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**Environment and Sustainable
Development Program**

Estimation of Medical Waste Products and Associated Factors in the Kingdom of Bahrain

Submitted by
Khadija Al-Omran
ID Number: 20002267

Supervised by
Dr. Ezzat Khan
Associate Professor
University of Bahrain

Kingdom of Bahrain
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Thesis Discussion Committee Decision

Student Name: Khadija Mohamed Jaafar Husain	Student ID: 20002267
Department: Choose an item.	College: Science
Program: PhD in Environment and Sustainable Development	
Thesis Title: Estimation of Medical Waste Products and Associated Factors in the Kingdom of Bahrain	
Supervisor Name: Dr. Ezzat Khan	Student GPA: 3.95

The Discussion Committee met on 13-Jun-24 In the College of Science – Room S41-0002. Upon discussing the student whose details are stated above in public, the discussion committee recommends the following:

The student is awarded a grade PASS in the thesis subject.

- ☐ Without making any changes to the thesis.
- ☒ After making the modifications attached with this decision.

Discussion Committee Members Approval:

Name

1. Dr. Ezzat Khan (Advisor)
2. Dr. Suad Ahmed Rashdan (Internal Examiner)
3. Prof. Dr. Aysun Sofouglu (External Examiner)

Signature

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Aysun Sofuoğlu

DEDICATION

To my dearest Family,
whose constant love and support have made this achievement possible.

ACKNOWLEDGMENTS

First and foremost, praises and thanks to God, the Almighty, for showering blessings upon me throughout my research journey, enabling the successful completion of this thesis.

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ABSTRACT

As a global concern, medical waste (MW) links public health and the environment. The main aim of this dissertation is to estimate the MW generation and identify the associated factors in the Kingdom of Bahrain. Firstly, two MW issues were assessed, the increasing quantities of MW and its management, using Integrated Environmental Assessment methodology, including the DPSIR framework, analysis of existing policies, and the outlook. Consequently, related policies for the last two decades (2001-2021) were collected and analyzed. It was found that most of the existing policies address the impact of the MW issues but are lacking in tackling the drivers and pressures. To overcome MW issues, reforming regulations is recommended to reduce and manage MW efficiently to focus more on drivers and pressures causing an elevation in MW issues.

The MW generated during the COVID-19 pandemic from different sources in Bahrain and other selected GCC countries were estimated using data from different public domains. In Bahrain, MW was estimated as 3,547.974 kg/day (facemasks), 1,894 kg/day (PPEs by the selected health facilities), 16,633.505 kg (vaccination) and 53,551.240 kg (PCR-tests) until May 11, 2021. The calculated MW in GCC was 110,797,952 kg/day (facemasks), 2,554,812 kg (vaccination), and 2,595,772 kg (PCR-tests) until March 2022.

The factors associated with COVID-19 MW generation from February 2020 to May 2022 were explored using SEM. Amounts of COVID-19 waste from Bahrain Waste Treatment Company were used in addition to data from the public domains. The results revealed that the vaccination and infected cases are statistically significant predictors for waste generation during the pandemic. Moreover, the stringency index factor was found to be a significant moderator between the COVID-19 waste and the two predictors.

The MW generation rate was determined in governmental and private hospitals as 2.610 and 1.040 kg/occupied-bed/day, respectively. Machine learning was implemented to predict MW generation and significant features in one governmental and one private hospital. Two monthly datasets obtained from the hospitals were utilized. The ensemble voting regressor was determined as the best model for both datasets. The two proposed models have superior accuracy. For the governmental hospital, the significant features were the number of inpatients, population, surgeries, and outpatients, in descending order of importance. While in the private hospital, the number of inpatients, deliveries, surgeries, outpatients, population and personal income.

The psychological factors that drive health workers to engage in the segregation of MW were examined using survey data. An integrated model that combines the Norm Activation Model and the Theory of Planned Behavior was employed and analyzed by the PLS-SEM method, and eleven hypotheses were formulated and tested. The model illuminates insight into motivations for MW segregation intention, explaining 70% of the total variance. The findings indicate that personal norms and perceived behavioral control significantly influence MW segregation intentions.

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LIST OF PUBLICATIONS

1. **Al-Omran**, K., Khan, E., Ali, N., & Bilal, M. (2021). Estimation of COVID-19 generated medical waste in the Kingdom of Bahrain. *Science of the Total Environment*, 801, 149642. DOI: <https://doi.org/10.1016/j.scitotenv.2021.149642>
2. **Al-Omran**, K., Khan, E., Perna, S., & Ali, N. (2023). Factors associated with medical waste under pandemic situation: a case study of the Kingdom of Bahrain. *Journal of Material Cycles and Waste Management*, 25(5), 2951-2963.
3. **Al-Omran**, K., Abahussain, A., & Khan, E. (2023). Integrated Environmental Assessment of Medical Waste Management in the Kingdom of Bahrain. *Sustainability*, 15(3), 2397.
4. **Al-Omran**, K., Khan, E., & Perna, S. (2023). Medical waste generation during COVID-19 pandemic in selected member countries of Arabian Gulf region; Google trend analysis. *Arab Journal of Basic and Applied Sciences*, 30(1), 79-91.
5. **Al-Omran**, K., & Khan, E. (2024). Predicting medical waste generation and associated factors using machine learning in the Kingdom of Bahrain. *Environmental Science and Pollution Research*, 1-15.
6. Factors associated with health workers' behavior toward medical waste segregation by integrating the Norm Activation Model and Theory of Planned behavior. (In progress).

Chapter 1

Introduction

1.1 General Overview

The rapid advancement of industrial and economic development, urbanization, as well as increased populations and density have resulted in an increase in the amount of waste produced per capita. In addition, a growing number of hospitals, clinics, and other healthcare institutions have been established as a result of these advancements (Malekahmadi & Yunesian, 2014). As a result of the increase in the number of health facilities, large amounts of medical waste (MW) are being generated. According to the World Health Organization (WHO), the waste produced from hospitals or healthcare processes should be treated as a particular waste (Rushbrook et al., 2000). Likewise, the United States Environmental Protection Agency (US EPA) has described this type of waste as hazardous (Bennett, 1992). Generally, it is known that specific categories of MW that arise in communities constitute a significant portion of the most hazardous and potentially dangerous wastes.

Taking care of the public's health is the responsibility of hospitals and other healthcare establishments. This can be either directly through patient care or indirectly by ensuring their employees and the community have a clean, healthy environment. During the health care process, waste is produced, including human tissues, sharps or other infectious materials and body parts (Patil & Pokhrel, 2005).

There is no doubt that MW is a public health as well as an environmental issue that draws attention in both industrialized and developing countries. If MW is improperly handled, it can pose a serious health risk by transmitting diseases to other people, such as health workers, patients, and their relatives, thereby exposing them

to the risk of infections and injuries (Chartier, 2014). In addition to health hazards, environmental hazards are another threat that is considered a major source of soil and water contamination, in addition to the poisonous emissions that could result from improper MW burning/incineration. In the long term, MW can impair the life quality of the community and affect the entire population's welfare and the national economy as well (Ahmed et al., 2014).

Poor management system for such MW causes pollution of the environment and poses a health risk to humans (Sabour et al., 2007). Therefore, there is a dire need to have a well-established management system in place. However, it is very challenging to establish such a waste management system in a hospital environment where waste production is complex and heterogeneous (Golbaz et al., 2019). Several factors play a crucial role in the effective start-up of such a complex system, including the accuracy of estimating waste generation rates, either short-term or long-term, at a given time. The short-term estimation of MW generation rates is essential for better and more effective design and management of storage, collection, and transfer systems (Matsuto & Tanaka, 1993; Sengupta & Agrahari, 2017), and long-term estimation is necessary for making the right decision about waste treatment and related technologies, selecting landfill sites, or assessing the impacts of initiatives and new policies (Sengupta & Agrahari, 2017). In order to influence an effective MW management system (and perhaps even prevention) at a regional and national level, it is, therefore, necessary to understand the nuances of regional MW generation, the differences in generated quantities, as well as the underlying causes that might be responsible for those differences (Denafas et al., 2014).

The growth in industrialization, consumption, and the concentration of the population in the cities favoured a consequent increase in the production of waste. The quantity of MW is relatively small compared to the other generated total waste; nonetheless, there is a potential for it to cause significant damage to both human and

environmental health. As a result, hazardous MW waste is subject to stricter controls and legislation (Schuhmacher et al., 2014), as its mismanagement could lead to substantial degradation of groundwater, soil, human and animal health and the overall environment in general (Zakaria et al., 2013).

