Solving Waste Management Issue in the Healthcare using advanced analytics

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Part I

1. Role of Analytics in Healthcare

With the advent of Fourth Industrial Revolution, all sectors are facing technology disruption from the variety of technologies and the results of the analytics has proven strong in all areas. In Healthcare, the demand for analytics is extremely required as the challenges are more, the risk factor is high and the human life is on the equation with factors such as: - medical history, disease report, treatment facility, available equipment waiting time, and patients' category- high, medium or low. The analytics proved strong in effectively analysing and extracting information from large/complex datasets in the heart transplantation surgery where there is an imbalance between demand and supply (Dag, et al., 2017). Other decision support systems model 'patient monitoring system' is aimed at providing the healthcare to rural areas where challenges are high due to poverty, low literacy, inadequate monitoring of patients and poor infrastructure (Barjis, et al., 2013).

The healthcare is not only dealing with the proactive approaches to deal with the challenges but also acting reactively, by acquiring data about the healthcare consumers' behaviours and attitudes. In one of the model, data is collected in the form electronic medical records and customer are divided into segments and then data is analysed for their past records, demographic and geographical areas to know the relationships (Swenson, et al., 2016). Big Data Analytics is impactful in various fields such as: - retail, finance, and social networks. Healthcare wearable devices such as: - Fitbit, Jawbone, and Garmin are widely used by consumers for monitoring day to day activities offering providers a research into new areas for example: - monitoring blood by the skin and analysing glucose levels. These devices can collect real-time data in large amounts which can help in many health-related problems (Wu, et al., 2017). As of now, most of the models are conceptual or data models need more analysis or more testing but analytics has massive power to revolutionise the healthcare if right data is collected, assumptions are correct and the all the factors are included in the equation.

2. Different areas where data analytics is used & its applications

In the last couple of decades, the Internet has changed the face of the world by providing a network. Today, businesses can interact with customers by providing applications on handheld devices such as: - mobiles, tablets and e-readers. Also, Internet of Things (IoT) devices are now collecting data at a massive speed and with information so ubiquitous, it is hard to not explode our minds with data. Analytics is playing a key role in making businesses understand the power of patterns generated by the data collected from their customers. This disrupting phenomenon is touching every sector finance, healthcare, operations and even legal (Downes & Nunes, 2013). However, these areas can further be subcategorized into domains: Web Analytics, Google Analytics, Software Analytics, Crisis Analytics, Knowledge Analytics, Marketing Analytics, Customer Analytics, Human Resource Analytics, Talent Analytics, Process Analytics, Supply Chain Analytics, Risk Analytics, Financial

Analytics (Holsapple, et al., 2014). The domains are self-explanatory for the areas they can be applied in the company.

Analytics is not only used in mainstream business areas but also for "Intermodal freight transportation" where Data analytics can also be used to visualize the impact of government regulation on the ports and the economy. One of the conceptual models also talked about the human trafficking issues and this paper discussed a current range of applications of Operations Research (OR) and analytics to anti-human trafficking efforts and suggests ideas about methods which can be further developed and applied to benefit this sector (Konrad, et al., 2016). Analytics is not limited to one field or an area, it can be applied anywhere where the data is collected by generating simple visualizations and understanding the patterns of occurrences.

3. Advantages and challenges of using data analytics in healthcare

Predictive analytics such as: - Data Mining, Text Mining and Web Mining provide good opportunities to support executives at all levels such as: - strategic, tactical, and operational for their decision-making needs management. Strategic manager can apply the analytics for competitive intelligence, finding market opportunities, product launch evaluations and product positioning techniques in his work, Tactical managers can apply analytics in the sales forecasting, direct marketing, customer acquisition, retention and extension purposes, and marketing campaign analysis and Operational managers can use analytics for utilization of the facilities or supply chain (Bose, 2008). Further, Bose says that companies can also be benefited by customer segmentation attracting them by effective strategies and consumer driven health insurance based on their risk profiles.

