.10, 0.80, 0.90)

**Step 3.** Calculated the aggregated Direct-Relation Matrix (DRM)

$z_{ij}^k = (T_{ij}^k, I_{ij}^k, F_{ij}^k)$  denotes the Single-Valued Neutrosophic (SVN) assessment provided by the  $k$ th expert, representing the evaluation of criterion  $i$  on criterion  $j$ . Here,  $x_{ij}$  indicates the level of influence that criterion  $i$  has on criterion  $j$ . Table 3 shows the linguistic To SVNS value table for the level of influence according to the following Step 3.

Table 3. Linguistic Variable for Influence

Linguistic terms	SVNS (T, I, F)
No Influence (NI)	(0.0, 1.00, 1.00)
Extremely Low Influence (ELI)	(0.20, 0.85, 0.80)
Low Influence (LI)	(0.40, 0.65, 0.60)
High Influence (HI)	(0.60, 0.35, 0.40)
Extremely High Influence (EHI)	(0.80, 0.15, 0.20)

$$a_{ij} = SVNSWA(Z_{ij}^1, z_{ij}^2, \dots, z_{ij}^k) \\ \sum_{k=1}^l \lambda_k Z_{ij}^k = (1 - \prod_{k=1}^l (1 - T_j)^{w_j}, \prod_{k=1}^l (I_j)^{w_j}, \prod_{k=1}^l (F_j)^{w_j}), \quad (2) \\ i=1, 2, \dots, m; j=1, 2, \dots, n,$$

Here,  $\lambda_k$  is the importance weight of  $k$ th expert;  $a_{ij}^k$  corresponds to the SVN of the  $k$ th expert's opinion when comparing  $i$  to  $j$ .

**Step 4.** Direct-relation matrix is generated with the following equation:

$$E(z) = \frac{(3+T-2I-F)}{4}, \quad (3)$$

**Step 5.** In this step, normalised Direct-Relation Matrix is generated with below equation:  $X=k*A$ , where,

$$k = \min \left( \frac{1}{\max_{1 \leq i \leq n} \sum_{j=1}^n |a_{ij}|}, \frac{1}{\max_{1 \leq j \leq n} \sum_{i=1}^n |a_{ij}|} \right) \quad i, j \in \{1, 2, 3, \dots, n\}, \quad (4)$$

and  $A$  is the normalised Direct-Relation Matrix.

**Step 6.** The total relationship matrix is obtained through the following equation, where  $T$  is the total-relationship matrix,  $I$  is the identity matrix, and  $x$  is the normalised Direct-Relation Matrix.

$$T = X(I - X)^{-1}, \quad (5)$$

where  $I$  is an identity matrix. Below is the total relation matrix in Table 4 achieved from equation 5.

Table 4. The total relation matrix

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	0.344684542	0.565095723	0.509889263	0.542522906	0.408935522	0.604848	0.592927	0.560304	0.602517
C2	0.446009086	0.462103637	0.498025711	0.42219896	0.27965889	0.587802	0.569784	0.560245	0.572569
C3	0.524974936	0.720626096	0.548898174	0.604145068	0.460441036	0.701616	0.696669	0.689803	0.670685
C4	0.317873346	0.562906258	0.52393275	0.364583579	0.332912191	0.530414	0.53504	0.550586	0.470396
C5	0.33962309	0.608372206	0.560367143	0.509816414	0.27241215	0.585243	0.46822	0.574646	0.577688
C6	0.500885605	0.691517822	0.648045675	0.58000164	0.461157966	0.573008	0.668193	0.63482	0.691865
C7	0.423472337	0.543006674	0.523856664	0.465260573	0.350475916	0.547356	0.457425	0.583904	0.588997
C8	0.38446656	0.598839743	0.560502551	0.466055455	0.279408014	0.578212	0.539734	0.454812	0.587179
C9	0.462650138	0.621869728	0.584697452	0.535715791	0.310589685	0.61703	0.628877	0.579561	0.502146

Here, the red cells value surpass the threshold which is 0.633

**Step 7.** To plot the causal diagram, the summation of rows and columns, which are  $R$  and  $D$ , respectively are calculated with equations below.

$$T = [t_y]_{n \times n}, \quad i, j = 1, 2, \dots, n,$$

$$R = \left[ \sum_{i=1}^n t_y \right]_{1 \times n} = [t_j]_{1 \times n}, \quad (6)$$

$$D = \left[ \sum_{j=1}^n t_y \right]_{n \times 1} = [t_j]_{n \times 1}, \quad (7)$$

A criterion is considered a cause-and-effect criterion if  $(R-D)$  is positive and  $(R-D)$  is negative, respectively.

Below is the table for casual diagram achieved from equation 6,7. In Table 5, cause or influence and effect or prominence have been shown.