1.2 Study Background

1.2.1 Definition of medical waste

Historically, the potential health risks caused by MW were first discussed in the US in the 1980s, when MW was seen on East Coast beaches and in the oceans and nature trails, promoting the government of the US to enact the "Medical Waste Tracking Act (MWTa) of 1988". This comprised guidelines for an MW tracking system, the standards for packing, separating, labelling waste and storing, and imposing penalties for violators, especially not keeping records of the generated MW, in addition to defining MW (EPA, 2022b). The effective outcomes of MWTa 1988 were subsequently extended to and applied in each county to build standard strategies for MW management.

Medical waste is defined by the US Medical Waste Tracking Act, 1988 as "any solid waste that is generated in the diagnosis, treatment, or immunization of human beings or animals, in research pertaining thereto, or in the production or testing of biologicals" (US Congress, 1988). WHO estimated that 15-20% of MW is classified as hazardous materials that may be infectious, toxic, or radioactive, while the remaining 80-85% is a general and non-hazardous waste (Birchard, 2002; WHO, 2018). Unfortunately, there is no uniform, universally, and globally agreed definition of MW, which is challenging from the angle of comparison, as changing definitions lead to difficulty in meaningful comparisons between countries and regions. Moreover, the absence of a standardized definition of MW has led to a lack of

standard streams for MW and disposal receptacles (Insa et al., 2010; Windfeld & Brooks, 2015).

Rutala & Mayhall (1992) mentioned that there are four terms used for MW discussion, and all are used interchangeably, with globally unaccepted or agreed definitions for each term. These terms include medical, hospital, infectious, and regulated medical waste. Another source mentioned seven terms that refer to waste produced during the healthcare procedure that could be either contaminated or potentially contaminated by infectious material (Medical Waste, Clinical Waste, Biomedical Waste, Regulated Medical Waste (RMW), Biohazardous Waste, Healthcare waste, Infectious Medical Waste) (MedPro, 2022). The terms are used interchangeably, but there is a difference between general healthcare waste and hazardous MW. The WHO categorizes human tissue, sharps, fluids, and contaminated supplies as "biohazardous", while non-contaminated equipment as "general MW". Although sweeping waste, kitchen waste, and office paper from healthcare facilities are not regulated or hazardous in nature, they still technically belong to the category of MW (MedPro, 2022).

To provide consistency and clarity throughout this thesis, the term "Medical Waste" is used to refer to all hazardous waste that could be produced at any healthcare or healthcare-related facility, which is consistent with the definition given by the US EPA (EPA, 2022a).

1.2.2 Classification of Medical Waste

The classification of waste generated in healthcare institutions in Bahrain follows WHO standards (Chartier, 2014). Healthcare or medical waste refers to all the waste produced within healthcare facilities, laboratories and research centres related to medical procedures. It also includes the same types of waste that originate from smaller or decentralized sources, such as waste generated during the course of

health care undertaken at home in the course of self-care, for example, self-administration of insulin, home dialysis, and recuperative care. Healthcare/medical waste is classified as either Non-hazardous (general) or hazardous waste (Chartier, 2014), as summarized in Figure 1.1.

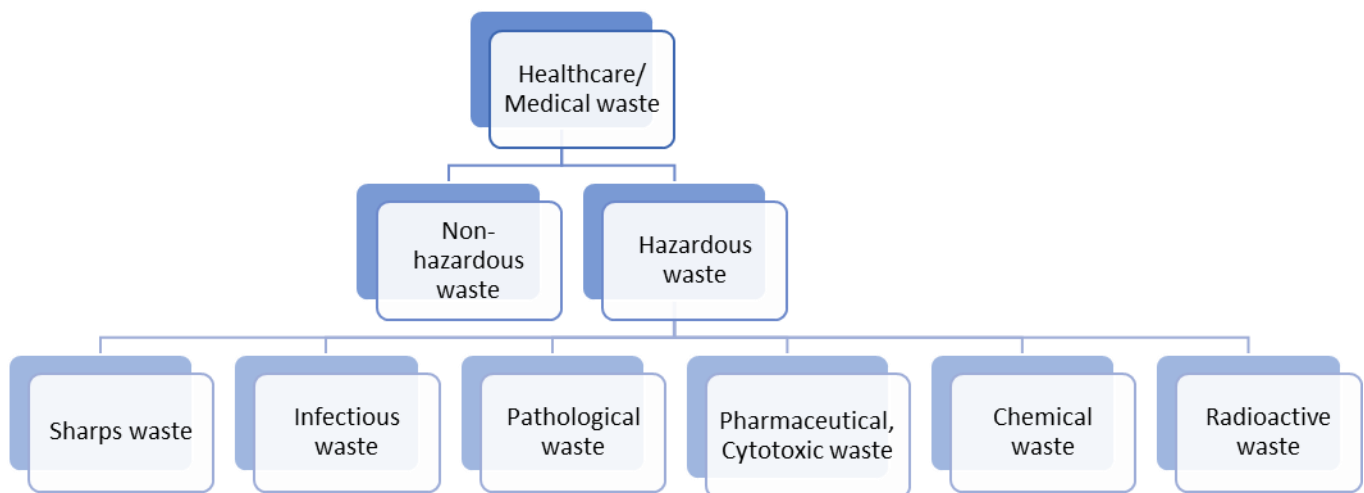


Figure 1.1 Classification of medical waste.

Non-hazardous waste refers to waste that has not been exposed to infectious agents, radioactive substances or hazardous chemicals and does not pose a sharps hazard to human health. Most healthcare facilities' waste (80-85%) is a non-hazardous category, and it usually has characteristics comparable to those of municipal or domestic waste; it is also called "general healthcare waste". Mainly, it comes from the administrative, housekeeping functions and kitchen at healthcare facilities (Chartier, 2014).

Hazardous waste generated in healthcare facilities is the category that may pose a risk to the environment and public health and represents about 15-20% of healthcare waste. Hazardous MW has different categories: Sharps, Infectious, Pathological, Pharmaceutical and Chemical waste. Sharps waste that may cause injury through cuts or puncture wounds, including needles, scalpels and other blades,

hypodermic needles, knives, saws, broken glass, infusion sets, and pipettes. Regardless of whether they carry infectious agents, such items are considered highly hazardous MW and should be treated as potentially infectious. Infectious waste is suspected of containing pathogens, posing a risk of disease transmission. For example, waste contaminated with blood and other body fluids; microbiological stocks and laboratory cultures; waste including excreta and other materials that have been in contact with patients infected with highly communicable diseases in isolation wards. Pathological waste includes human fetuses, organs, tissues, body parts and other waste from surgery and autopsies on patients; it is further categorized into two main subcategories (one is considered for burial, and the other is not considered for burial). Pharmaceutical waste includes unused, expired, spilt, and contaminated pharmaceutical products, drugs, sera and vaccines. It also includes discarded items contaminated while handling the pharmaceuticals, such as bottles, vials and boxes containing pharmaceutical residues, masks, gloves and connecting tubing. A subcategory of pharmaceutical waste is cytotoxic waste, which is highly hazardous and contains substances with genotoxic properties. For example, waste containing cytostatic drugs usually used in cancer therapy are genotoxic chemicals. It is often generated in oncology wards and clinics. The chemical waste consists of discarded solid, liquid, and gaseous chemicals, such as laboratory reagents, disinfectants that are expired or no longer needed, film development, solvents, and waste with a high content of heavy metals. This category of waste has at least one of the following properties: toxic (harmful), corrosive (e.g., acids of pH 12), flammable, reactive (explosive, shock-sensitive, water reactive), or oxidizing. Lastly, radioactive waste refers to waste materials containing radioactive substances, such as unused liquids from radiotherapy or laboratory research, packages, contaminated glassware, or absorbent paper, as well as urine and excreta from

patients who have been treated or tested with unsealed radionuclides and sealed sources (Chartier, 2014).

1.2.3 Sources of Medical Waste

MW is generally produced from various sources and is not limited to hospitals and healthcare centers. The most important sources of waste are hospitals, blood banks, laboratories, dialysis centers, biotechnology companies, medical and dental clinics, pharmaceutical factories, outpatient clinics, research centers, veterinary clinics, in-home treatment, pharmacies, and more (Chartier, 2014).

1.3 Medical Waste and the Interlinkage with SDGs

The MW estimation, encompassing assessment of waste generation and identifying the associated factors, is a critical component of effective MW management. Beyond the operational necessity of estimation, there exists a deep connection between this process and the broader goals set forth by the United Nations Sustainable Development Goals (SDGs). The MW management achievements will inevitably accelerate progress toward achieving the SDGs (HCWH Global, 2023; Leal Filho et al., 2023).