One of the main challenges in data analytics is "data sharing" as companies do not prefer to reveal data collected from their customers for security concerns or regulations. Second, Advance analytics is not an easy concept to use or understand, business managers need to be trained to understand the solutions. Third, if technology evolves, changes and advances then businesses should evolve with them otherwise the current technology used in the business becomes outdated (Bose, 2008). Further, Data analytics is performed on the code which does not act like human and many algorithms generate patterns but the meaning is interpreted by a human. Hence, one of the problems while applying data analytics could be repetition of information as in the case of healthcare patients' data collected many times in electronic health record (EHR) when a diagnosis could be listed on the patient's problem list or in medical record, billing records, reason for visit, clinical narrative, etc. (Ward, et al., 2014). This data repetition will be calculated more than once in the final visualization, if not properly analyzed. This also includes improper data as an input to the system. For example, 'crème' and 'creme' has an accent difference which could be a spelling mistake but that needs to be cleaned before analyzing data.

Part II

1. Problem

Carolina Healthcare System identified reducing waste as one of the opportunities to enhance DA[2] while also wanted to improve outcomes (QUELCH & RODRIGUEZ, 2015). Waste in the healthcare industry is a complicated issue and pose a serious challenge as the population is increasing, demand for medical services is increasing. If the waste is not handled and disposed properly, there is a high risk of infection or injury to medical personnel as well as lesser risk to the public through micro-organisms (Windfeld & Brooks, 2015). Healthcare waste is generated in health-care establishments, research facilities and laboratories consist of pathological, infectious, sharps, body parts, genotoxic, chemicals, pharmaceuticals, medical devices and radioactive materials (Prüss, et al., 1999). For the safe environment, the waste must be handled carefully but there is a cost of handling and destroying waste is associated with it.

2. Aim

The aim of the system is to focus on the sustainable waste management to reduce waste and improve cost by using Fuzzy Goal Programming Approach and to help decision makers to tackle the waste management challenges while improving the outcomes of the present system.

3. Input data

The data required will be the types of healthcare waste and the cost associated with it. Based on several definitions provided in Exhibit 1, the healthcare waste is categorized into two major categories: communal waste and biomedical waste (as shown in figure 1). The different treatment of medical waste used in healthcare are private haulers that transport medical waste to treatment facilities, Electro-Thermal-Deactivation (ETD), hydro pulping, microwaving, and grinding before dispensing into the municipal sewer (Klangsin & Harding, 2011).The cost will include all capital, transportation, on-site treatment and operational costs for the disposal of waste to the municipal corporation. The equipment purchased such as: - incinerators, microwaving, and autoclaving to deal with on-site handling the hazardous waste (Özkan, 2013) will be treated as an initial investment, if not purchased already. The other cost will be the salary given to the personnel for handling the waste. Other constraints would be the capacity limit on the waste due to the equipment capacity or environmental regulations. The input data in the system is the type of waste that is entering the system. Then it will be sent to the sorting facility where it is treated or disposed depending on the nature of the waste as shown in Figure 2. Dataset must be prepared from the past records on waste and audit data for waste disposal of the company