Table 5. R+D, R-D table

Criteria	R	C	R+C	R-C
C1	4.731723388	3.74464	8.476363	0.987084
C2	4.398395754	5.374338	9.772734	-0.97594
C3	5.617858511	4.958215	10.57607	0.659643
C4	4.188644028	4.4903	8.678944	-0.30166
C5	4.496388352	3.155991	7.65238	1.340397
C6	5.449494808	5.325529	10.77502	0.123965
C7	4.483753901	5.156869	9.640623	-0.67312
C8	4.44920971	5.188681	9.63789	-0.73947
C9	4.843136498	5.264041	10.10718	-0.4209

**Step 8.** To identify types of criteria, coordinates of  $(R + D, R - D)$  in the Cartesian plane are used to segregate criteria into four types.

## 4. Result and Analysis

This section includes obtain result from two aspect of this study. In section 4.1 includes IoT-application results. Section 4.2 includes SVN-DEMATEL application results.

### **IoT-application results:**

After successfully implementing the smart bin prototype, every time the dustbin is full or set to trigger at a certain level, e.g., 88%, this will send a notification via text messages, and the authority can also get the real-time information about the dustbin through the connected private server provided and Blynk application.

Figure 4 presents overall monitoring results. In Figure 4(a) the image is of the text message received when the bin is full. This text also provide a link of the real time location of the dustbin. Figure 4(b) shows the real time waste percentage and depth height through the Blynk app. The information percentage is also displayed on the LCD in Figure 5.

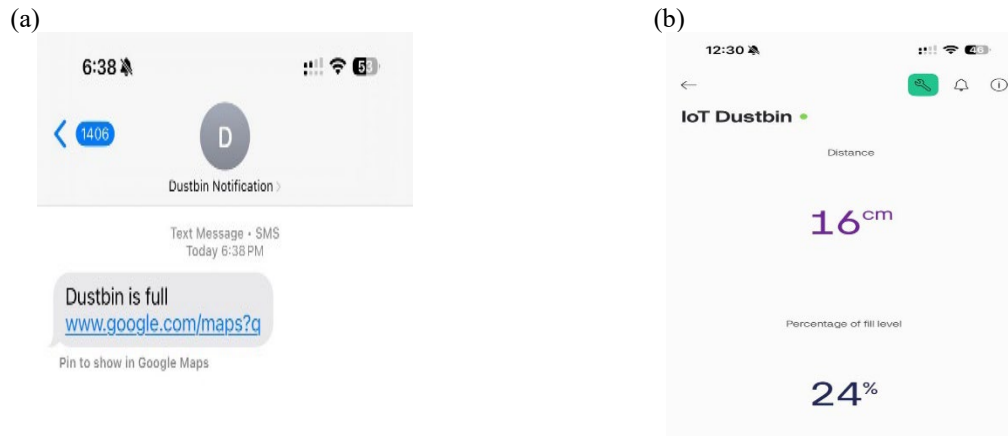


Figure 4. Real-time monitoring with Blynk IoT app and GSM module.



Figure 5. 16x2 I2C LCD.

To illustrate the SVN-DEMATEL results, three types of analysis is done, cause-and-effect analysis, quadrant analysis and network analysis.

#### **Cause-and-Effect Analysis:**

To identify the causal and effectual roles of the criteria, the following metrics were computed:

Sum of Rows (R): Represents the total influence exerted by a criterion on others.

Sum of Columns (D): Represents the total influence received by a criterion from others.

X-axis (R + D): Represents the prominence or total involvement of a criterion in the system (both as cause and effect). A higher value means the criterion is more central to the system. The cause-and-effect diagram depicted in Figure 2, represents interdependence among the criteria.

Y-axis (R - D): Represents the net influence:

Positive (R - D > 0): Criterion is a cause (it influences others more than it is influenced).

Negative (R - D < 0): Criterion is an effect (it is more influenced by others).

Key insights from the analysis include:

Criteria C5 emerged as the most influential cause, which is the carbon footprint.

Criteria C2 emerged as the most influential effect, which is the real-time monitoring.

Cause Group (R - D > 0):

C5, C1: Strong cause criteria with high prominence and strong net influence.

C3, C6: Also causes, butwith moderate influence.

Effect Group ( $R - D < 0$ ):

C4, C9: Moderate effect, low net influence but still significant.

C7, C8: Mild effect criterion.

C2: Strongest effect criterion (most influenced by others), with the lowest net influence and low prominence.

Figure 6 is the casual diagram which depicts the cause and effect relationship. Based on that result a quadrant analysis has been done and the results are presented in Figure 7.