The MW addresses SDG 3 “Ensure healthy lives and promote well-being for all at all ages”, Target 3.3 (end the epidemics of AIDS, tuberculosis, malaria and neglected tropical diseases and combat hepatitis, water-borne diseases and other communicable diseases) and 3.9 (reduce the number of deaths and illnesses from hazardous chemicals and air, water and soil pollution and contamination). Contaminated medical equipment causes the spread of disease and an epidemic. Hence, it is crucial to have a proper MW management system. The MW management is an under-resourced area wherein significant improvements must be made, particularly in infectious diseases, including COVID-19. Hence, tremendous indirect

effects can be observed among the patients, workers as well as the society. Therefore, solving this issue could eliminate direct and indirect threats to the health of more than half of the worldwide population (Nor Faiza et al., 2019). The SDG 6, “Ensure availability and sustainable management of water and sanitation for all”, Target 6.3 aims to “improve water quality by reducing pollution, eliminating dumping and minimizing release of hazardous chemicals and materials”, in addition to improving wastewater treatment. Detecting the interrelationship between water and waste, the WHO has integrated healthcare waste management into its program of water, sanitation, and health. To achieve this goal successfully, this program must implement waste treatment, including MW treatment technologies that do not cause toxic residues or emissions (Nor Faiza et al., 2019). Moreover, MW is linked to SDG 7, “Ensure access to affordable, reliable, sustainable and modern energy for all”, as Target 7.3 states “Increase the share of renewable energy in the global energy mix”. The MW generates a high proportion of plastic waste, which can be converted into valuable energy products like oil, gas and char through pyrolysis (Dharmaraj et al., 2021). Besides, SDG 8, “Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all”, Targets 8.3 (promote development-oriented policies that support productive activities, decent job creation, entrepreneurship, creativity and innovation, and encourage the formalization and growth of micro-, small- and medium-sized enterprises, including through access to financial services) and 8.8 (protect labour rights and promote safe and secure working environments for all workers, including migrant workers, in particular women migrants, and those in precarious employment) are associated with MW issues. Tackling MW issues not only ensures the safety of healthcare workers but also promotes occupational health and well-being, underpinning the foundation of decent work practices within healthcare settings (HCWH Global, 2023).

Innovative policies were created in plastic waste management, including those produced from the MW as a means for economic growth (Oyake-Ombis et al., 2015).

Furthermore, SDG 11 “Make cities and human settlements inclusive, safe, resilient, and sustainable”, tackles this problem, where Target 11.6 aims to “Reduce the adverse environmental impact of cities; special attention to waste management”. SDG 12, “Ensure sustainable consumption and production patterns”, specifically Target 12.4 and 12.5, addresses this issue by emphasising the importance of sustainable consumption and production patterns. This goal underscores the significance of tracking and reducing waste generation within the context of MW estimation and identifying associated factors. Accurate estimation is an essential step toward responsible consumption and production as it identifies excess waste, thereby promoting efficient resource utilization and minimization (HCWH Global, 2023). MW is holistically associated with SDG 13, “Take urgent action to combat climate change and its impacts”. Focusing on Target 13.2 and 13.b reducing waste, isolating at the source, avoiding burning, recycling all resources, and conserving energy contribute to achieving this goal. It has been proved that autoclaving technology emits at least fifteen times less carbon dioxide emissions than incineration of waste (HCWH Global, 2023), and some MW treatment technologies could help mitigate climate change (Nor Faiza et al., 2019).

This issue is also linked to both SDG 14 “Conserve and sustainably use the oceans, seas and marine resources for sustainable development” (Target 14.1), and SDG 15 “Protect, restore, and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss” (Target 15.1). One of the examples taken during the COVID-19 pandemic, all citizens were required to wear facemasks, which caused the masks to spread everywhere and pollute the seas and lands. Throwing facemasks in public areas and beaches is a threat to the environment and

water resources, even in places with waste collection services. It's important to reduce the harmful effects of all waste on the environment and human health through prevention (Al-Omran, Abahussain, et al., 2023; Dybas, 2021).

By addressing the MW issues and realizing the sustainability scenarios that reduce the quantity and efficient MW management, the Kingdom of Bahrain would achieve the aforementioned related SDGs (Figure 1.2).



Figure 1.2 The interlinkages between MW and the SDGs, adopted from (Al-Omran, Abahussain, et al., 2023).

Considering the comprehensive development process and ensuring a green future for all, Bahrain actively participated in the 26th UN Climate Change Conference of the Parties (COP26), held in Glasgow, Scotland. The Kingdom of Bahrain is committed to reaching "Net Zero" by 2060 and has set a range of goals to ensure proceeding without delay. By 2035, it targets to reduce emissions by 30% through carbon removal solutions and efficiency initiatives (Bahrain News Agency, 2021a; World Resources Institute, 2021). This research aims to reduce the quantities of MW, as well as CO₂ and other unwanted gases; hence, this study contributes to

achieving the Net Zero target and Bahrain's commitment to COP26, as this study aims to reduce MW and the resultant emissions.

1.4 Medical Waste Treatment in Bahrain

The Kingdom of Bahrain is a small island developing state (SIDS), with a population of 1,701,583, a population density (people per km² of land area) is about 21,812; and a population growth in 2020 of 3.6% (The World Bank, 2022b). Over the years, the people in Bahrain have been supported by the government with advanced healthcare solutions and programs. The top priority for the government is to ensure a healthy nation, which met the objective of "Healthcare for All" in the 1990s. Until today, a range of subsidized and free healthcare services continue to be provided to people (Bahrain's National Portal, 2022).

In Bahrain, prior to 2002, the MW in the hospitals, i.e., Salmaniya Medical Complex (SMC), was treated in an on-site manner by burning. But in 2002, Bahrain Waste Treatment Company (BWTC) was established to collect, transpose, dispose of and treat MW from the government and private hospitals. The BWTC is located in askar area in the southern governorate of Bahrain (26°5.312'N, 50°34.472'E, Figure 1.3). The company has two incinerators with a processing capacity of 150 tons/month. The categories of waste that the BWTC deals with are hazardous MW, expired medicines and industrial waste, in addition to the category COVID-19 waste, which was added when the pandemic started, and was the highest proportion among all the categories of the company from February 2020 to May 2022 as shown in Figure 1.4. The BTWC is responsible for collecting and treating MW for most hospitals and healthcare facilities in Bahrain, with more than 1000 varied-sized healthcare facilities (Al-Omran, Khan, Perna, et al., 2023).



Figure 1.3 Google Earth Image of the BTWC Location, Source: BWTC company.

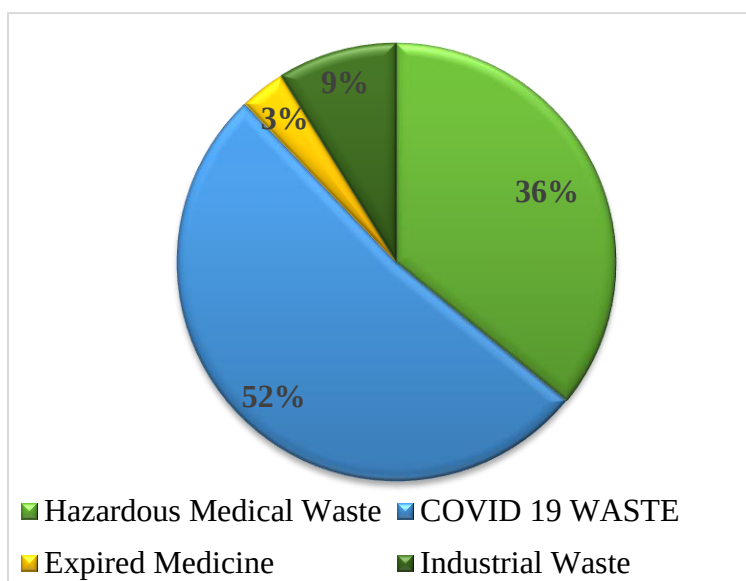


Figure 1.4 The proportions of the total amount of waste categories in BWTC from February 2020 to May 2022; source of data is BWTC company, adopted from (Al-Omran, Khan, Perna, et al., 2023)

1.5 Medical Waste Collection and Disposal

As a general practice, produced hazardous MW at hospitals and healthcare institutions is placed separately in colored plastic bags, yellow (infectious waste like blood/body fluids) and red (for body parts, organs), depending on the type of waste, that needs to be incinerated. Sharps and needles are placed in yellow-colored hard plastic boxes (NHRA, 2017) and should be anti-puncture and leakproof, in accordance with the resolutions and instructions regulating the council of National Health Regulatory Authority (NHRA) (NHRA, 2023b) and under Decision No. (3) of 2006 on Hazardous Waste Management (SCE, 2012). As a safety procedure, sharps containers should be disposed of when the contents are $\frac{3}{4}$ of their size or after 30 days from the commencement of their use. The bags should be tightly tied and then temporarily stored in designated MW rooms of the hospitals; the waste rooms should be in the required specifications. For instance, materials should not be exposed to sunlight or heat, also the room should be equipped with suitable fire extinguishers according to the type of the stored materials (NHRA, 2023a).