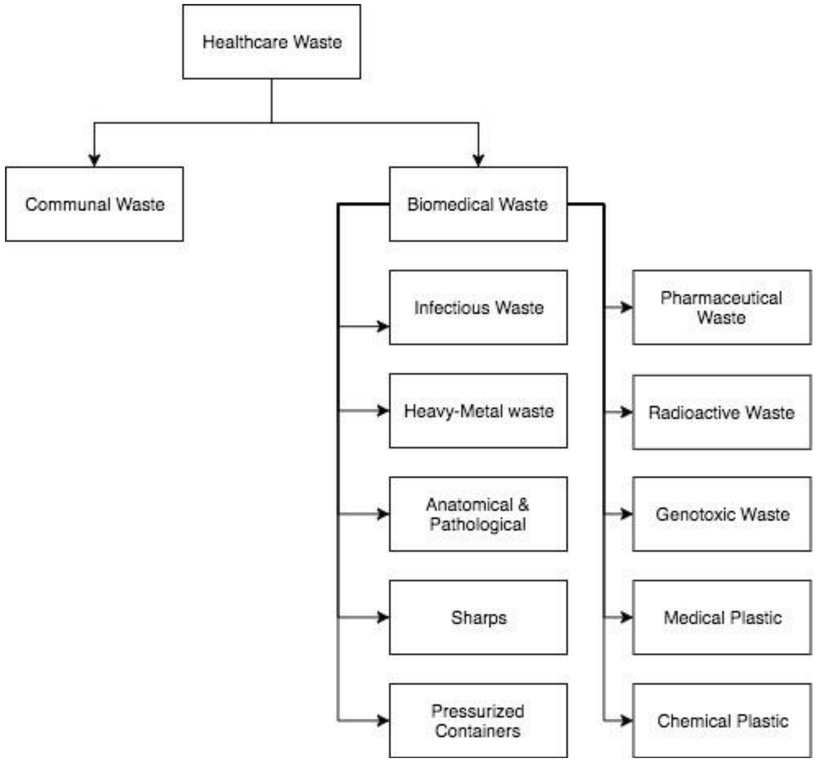
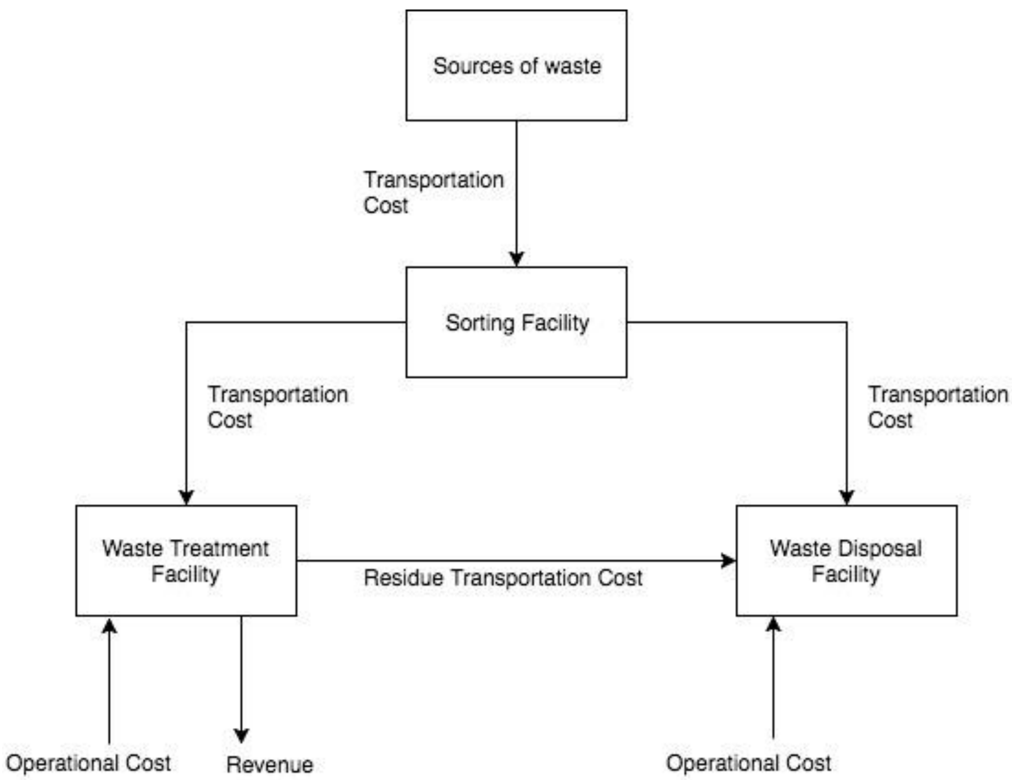