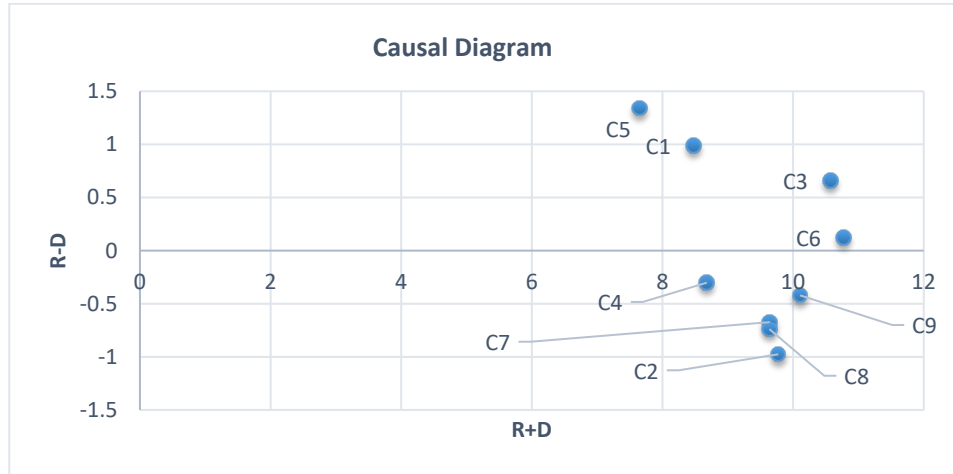


Figure 6. Scattered causal diagram for all nine criteria.

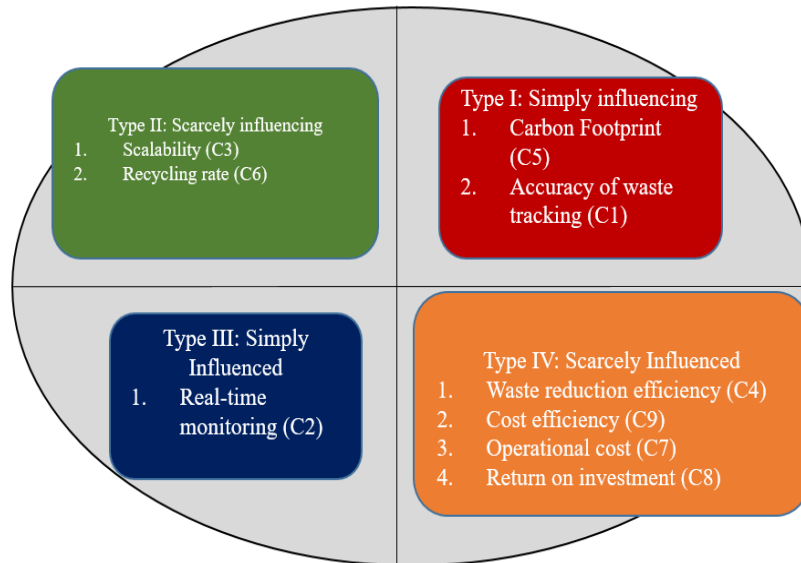


Figure 7. Quadrant analysis of all nine criteria.

Table 6 shows different existing researches in both waste management and healthcare waste management where methodology such as IoT, MCDM has been implemented

Table 6. Comparison with existing work

IoT in HCWM	MCDM in HCWM	Smart bin for waste disposal	Real-time monitoring	References
✘	✘	✓	✘	(Mirchandani et al., 2017)
✘	✘	✓	✘	(Jayashree et al., 2021)
✘	✓	✘	✘	(Ishaq et al., 2025)
✓	✘	✓	✓	(Shah et al., 2025)
✓	✘	✓	✓	(Kittappa et al., 2025)
✓	✓	✘	✓	(Koohkan et al., 2025)
✘	✓	✘	✘	(Beheshtinia et al., 2025)
✓	✓	✓	✓	This work

## 5. Conclusions

In this study, an IoT-enabled smart bin prototype is presented, and a MCDM method named SVNS-DEMATEL is used to determine how the system can practically impact overall operation in HCWM, where the “Carbon Footprint” (C5) criterion is proven as the most influential cause, and the criterion “Real-time monitoring” (C7) came out as the most influential effect. As the MCDM model helps to determine inconsistency and ambiguity, this study has comprehensively shown the complex cause-and-effect relationship. The complete process of collecting opinions from the experts is done from a Google Form from the prime hospitals and healthcare institutions of Dhaka, Bangladesh. With the application of this study, future practitioners can adopt and implement this smart-bin model in HCWM where they can prior idea about the key criteria for application. In that basis, they can take informed steps, and further research on this study will be conducted.

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## **Biographies**

**Kazi Irteza Islam** graduated from Ahsanullah University of Science and Technology in Industrial and Production Engineering (IPE), Dhaka, Bangladesh. He has work experience as logistics and supply chain executives at Smart Technologies BD.Ltd. He is pursuing a master degree in Applied Statistics and Data Science from Jahangirnagar University. His general research interests include machine learning, IoT, and advanced manufacturing.

**Niloy Goswami** received his B.Sc. degree in Electrical & Electronic Engineering (EEE) in 2021 from American International University-Bangladesh (AIUB) and received his MSc. degree in EEE from AIUB in January 2024. He is currently working as a Lecturer at the Department of EEE at AIUB. The main areas of his research focus include next-generation antennas (UWB, THz), microwave sensing devices, and semiconductor devices/nanodevices. He can be contacted at email: ngoswami@aiub.edu