For instance, in SMC, the hazardous MW bags are collected daily by designated collection vehicles of BWTC for incineration. The number of MW bags collected daily from the hospital is recorded. Then, the MW is weighed in the treatment plant before getting incinerated. The MW collection in SMC is carried out two or three times a day, depending on the quantities, and it is collected at the beginning of each shift at 8:00 a.m., 11:00 p.m. and/or 3:00 p.m. They are collected by housekeeping employees from each department and packaged in colored plastic bags. As stated by WHO, the collection times of MW in each area of the healthcare facility should be fixed and suitable to the waste quantity produced. The general waste and infectious or other hazardous wastes should not be collected simultaneously or in the same container (Chartier, 2014). Black bags are used for

general waste to be disposed of with the general domestic waste, which is then transported to an on-site storage container, and the Municipality of Bahrain collects solid wastes from that storage container every morning and transports them along with general domestic waste to an open dumping site at Askar Landfill (MUN, 2023).

1.5 Research Problem

MW is a hazardous waste due to its adverse effects on workers in health institutions, society and public health if not managed properly. Many diseases can be transmitted through MW, such as hepatitis B, hepatitis C, AIDS, and others. Diseases, through exposure to wounds with sharp MW, such as needles contaminated with the blood of patients carrying such germs (Chartier, 2014). These risks should be considered in the management system that should be applied in healthcare centers. Most of these risks are present in public hospitals and in small healthcare centers such as primary healthcare centers, medical laboratories, dental clinics, etc., and must be prevented. This has been confirmed by many authors and public health scientists (Al-Dahiri et al., 2008; Al-Hadlaq et al., 2013; Jasem M Alhumoud et al., 2014).

In the Kingdom of Bahrain, at the end of 2022, the population reached 1,701,583, with a population growth of 3.6% in 2020 (The World Bank, 2022b), with more than 800 healthcare facilities (NHRA, 2021a). It was reported that there is a steady growth in the health sector in the kingdom, and the growth rate in the number of health facilities increased from 2017 to 2020, reaching 18% (Bahrain News Agency, 2021). The number of private healthcare facilities has increased from 500 in 2018 to 800 in 2019, leading to more health services and, thus, a high amount of MW in the country (EDB, 2019; FCCIB, 2019). In response to the growing need for

medical treatment as well as the growth of the population, the number of hospitals and healthcare institutions is increasing rapidly. As a result of the increase in the number of hospitals and healthcare facilities, the amount of MW has also increased, which needs to be managed properly. If improperly managed, the MW can potentially cause high health and environmental risks (Mohee Romeela, 2005). Moreover, Bahrain witnessed a substantial, more than double increase in medical waste in 2020 as a result of the impact of the COVID-19 pandemic, which caused additional waste problems (DERASAT, 2021; Information & eGovernment Authority, 2022).

It was reported by SCE (2012) that the level of concern in hazardous waste, including hazardous MW, was found to be low, despite the ability to control this problem being determined to be high, and a vast majority of the organizations surveyed found no available statistical data. One of the significant obstacles Bahrain faces in dealing with this issue of MW management is the limited documentation regarding generation (Mohamed et al., 2009). In Bahrain, limited studies have focused on regional MW issues. Therefore, a thorough investigation of Bahrain must be conducted due to the possibility of health and environmental issues being adversely affected. There is a need to estimate MW and explore the significant factors associated with this issue.

Accurate estimation and quantification of MW are fundamental to effectively managing this type of hazardous waste, figuring out the proper disposal methods and improving waste management (Uysal & Tinmaz, 2004). Moreover, exploring the factors influencing MW generation is vital for appropriate management due to its hazardous nature.

Creating and implementing a data system for generating and managing MW is among the most challenging tasks. To be able to systematize the current situation in Bahrain and attempt a forecast for the generation of MW, there are still dozens of flaws in the method of analysis that need to be addressed and resolved. However, by having a deep understanding of the nuances of MW generation, the differences in their quantities, and their significant factors, it would be possible to influence the development of a successful MW management system at the country's level. This insight is an attempt to draw the attention of the governments, environmental and healthcare agencies, and the public to the quantities of generated MW and its potential risks. And to highlight the most important factors associated with the generation rate of MW.

1.6 Research Questions

1. What are the current status, drivers, pressures, impacts and responses of MW issues in Bahrain? What actions could be taken for a sustainable future for MW?
2. What are MW quantities generated from the COVID-19 pandemic in Bahrain and other GCC countries?
3. What factors are associated with MW generated during the COVID-19 pandemic in Bahrain?
4. What are the factors associated with MW quantities under normal situations?
5. What factors influence the compliance of health workers with MW segregation practices?

1.7 Research Objectives

Based on the background above, it becomes apparent that it is vital to quantify the amount of MW for better management. Thus, the overarching aim of this

research is to estimate and predict the quantities of MW and explore the associated factors with MW generation. The supporting objectives are:

1. To investigate the main issues related to MW in Bahrain through the Integrated Environmental Assessment (IEA) method. Consequently, figure out the driving forces and pressures and determine their impacts on the environment and humanity, then comprehensively study the existing MW policies. Accordingly, set future sustainable scenarios, options and suggestions.
2. To estimate the amount of MW generated in the Kingdom of Bahrain and other GCC countries during the COVID-19 pandemic.
3. To explore the factors associated with MW quantities during the COVID-19 pandemic in Bahrain.
4. To predict the amount of MW generated in Bahrain and associated factors during the normal situation by examining two hospitals (governmental and private) as case studies.
5. To investigate the factors influencing compliance among health workers with MW segregation behavior.

Below Figure 1.5 summarizes the research framework that illustrates the three phases in addition to their methods and objectives.

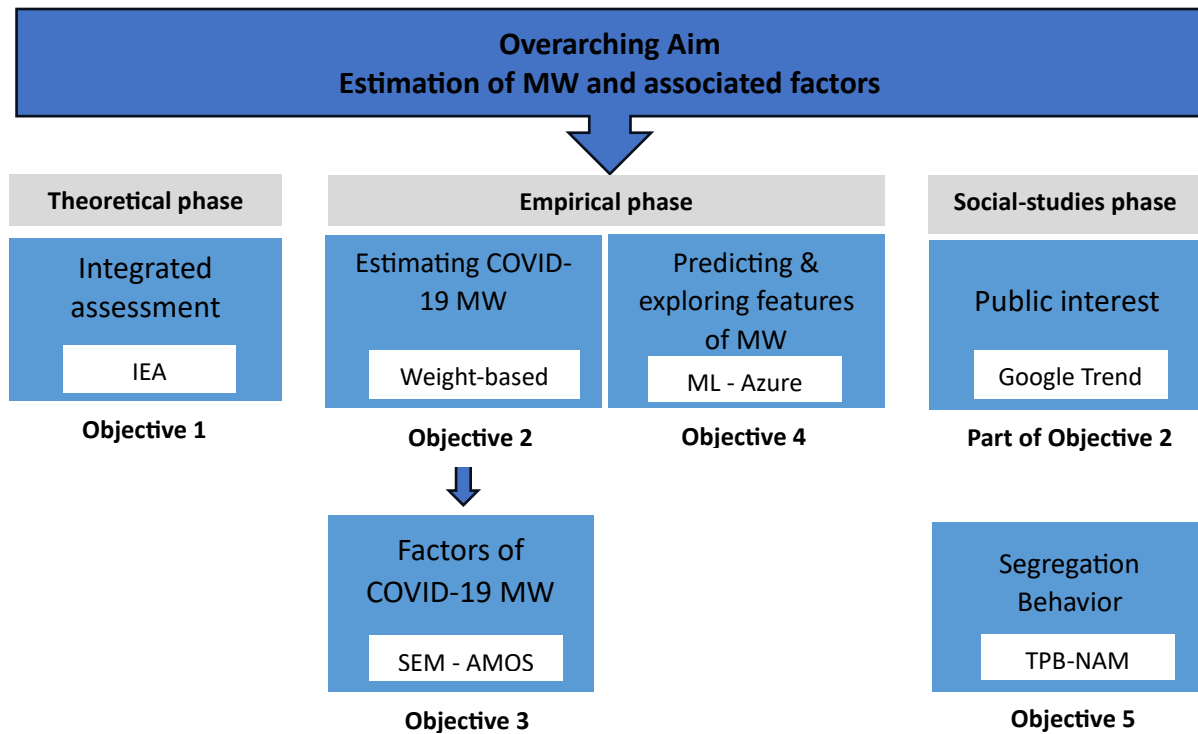


Figure 1.5 Research Framework.