Figure 1: Healthcare waste management research: A structured Analysis and Research (2005-2014) (Thakur & Ramesh, 2015)



F*igure 2: A Fuzzy Goal Programming Approach for Solid Waste Management* ***under*** *Multiple Uncertainties* (Biswas & De, 2016)

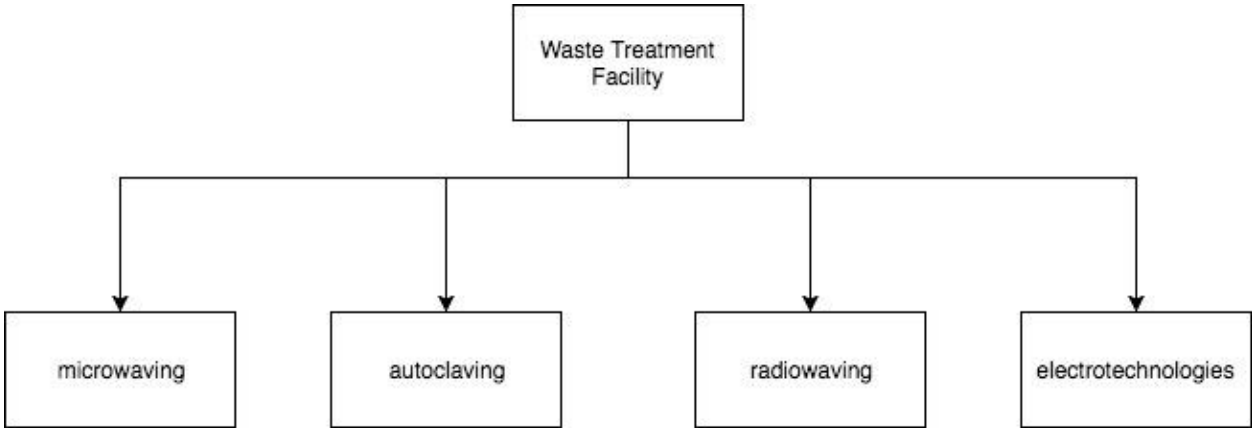


Figure 3: Types of waste treatment in health care (Lee, et al., 2004)

4. System output

The output will be generated based on priorities of the goals which will result in positive and negative deviational variables resulting from trying to satisfy multiple criteria of the goal programming. The decision maker or management must be consulted to know which deviation variables should be minimized. Based on the expert's advice, the criteria should be satisfied for multiple goals in the model that could be equipment's capacity or cost to treat waste.

5. Algorithms

Real world problems often have more than one objectives based on which criteria is optimized considering many decision factors where Goal Programming will help to achieve multiple goals (Petridis & Dey, 2016). Goal Programming is introduced by (Charnes & Cooper, 1955) as an extension to linear programming where the objective function satisfies one criterion. In typical Goal Programming, decisions are set by management and one goal is achieved at the cost of another goals. In this method, a positive and a negative deviation variables are introduced to fully achieve the goals. The objective is to minimize the deviation variables (Render, et al., 2003). The goal programming for every case is a different as criteria and constraints are unique to the problem. The algorithm proposed has used three different cases solid waste management using multiple criteria (Biswas & De, 2016), capacity management for the waste treatment plant to meet the environment criteria (Petridis & Dey, 2016) and effective hazardous waste management (Büyüközkan & Gocer, 2016).

For treatment of waste, some hospitals use on-site incinerators for treating medical waste. Sometimes, these wastes contain disinfectants or poly-vinyl chloride(PVC) or some amounts of heavy metals when incinerated, it can produce dioxins, furans and ashes. For disposing of the healthcare waste and in on-site incinerators Lee et al.'s evaluated the four methods of treating waste microwaving, autoclaving, radiowaving and electrotechnologies which can provide better results compared to incinerators.
This model is based on these four methods of in-house waste treatment. Further, the waste must be separated for the right treatment as microwaving is better for batch processing but not sufficient for sterilization above 120 degrees Celsius as spores

may survive. For spores' treatment, autoclaving is the right choice as temperatures are higher than the microwaving technique for killing spores (Lee, et al., 2004).