1.8 Research Significance:

Considering the literature review conducted during this study, it was found that no study has been performed on MW in Bahrain for more than a decade. The results and findings of this study may help certain groups. Firstly, the policymakers, estimating and predicting the future amount of MW will help the policymakers in Bahrain in evidence-based decision-making for managing and treating the MW, promoting best practices, establishing comprehensive frameworks, and enforcing compliance with waste segregation protocols, ultimately leading to safer healthcare environments. In addition to taking steps towards mitigating climate change and achieving SDGs, accurate estimation of MW quantities and understanding the factors influencing waste generation are crucial for policy development and regulatory compliance. This research provides valuable insights that can inform the formulation of guidelines and regulations on MW management.

This research is considered the first comprehensive study in the Kingdom of Bahrain and will provide future researchers with accurate, up-to-date, and useful information and quantified data on Bahrain. Moreover, the findings of this research have the potential to drive innovation by fostering the creation of new incentives, such as Non-governmental Organizations (NGOs), that focus on enhancing MW reduction and recycling efforts.

This work contributes to the broader sustainability concept and promotes a circular economy within the healthcare sector. The waste reduction, and recycling principles could be advanced by accurately estimating MW, identifying associated factors, and improving waste segregation practices. It aligns to minimize waste generation, optimise resource utilization, and promote environmentally friendly practices within the healthcare industry.

This study could influence healthcare workers, promoting positive behavioral changes concerning MW segregation. By fostering the health workers' personal norms and positive attitudes and encouraging effective MW segregation practices. Thus, the study contributes to a more environmentally sustainable and safer healthcare environment. Ultimately, this benefits public health and the broader community by promoting the well-being of health workers and handling MW effectively.

1.9 Research Terminology

Terminologies that are used throughout this thesis are defined. The key terminologies are as follows:

Confirmed	Cases meet all the essential criteria for the illness, which may include the presence of a positive laboratory test result or the disease's symptoms (UVAHealth, 2023).
Coronavirus	A viral family comprising seven viruses capable of infecting humans and causing various diseases. Coronaviruses can cause illnesses like the common cold and more severe conditions like Middle East Respiratory Syndrome (MERS) and Severe Acute Respiratory Syndrome (SARS). The COVID-19 disease is specifically caused by the SARS-CoV-2 virus (Yale Medicine, 2022).
COVID-19	Disease resulting from the SARS-CoV-2 virus. The term "COVID-19" is derived from the acronym for "Coronavirus," with "19" signifying the year of its initial identification (UCDAVIS, 2021).
IEA	Integrated Environmental Assessment is an assessment that incorporates environmental, economic, and social aspects in analyzing environmental state and trends connected with policy analysis. It generally involves a broad spectrum of issues, policies, and all environmental aspects. It may include global, sub-global, national, historical and future perspectives in an integrated analysis of change in environment and human well-being (Boileau et al., 2019).
Medical waste	"Any solid waste that is generated in the diagnosis, treatment, or immunization of human beings or animals, in research pertaining

thereto, or in the production or testing of biologicals" (US Congress, 1988).

ML	Machine Learning is a branch of artificial intelligence that uses data and algorithms to progressively simulate human learning processes to enhance accuracy over time (IBM, 2023).
Pandemic	Occurs when a novel virus rapidly transmits among individuals, particularly those lacking immunity against the disease (Yale Medicine, 2022).
SARS CoV-2	The coronavirus's name that causes COVID-19 (UCDAVIS, 2021).
Vaccines	Stimulate the immune system to generate antibodies by introducing weakened or deceased pathogens into the body through ingestion, injection, or inhalation (Yale Medicine, 2022).

1.10 Research Outline

This thesis consists of the following five chapters in addition to the references and appendices.

- | | |
|-----------|---|
| Chapter 1 | Gives a general overview and describes the background, objectives, statement of the problem, research questions, significance of the study and research terminologies. |
| Chapter 2 | Reviews previous studies, research, and reports that address the estimation of MW and explore relevant associated factors to fully understand earlier studies on the same issue. |
| Chapter 3 | Presents the applied methods and techniques for this work and the implementation of the used framework. Moreover, it highlights the data collection and the statistical analysis tools used to do the analysis. |

- Chapter 4 Focuses on the data analysis and results and presents a discussion of the research questions.
- Chapter 5 Concludes the performed study and enlists the recommendations; future research suggestions and limitations are given at the end of the thesis.

Chapter 2

Literature Review and Theoretical Framework

2.1 Introduction

The plan of this chapter is to review various relevant studies on MW, highlight the important issues related to the topic under study and discuss factors related to the MW generation rate. Accordingly, the literature review helped draw attention to the works of past research, essential principles, and suggestions of diverse researchers. Additionally, this review aided in constructing and shaping the methodology for this study. This review is classified into four sections. Integrated environmental assessment for the issues of MW is reviewed in section 2.2. Section 2.3 is dedicated to plastic issues. Section 2.4 provides empirical studies on estimating MW quantities pre- and during the COVID-19 pandemic. Previous studies about the factors associated with MW generation are presented in sections 2.5 and 2.6. Google Trend as a tool to measure public awareness and the theoretical framework to investigate the health worker's behavior toward MW segregation are discussed in sections 2.7 and 2.8. The pivotal findings derived from the literature studies are concluded at the end of the chapter in section 3.9.

2.2 Assessment of Medical Waste Issues

Integrated Environmental Assessment (IEA) is used to assess environmental issues by synthesizing and analyzing existing environmental, economic and social data to determine the state of the environmental issue using Driver-Pressure-State-Impact-Response (DPSIR) framework, policy analysis, including policy type, instruments and effectiveness, and consequently, setting future scenarios and policy options (UNEP, 2019). Numerous studies employed the DPSIR in a wide range of

environmental fields, including hazardous waste and municipal solid waste (Kanwal et al., 2022; Kazuva et al., 2018) and assessing facemask in the environment (Tesfaldet & Ndeh, 2022).

The rise in MW quantities and its mismanagement are growing issues worldwide. Furthermore, during the pandemic and population growth, the demand for medical services increased, producing MW in bulk quantities (Marinković et al., 2008). The DPSIR framework was adopted by the United Nations Environment Programme (UNEP) in 1995, and the Global Environment Outlook GEO assessments until the latest GEO 6 (UNEP, 2019). It represents a systematic analysis where the driving forces of economic and social development cause great pressures on the environment, leading to a dramatic change in the environmental state. Consequently, the change in the environmental state leads to impacts on, for instance, ecosystem health and human well-being. As a result, human responses could be made to address these impacts, like political interventions, social controls, or redirecting investments to influence human activity. Lastly, these responses would directly or indirectly affect the environment's state through the drivers or the pressures. Accordingly, the existing policies frequently need to be assessed and evaluated to tackle the drivers, pressures and impacts of environmental issues (UNEP, 2019).

William Jenkins defined public policy as "a set of interrelated decisions taken by a political actor or group of actors concerning the selection of goals and the means of achieving them" (Jenkins, 1978). There are different policy instruments to monitor and manage MW effectively. The Organization for Economic Cooperation and Development (OECD) (OECD, 2019) have set a range of policy tools, i.e., economic instruments, regulatory instruments, extended producer responsibility (EPR), public information, green public purchasing, monitoring and reporting, and enforcement. Most countries have a broad framework of regulations as a policy

instrument to govern the main waste management aspects. These comprise technical definitions for the main types of waste, including hazardous MW and necessities of waste disposal and treatment to protect the environment and human health (OECD, 2019). For instance, the policy tool “Monitoring and reporting” is vital for effective MW management. i.e., in Colombia, efforts to address waste issues were hampered by poor reporting in different areas, including waste management. In contrast, reforms have led to effective reporting and management of MW in the country. Hence, the OECD Environmental Performance Review called for better enforcement of existing reporting requests (OECD, 2019). Another effective policy tool in the minimization, prevention, and sound management of waste is the “Economic instrument”. Charges and fees are considered economic instruments that can be used to recover the waste management costs and support the user pays principle, ensuring the financial sustainability of waste management services. Both the Rio Declaration and Agenda 21 of the SDG emphasized the importance of economic instruments for environmental policy. Economic instruments embody a tool for national authorities to support the internalization of environmental costs and efficiently employ the polluter-pays principle (Panaiotov, 1994; Panayotou, 1995). In addition, the economic instruments could help encourage the behavior changes necessary to achieve policy objectives, for instance, waste reduction or investment in technology for improved waste treatment (OECD, 2019).