Fuzzy random variable

Fuzzy set theory has been applied in many areas/tasks such as: - operational research, safety, quality engineering and assessment and in ecosystem management. The advantage of using fuzzy sets is the ability to tackle uncertainties and imprecision. Not only the inputs from the experts are important for the evaluation of the model but also the imprecision and uncertainties of experts' and stakeholders' opinions for the problem (Vesely, et al., 2016). Nothing is permanent/fixed in any industry and as there are chances of uncertainty as the transportation cost for wastes, operation cost, revenue and capacity of the waste treatment facility may not be fixed, as it varies time to time. To capture these uncertainties into the model, these quantities must be treated as fuzzy variables in constraints. The right-hand side parameters of the equation for the constraints must be taken as fuzzy variables and coefficients of the objective function are also considered as fuzzy numbers. In this way, the fuzzy goal programming model is constructed and provide the most satisfactory results for the decision area (Biswas & De, 2016).

Computation Model

Waste management is critical and important in healthcare. With emergency situations, it is difficult to identify how much waste will be generated. As there is ambiguity in predicting the exact capacity of waste or the cost that will be required to treat the waste as the prices change with time. The computation model is based on fuzzy goal programming and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method to provide a more feasible solution and is divided into eleven steps as shown in figure 4.

1. For the goal programming model, the waste will come from different sources as an input identified in Figure 1. Next step is to determine the cost associated with treatment at the facility or for disposing of the waste. In this case, the disposal of waste is coming from the sorting facility and as a by-product of waste treatment facility. Also, there are transportation and operational cost other than the treatment cost. The daily/hourly capacity of the equipment at the healthcare facility must be identified which should be in check with the environment regulation.

2. Identifying decision variables is a crucial and most important step in the formulation of the objective. In this step, unknown entities are identified such as: - the amount of the waste from different sources. The amount of the flow for each category of waste to the facility will be calculated from source to sink i.e. from hospital to treatment facility. The relationship of the cost, capacity and waste will be identified in the form of equations.

3. In the real world, business often suffers from imperfect information about the system or plagued by the constant supply demand gap. In this environment, it becomes necessary to involve someone who has the experience about the parameters that changes on day to day basis (MARTEL & AOUNI, 1990). In their paper, Martel & Aouni also suggested the involving the decision maker to act on the suggested choices made by the mathematical model or at threshold places. In this way, the manager is constantly involved and is in the position to take decision for the business.

4. Constraints limit the outcomes of the decision variables and the value of the decision variables cannot be decided based on two or three equations (Render, et al., 2003). For example: - the capacity of the microwaving is 5litres and waste is 25 litres. Decision Maker is the one who decides the restrictions for the constraints, usually the right-hand side of the equation. He/ She must be the person to know which deviational variables are unwanted.

5. In Goal Programming, it is important to obtain the weight/rank of the goal to know the priority of the challenges. As one goal is satisfied at the expense of another goal, it is necessary that the priorities of the goals are set since it is not possible to achieve every goal. The priorities can be obtained from the decision makers or management based on their experience with the situation (Render, et al., 2003). The priorities can also be predicted by using TOPSIS method in the equation in which weight of each criterion is given linguistic term characterised by fuzzy numbers then intuitionistic fuzzy positive and negative ideal solution is calculated on the Euclidean distance, relative closeness coefficients of alternatives are obtained and alternatives are ranked. TOPSIS method combined with fuzzy sets is better in predicting the uncertain values (Boran, et al., 2009).