Furthermore, several disposal and treatment technologies are used for MW, such as incineration, pyrolysis, gasification, and carbonization. The pyrolysis method burns the MW in an oxygen-free environment, and this process breaks down the material thermally, releasing volatile gases; these can be captured and used as fuel, bio-oil; a condensable liquid with potential uses as fuel, and char; a solid residue rich in carbon, often used as a soil amendment or fuel source. Gasification is similar to pyrolysis, but with limited oxygen, this creates an explosive gas mixture

(syngas). The carbonization is a method that focuses on maximizing the solid carbonaceous residue, and MW is heated with minimal oxygen (Dharmaraj et al., 2021; Schneider et al., 2017). Therefore, the policies must be reviewed, revised, or approved to deal with MW management, as this waste poses a serious risk to the environment and human health as well.

2.3 Plastic in Medical Waste

Plastic is widely used worldwide and is widespread in medical supplies (McKeen, 2014). Plastic has become a persistent pollutant in all areas, causing severe environmental impacts and threatening wildlife (Wilcox et al., 2015; Worm et al., 2017). Numerous international initiatives have been undertaken to raise awareness of the harmful effects of plastics and induce the use of biodegradable materials as an alternative (Hermabessiere et al., 2017; Lambert & Wagner, 2017; W. C. LI et al., 2016). Incineration is a common method for MW treatment and inactivating pathogens in biohazardous residues (Ghodrat et al., 2017). When plastic is burned, persistent chemical pollutants are released, for instance, dioxin and polycyclic aromatic hydrocarbon (PAH) (H.-Y. Li et al., 2019; Wisniewski et al., 2020). These chemical contaminants are highly dangerous to the environment and human health (Andersen et al., 2018; Lv et al., 2020; Mocarrelli et al., 1996).

There is no doubt that medical plastic waste has potential negative effects (Espejo et al., 2020; Klemeš et al., 2020; Prata et al., 2020; Saadat et al., 2020). For instance, in a disposable surgical mask and a single N95 mask, there are approximately 4.5 and 11 g of polypropylene and/or other plastics derivatives (e.g. polyurethane, polyethylene, polystyrene, polyacrylonitrile, polycarbonate), respectively (Liebsch, 2020). Plastic contains thermoplastic polymer fractions, which may disintegrate into smaller particles (microplastics) due to some factors.

These factors could be UV exposure, high temperature, change in pH, and hydrophobicity (Khoironi et al., 2020).

Polypropylene's complete mineralization/degradation is impossible because of its exceptionally resistant nature, high molecular weight, hydrophobic properties, and high surface roughness (Jiang, 2018). Consequently, a large portion of the polypropylene stays in the environment as microplastics, which could maraud almost every ecosystem (Lant, 2018). Nonetheless, a significant part ends up in the water bodies and reaches the marine environment. In 2020, many facemasks were found on highways and drainage in Nigeria and the Hong Kong oceans, serving as a microplastics source (Fadare & Okoffo, 2020). Fadare & Okoffo (2020) investigated the plastic degradation in the facemasks found in the environment using the FTIR spectra, wherein peaks of polyethylene in the inner layer and polypropylene in the outer layer were observed. Their results indicated that plastic particles could accumulate in the environment rapidly and in a short time. Previously similar results were reported from four sea surface stations along the Arabian Gulf coastline and eight sandy beaches (Abayomi et al., 2017); high proportions of polyethylene (228 particles/m²) and polypropylene (36 particles/m²) were found. It was expected that such a fraction of microplastic would continue growing in the next few years, especially after the COVID-19 pandemic, due to the excessive use of facemasks. It was stated that there are no regulations in many regions of the world, including GCC countries, regarding strategies for microplastic pollution management (Plackett, 2017). This situation may contribute to transmitting pathogens, including coronavirus, resulting in future disease outbreaks.

2.4 Estimation of Medical Waste Generation

A study (N. Singh et al., 2022) showed that the MW generation rate in developed and high-income countries is significantly higher than in low and middle-

income countries. It found that, between 2000 and 2020, among 50 countries from Asia, America, Europe and Africa, the average MW generation rate ranged from 0.3–8.4 kg/bed/day. The highest amount of MW was generated by the United States and Canada, with 8.4 and 8.2 kg/bed/day, respectively. Kazakhstan and Iran produce the highest amount of MW in Asia, with 5.4 and 3.7 kg/bed/day, respectively. While in Europe, Spain and Italy generate the highest MW with 4.4 and 4.1 kg/bed/day, respectively. Greece and Pakistan show the lowest amount of MW generation (about 0.3 kg/bed/day each). Other studies also found similar trends in the MW generation rate, where affluent countries have a much higher generation rate of MW as compared to countries with transitional economies (Figure 2.1) (Ansari et al., 2019; Minoglou et al., 2017; Windfeld & Brooks, 2015).

The higher utilization of healthcare materials and services in affluent countries, driven by improved healthcare services and an ageing population, may explain these differences. Conversely, the economic progress witnessed in developing nations has uplifted numerous individuals out of poverty, granting them access to improved healthcare services. However, the surge in demand for medical resources during the COVID-19 pandemic, as well as in the post-pandemic period, could potentially contribute to a rapid increase in global MW generation (Guterres, 2020; Rahman et al., 2020).

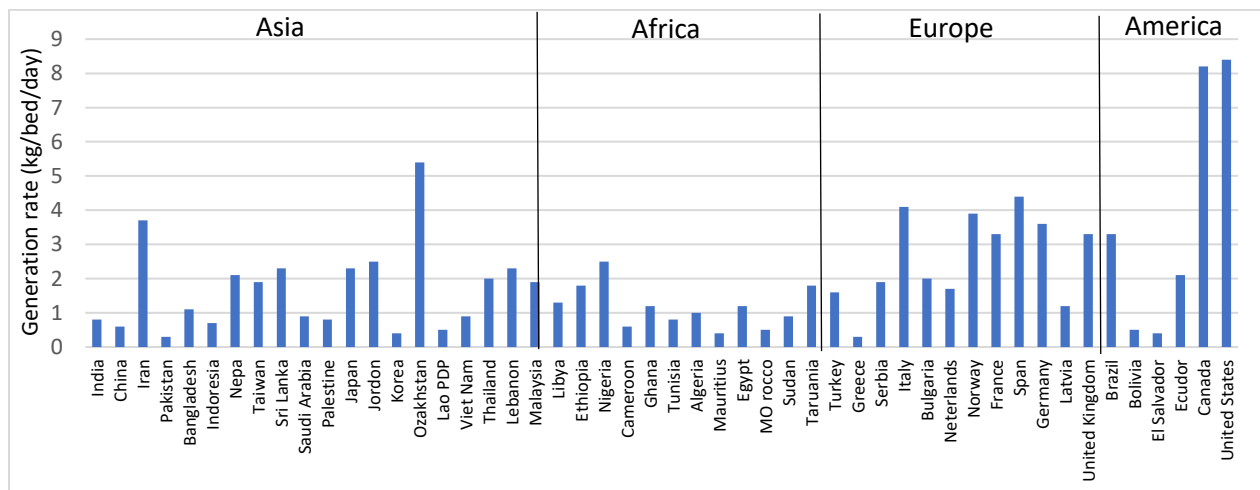


Figure 2.1 MW generation rate in kg/bed/day in some countries in four contents, Source of data: (N. Singh et al., 2022)

2.4.1 Pre-COVID-19 Research Works

In the Kingdom of Saudi Arabia (KSA) in 2018, the production rates in hospitals and health centers were evaluated in a specific sample area in the eastern province (Alagha et al., 2018). The study found the average production per hospital to be 640.74 (± 0.59) tons/year, and per health center was 0.598 (± 0.119) tons/year. The average MW generation rate was calculated as 0.51 kg/bed/day and 1.66 kg/patient/day, and the estimated MW generation in the province's hospitals was about 5781.9 tons/day. In addition, the study exposed that the practice used in all hospitals and healthcare centers in the Eastern Province is to separate MW from other solid waste and collect and transfer it for final dumping in a non-engineered landfill by private authorized companies. Lastly, this study recommended treating the plastic part of the MW at the collection site using autoclave technology and reusing it as fuel in waste-to-energy facilities or as a fuel alternative in the cement industry.

Komilis, Fouki, & Papadopoulos (2012) calculated hazardous MW generation rates in Greece. The study measured the weights of the hazardous MW for 132 healthcare facilities (private and public healthcare facilities) over 22 months between 2009 - 2010, where the waste was regularly transferred to the sole MW incinerator. The study found a considerable variation in the generation rate of hazardous MW, even among hospitals of the same division. The average total generation rate varied from 0.012 kg/bed/day for psychiatric public hospitals up to 0.72 kg/bed/day for public university hospitals. While for the private hospitals, the average generation rate ranged from 0.0012 kg/bed/day for the psychiatric clinics up to 0.49 kg/bed/day for the birth clinics.

A study (Awad et al., 2021) evaluated waste management practices in healthcare facilities operated by the Dubai Health Authority (DHA), United Arab Emirates (UAE) through a survey. One important finding was that the selected hospitals' MW generation rate varied from 0.28 to 0.33 kg/bed/day with an average of 0.3 kg/bed/day.

Mohamed, Ebrahim, & Al-Thukair (2009) investigated the hazardous MW in the Kingdom of Bahrain through a survey, interviews, and facility inspections on selected public and private healthcare premises. The study found that the MW generation rates at the studied healthcare facilities vary from 0.038 to 1.177 kg/patient/day for a small hospital with 10 beds and a vast complex hospital with 882 beds, respectively. These results were consistent with other studies' findings on hazardous healthcare waste generation (Diaz et al., 2008; Mohee Romeela, 2005), in which the generation rate increases with the increase in the size of the facility and its activities. The study also found that the public health service was the main source of the country's total hazardous MW (80%), and 74% of the public health services come from one large facility, SMC. Moreover, the study found that the hazardous MW generation rates at SMC for inpatients and outpatient activities were 1.28 and 0.17 kg/patient/day, respectively. The main operations, pediatrics, internal medicine, obstetrics and gynecology, nephrology and surgery, were found as the main sources of the hazardous MW produced for inpatient activities at SMC. While the laboratory, radiology, sterilization, emergency, and outpatient clinics were the leading sources of outpatient hazardous wastes at SMC. It was also found that each person in the country produced an annual average of 1.45 kg of hazardous healthcare waste.

A study (Jasem M. Alhumoud & Alhumoud, 2007) calculated the amount of different kinds of solid MW in the governmental hospitals of Kuwait. This study assessed all governmental hospitals for six months (September-December 2005 and June-July 2006). The study calculated the weight fraction of each component in the

sorting sample by the weights of the components. In addition, the amount of infectious and non-infectious waste produced in kg/day was determined and recorded in each ward and several hospital blocks. This work found that the waste generation rate was between 3.87 and 7.44 kg/bed/day. Subsequently, 71.44 % was domestic waste (10,534.5 kg), 27.8 % was hazardous/infectious waste (4,099.4 kg), and 0.76 % sharps (112.1 kg). Hospital waste constitutes around 30% of all the hazardous MW resulting in Kuwait. Moreover, most hospitals practice waste segregation, and all medical/infectious wastes are disposed of through incineration.

2.4.2 During COVID-19 pandemic

According to the WHO, the response to the COVID-19 pandemic has generated tens of thousands of tons of additional MW in 2021 (REUTERS, 2022; WHO, 2022). As a result, it placed enormous pressure on healthcare waste management systems worldwide, threatening human health and the environment and exposing a dire necessity to improve waste management practices. In the context of COVID-19, The WHO estimated in a global analysis of healthcare waste that between March 2020 and November 2021, approximately 87,000 tons of personal protective equipment (PPE) were shipped to support the urgent COVID-19 response to the countries' needs through a joint UN emergency initiative. Undoubtedly, these pieces of equipment end up as waste (WHO, 2022).

During the outbreak of COVID-19 in Hubei Province, China, infectious MW rose by 600% from 40 tons to 240 tons per day. Consequently, the existing infrastructure for transporting and disposing of MW around hospitals was quickly overwhelmed. Other countries faced similar challenges, and additional waste management systems were put in place to reduce the spread of COVID-19 and prevent the emergence of other diseases. The Asian Development Bank (ADB) (ADB, 2020) has been a key player in addressing the challenges posed by the COVID-19 pandemic; it has compiled some considerations and suggestions to

support its member countries and enable governments to respond rapidly to these unprecedented challenges. Among ADB's efforts, it has taken on the task of estimating the volume of MW generated during the pandemic. This estimation is crucial for developing effective waste management strategies and allocating resources to ensure the proper disposal of MW, thus safeguarding public health and the environment. The ADB could estimate the amount of MW (in kg) generated during COVID-19 by multiplying the number of infected persons by 3.4 kg. This equation has already been applied in different studies in Asian countries (Al-Omran et al., 2021; Purnomo et al., 2021), which helps the governments to estimate the potential increase in tonnage over time.

Nzediegwu & Chang (2020) highlighted the critical issue of facemasks disposal, which is a significant source of increase in MW, during the COVID-19 pandemic in developing nations. It underscores that improper management of discarded facemasks could contribute to virus transmission. Proper disposal of facemasks is crucial for public health and reducing environmental contamination in the regions. The study estimated the total daily number of facemasks by considering the population size, the percentage of the population residing in urban areas, the rate at which people accept and wear facemasks, and the average number of facemasks used per person per day.

Mihai (2020) estimated the MW generated from the main potential infectious waste sources: COVID-19 patients, ICU patients, self-isolated, and quarantined persons in Romania. The estimation was divided into different stages: prior emergency (February 26–March 15), emergency (March 16–May 14) and alert state (May 15–June 15). The number of patients in each category was available to the researcher, and the generation rate for each category was obtained from the previous studies at the national level. The proposed model in the study estimated the COVID-19 MW flow from February 26 to June 15 to be 4312 tons at the national level, of

which 2633 tons were during the emergency state period (March 16–May 14). The limitation of this study was that the medical/municipal waste generation rates were taken from previous studies. However, in order to adjust waste generation rates and determine the MW composition, experimental studies were suggested to be conducted at various COVID-19 hospitals and isolated/quarantined places.

Abu-Qdais and coauthors (2020) assessed the generation rates and the composition of the MW produced during the COVID-19 period in a major tertiary care hospital, King Abdullah University Hospital (KAUH) in Jordan. The records on MW generation from the hospital sections of the infected patients' treatment, including the laboratory, emergency section, and isolation wards, were obtained daily for 19 days from the Environmental Health Section of the hospital. The number of beds in the studied emergency ward that dealt with the infected cases was 100 beds, and the number of patients varied during the study period. Then, the average generation rate of MW was estimated in kg/bed and kg/patients. Descriptive statistical analysis was applied, such as the 3-day moving average and the frequency distribution of the generated amounts. Besides, the best-fit correlation was applied to assess the impact of the number of infected patients on the MW generation at the hospital. The study found that the average MW generation rate produced due to coronavirus treatment was 14.16 kg/patient/day and 3.95 kg/bed/day, which were higher than the average generation rate during the regular days of the hospital by more than ten-fold. The best-fit correlation showed a positive relationship between the amount of generated MW and the number of patients, with a correlation coefficient of 0.87. Regarding the composition of the MW, it was found that 90% of the consumables used in the hospital were disposables, which was concluded as a reason for increasing the MW generation.

Abbasi and others (2020) quantified facemasks during COVID-19 and calculated the amount of generated (micro-) plastic in the Arabian Peninsula. Firstly,

the study computed the number of facemasks in each Arabian Peninsula country for different levels of average daily usage and acceptance rate using the equation found by Nzediegwu & Chang (2020). Then, the amount of polypropylene in terms of microplastic, which could end up in the marine and terrestrial environment, was calculated. The disposable surgical masks and N95 masks were considered in the study. According to (Liebsch, 2020), most of the masks are multi-layered and are made up of non-woven fabric. Polypropylene is the major component used for making masks. The polypropylene density in two layers of surgical masks is around 20–25 g/m², whereas, for N95 masks, it is around 25–50 g/m². The results were approximately 4.5 g for a single disposable surgical mask and for a single N95 mask, 9 g of polypropylene in addition to a further 2 g of polypropylene in the filter in the N95 mask. For the polypropylene calculation, the study considered 75% usage of disposable surgical masks and 25% usage of N95 masks. The study found that Saudi Arabia contributes up to 32–235 thousand tons of microplastic, which is the highest in the region and represents almost half the amount in the whole Peninsula. The study concluded that high facemask usage would increase the microplastic load in marine ecosystems. Consequently, this will lead to harmful effects that could be observed in the living organisms dwelling in marine habitats besides in corresponding terrestrial habitats. Finally, the study recommended that necessary and timely measures should be taken to prevent any undesirable ramifications in the future.

Nguyen, Kawai, & Nakakubo (2021) conducted a study in Vietnam to estimate the generation rate and the composition of COVID-19 waste. The study relied on the supply of equipment and resources to estimate the generation rate of COVID-19 waste-related sources from April 1, 2020, to March 31, 2021. The study calculated the amount of used PPE and associated it with waste sources, assuming it to be 100% of the supply. It found that 1486 tons of COVID-19 waste were produced

over a year during the pandemic: precisely 4.64 kg/bed/day from the treatment of isolated COVID-19 patients, 3.86 kg/bed/day from quarantine in medical facilities, 46.43 g/bed/day from centralised quarantine, 50 g/test from testing and 10.46 g/shot from vaccination. The study revealed that most of the waste was plastic, with 76.7%. In addition, PPE clothing was the largest component of the plastic in COVID-19 waste, consisting of high-density polyethylene.