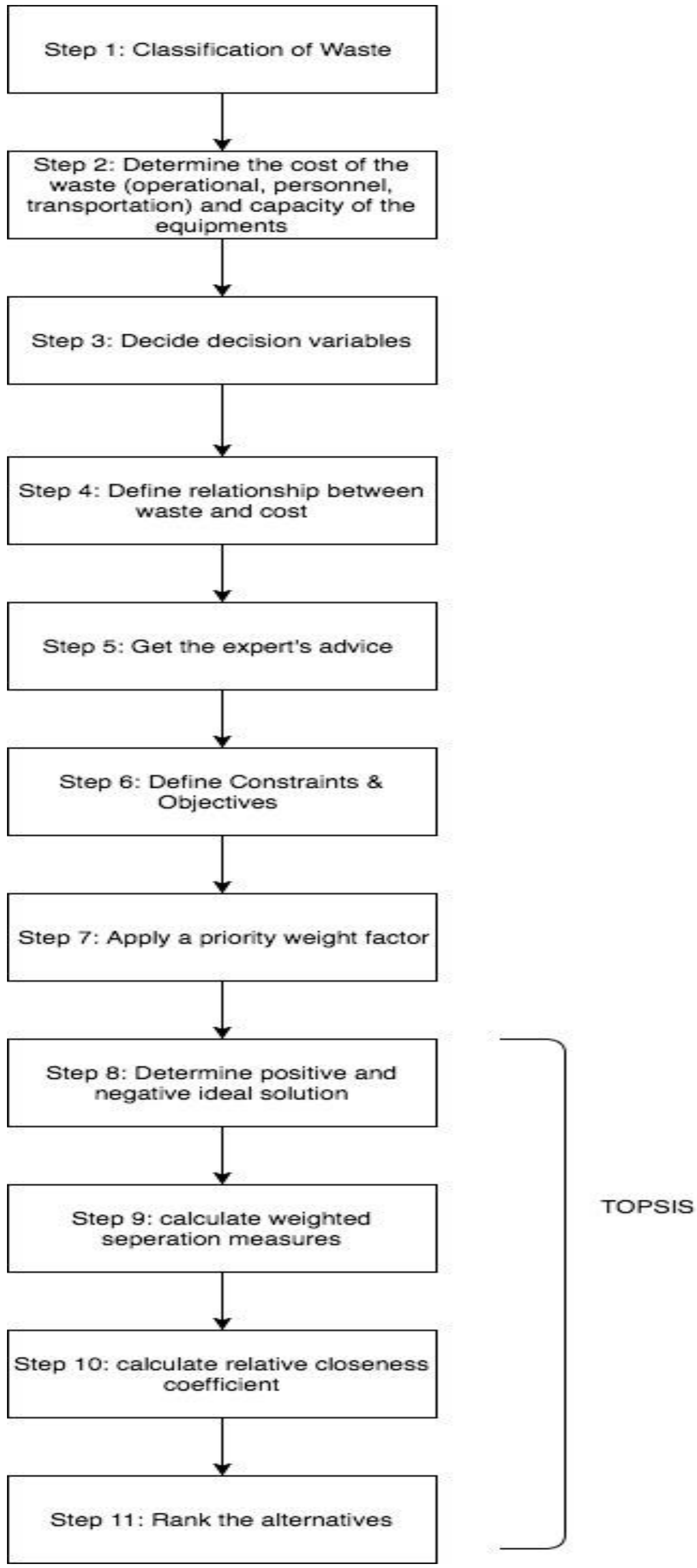


Figure 4: Goal Programming Computation Steps Source: (Büyüközkan & Gocer, 2016) (Biswas & De, 2016) (Boran, et al., 2009)

6. Validation

The process of validation is to compare the actual results of the past with the results generated by the models and it should save money in the long run. Though waste cannot be controlled as its source is dependent on the patients that come for the healthcare services. In this case, if the solutions are feasible and acceptable in the test run, conduct the sensitivity analysis on the model and analyze the sensitivity of decision parameters (Subulan, et al., 2015). As suggested in the paper by (Subulan, et al., 2015), first, the model should be tested for the variation in the waste from the sources. Second, fuzzy goal's variation on the satisfaction degree must be analyzed for waste. The value of the fuzzy goals will be changed in each scenario, so, functions should be revised before each scenario. The model should not be too sensitive to the change.

7. Assumptions

a. The conditions and constraints defined in the process are will not change during the analysis.
b. There must be a waste treatment facility for the infectious waste. If not, then the setup cost is not the part of the goal programming model.
c. The sources of waste are based on the healthcare waste management research which can be different to DA^2 waste.
d. Cost and waste will be variable as they change from time to time.
e. The waste treatment equipment cost is not included in the model.

8. Challenges in the design process of the system/use

a. Waste management is complicated management for any industry as the source of wastes cannot be controlled and it can get generated in vast quantity. In healthcare, where there are no waiting lines and emergency requirements vary from day to day, waste is becoming a serious issue. Though all of it cannot be tackled at once but the start is necessary to deal with the hazardous and infectious waste from healthcare.

b. Goal Programming results ultimately lie in the hands of the decision maker, it depends on "how many criteria the decision maker wants to achieve" and what are the trade-offs that are considered to achieve these goals as one goal is achieved at the expense of another.

c. Though fuzzy decision making criteria are beneficial for the ambiguities but sometimes, fuzzy sets can be inadequate for dealing with the uncertainties if the judgement of the decision maker for the variables is still vague (Büyüközkan & Gocer, 2016).

Exhibit 1:

Table 1. Definitions of HCW.

Definition	References
HCW is the by-product generated in hospitals and consists of sharps, blood, body parts, chemicals, pharmaceuticals, medical devices and radioactive materials.	World Health Organization, 1999
HCW is generated from healthcare facilities and is composed of two categories: general waste and medical waste.	Phengxay et al., 2005
HCW consists of two categories: infectious waste (articles such as urine containers, body fluids, excreta, human tissue, sharp-edged and glass pieces) and non-infectious waste.	Gupta and Boojh, 2006
Divided the HCW into five categories: recyclable waste (black bags), common waste (blue bags), infectious regulated medical waste (red bag), hazardous waste and low-level radioactive waste.	Alagoz and Kocasoy, 2007
HCW includes all the waste materials generated from the treatment, diagnosis, or immunisation of humans or animals at hospitals, veterinary and medical centres.	Mbongwe et al., 2008
HCW composed of solid waste and waste water. Healthcare solid waste further consists of non-risk (75–90%) and hazardous waste (10–25%).	Mesdaghinia et al., 2009
Classified HCW as follows: sharps, infectious waste, genotoxic waste, general waste, heavy metals, pathological waste, chemical waste, pharmaceutical waste, pressurised containers, and radioactive waste.	Al-Khatib et al., 2009
Divided the waste generated from healthcare facilities into following categories: medical waste, municipal waste, recyclables, sharps, liquid waste, hazardous waste.	Eker and Bilgili, 2011
Divided HCW into five categories: infectious, pathological, medical, pharmacy and chemical.	Chen et al., 2013a; Longe, 2012
HCW comprises of general waste (plastics, textiles, glass, metals, paper) and infectious waste (sharps, pathological, infectious, absorbent cotton, discarded medical plastic).	Eleyan et al., 2013
HCW is composed of: general, infectious, sharps, pharmaceutical, pathological and radioactive.	Tesfahun et al., 2014
European union legislation divided the clinical waste into the following three categories of materials: (i) any HCW that poses a risk of infection; (ii) HCW that is a chemical hazard; and (iii) medicines and medicinally contaminated waste containing a pharmaceutically active agent.	http://ec.europa.eu/environment/waste/legislation/a.htm (accessed on 20 May 2015)

HCW: healthcare waste.

Figure 5: Different Definition of Healthcare Waste Source: (Thakur & Ramesh, 2015)

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