A study assessed the environmental impacts caused by the COVID-19 pandemic in Brazil (Urban & Nakada, 2021). The study calculated the quantities of used facemasks in 30 cities using the equation obtained by Nzediegwu & Chang (2020). The estimation showed that more than 85 million facemasks might be disposed of daily. In Brazil, more than 35% of MW has not been appropriately treated, as revealed by the latest data on solid waste. In several cities, improper disposal of facemasks has been reported, which could cause an increase in the risk of COVID-19 spread. There was a high demand for disposable facemasks, and their improper disposal needs to be controlled. Therefore, the Brazilian government have recommended that health workers use disposable masks while the general population can use homemade reusable fabric facemasks by following the WHO recommendations (WHO, 2020b). Where Ho et al. (2020) measured the effectiveness of cotton facemasks as a substitute for disposable facemasks, they concluded that using washable cotton facemasks daily by healthy people in a community is a suitable measure.

As an environmental side-effect of the pandemic, plastic MW was investigated as one of the objectives of a study conducted in Iran in April 2021. The amounts of plastic waste were measured during a single PCR confirmatory test for COVID-19 in the three stages: sample collection, RNA extraction, and PCR amplification, and found as 31.893, 327.655, and 462.23 g, respectively, making a total of 821.778 g of plastic residue/test. This study included all types of required

PPE for conducting a single PCR test by the operator. As a result, the study recommended improving plastic waste management programs (Noorimotlagh et al., 2021).

Celis and others (2021) classified and estimated the amount of plastic generated from COVID-19 diagnostic tests for 125 countries around the world until August 2020. Also, the study analyzed the relationships between the plastics generated and the population size, number of confirmed cases, and Gross Domestic Product (GDP) in each country. It identified and weighed all plastic supplies in the three stages of the diagnostic test: sample collection, RNA extraction and PCR amplification. The study found the weight of a single PCR test to be 37.27 g of disposable plastics. Consequently, as of August 2020, a mass of 15,439.59 tons of plastic residues has been generated worldwide only using PCR tests. It classified the plastic types in the COVID-19 confirmatory test as 33.54 g, corresponding to polypropylene (89.99%), 3.06 g of polyester (8.22%), and 0.66 g of polyethylene (1.78%). The study found that almost 97% of the plastic residues from PCR tests were Biohazardous plastic, which is treated by incineration and releases toxic chemicals into the atmosphere. Moreover, the study concluded that there is no correlation between the amount of medical plastic from PCR tests and population size, the GDP of the country or COVID-19 confirmed cases.

The increasing amount of plastic MW generated from medical services during the COVID-19 pandemic in African countries in 2021 was estimated by Benson and others (2021). The number of used facemasks was calculated using the equation found by Nzediegwu & Chang (2020). Next, the total weights were measured, followed by finding the amount of plastic waste from the used facemasks. The study determined the polymer types in the samples of facemasks collected using Fourier Transform Infrared (FTIR) spectral fingerprint. As a result, facemasks were characterised as consisting of natural and artificial fibres, including natural latex

resin, polyester, and polypropylene. The study revealed that over 12 billion medical and fabric facemasks were disposed of per month, equivalent to about 105,000 tons of facemasks monthly, which could be discarded into the environment by Africans. Moreover, out of 57 African countries, there were 15 countries found to be significant plastic waste contributors, with Nigeria followed by Ethiopia, Egypt, DR Congo, Tanzania, and South Africa topping the list with 15%, 8.6%, 7.6%, 6.7%, 4.5% and 4.4%, respectively. It was published by the government of Dubai, United Arab Emirates (UAE) in May 2020 that over 350 tons of MW contaminated by coronavirus were treated by Dubai Municipality (Dubai, 2020). Alalawi and others (2022) reviewed the environmental implications of COVID-19 in the UAE. The review stated that the UAE was ranked nine out of ten countries with the most plastic residue generation worldwide. Besides, inadequate facemask disposal has caused environmental degradation in the region, mainly in towns and cities where technologies and modern waste collection facilities are insufficient. The review mentioned a study (S. A. Abbasi et al., 2020), that showed that facemasks in the UAE contributed to an increased contamination of the marine ecosystem with microplastics. The study also indicated that microplastics generated from facemasks make favourable conditions for the growth of pathogenic microorganisms, such as bacteria, spores, viruses, and fungal filaments.

A study (D. Singh et al., 2022) estimated the generation of MW and consumption of daily facemasks in Maharashtra, India, from May 2020 to August 2021. Datasets were regrouped and analyzed into three phases based on the number of COVID-19 cases (low, medium, and high). During the three phases, a questionnaire was used to estimate the maximum usage of facemasks for COVID-19 and non-COVID-19 patients. The consumption of facemasks was calculated using the equation of Nzediegwu & Chang (2020). The MW for COVID-19 patients utilizing medical facilities was calculated mathematically by multiplying the number

of all the confirmed COVID-19 cases by the percentage of the patients who use medical facilities, which was assumed as 80%, multiplied by the MW generation rate, which was considered as 3.5 kg/day based on a previous study (Thind et al., 2021), by the percentage of the patients admitted to hospital which was assumed as 50%, divided by 1000. Moreover, the One-way ANOVA test was used to find the influence of COVID-19 cases on MW generation facemask consumption. The results showed that the facemasks consumed by non-COVID-19 patients were more than that consumed by COVID-19 patients. It proved that population growth and urbanization influence the maximum consumption of facemasks. The MW generations were estimated as follows: July 2020 (152 tons/day), August 2020 (228 tons/day), September 2020 (364 tons/day), October 2020 (177 tons/day), March 2021 (405 tons/day), April 2021 (1,102 tons/day), May 2021 (705 tons/day), June 2021 (194 tons/day), and July 2021 (149 tons/day). The MW generation rates exceeded the existing treatment capacity of 132 tons/day. In addition, it was found that the daily emission rates produced from the generated MW incineration were in the order of Particulate Matter PM₁₀ > nitrogen dioxide NO₂ > carbon monoxide CO > sulfur dioxide SO₂. The maximum emission was PM₁₀ (85.61 kg/day). The ANOVA test showed that the growth in COVID-19 cases caused an increase in the consumption of facemasks and MW generation, amplifying the load on the MW incineration facilities.

2.5 Medical Waste Generation and Associated Factors.

Bdour and others (2007) determined the MW generation rate in 14 medium to large-size healthcare facilities in Irbid, Jordan. They developed a model to predict the waste quantities produced by the considered hospitals or similar sites in the city that are not included in the study. To determine the generation rates within the healthcare facilities, all solid wastes produced from each department in hospitals

were weighed for 50 days on a daily basis. Multiple linear regression (MLR) analysis was used to develop the model, with consideration of certain factors, including the number of beds, number of patients, and hospital type (private and public). It was found that the average generation rates of total MW in the hospitals were 6.10 kg/patient/day (3.49 kg/bed/day) for public hospitals, 5.62 kg/patient/day (3.14 kg/bed/day) for maternity hospitals, and 4.02 kg/patient/day (1.88 kg/bed/day) for private hospitals. Furthermore, concerning the medical laboratories, rates were estimated for governmental laboratories to be in the range of 0.053–0.065 kg/test/day and for private laboratories 0.034–0.102 kg/test/day. The study found that all the studied factors were significant.

Cheng and others (2009) evaluated the generated amount of MW and identified the associated factors in Taiwan. The study used data from 150 healthcare facilities for statistical analysis. The data was collected using a questionnaire and on-site visits. The studied factors included types of hospitals and clinics, the total number of beds, infectious disease beds, reimbursement payment by National Health Insurance, bed occupancy, outpatients per day and amount of waste recycled (in tons). MLR was used to find the significant factors. The study calculated the average annual generation rate and daily weight per bed for general and infectious wastes by the type of medical establishment. The average generation rate for general MW was found to be 2.41 - 3.26 kg/bed/day, and infectious waste was 0.19 -0.88 kg/bed/day. Moreover, the average quantity of infectious wastes produced from medical centers was higher than that from regional hospitals (267.8 versus 70.3 tons/year). Furthermore, it was found that the number of beds and the amount of insurance reimbursement were the significant factors for infectious waste. The amount of waste recycled was the significant factor for general waste. The study concluded that the major source of MW in Taiwan is the large hospitals. At all levels of healthcare

establishments, the amounts of MW treated as infectious are much greater than the amount recommended by the relevant authorities in the country.

Tesfahun and others (2016) estimated the amount of MW in Ethiopian hospitals. The waste quantity was estimated by collecting and weighing the generated waste from all departments of the selected hospitals. A longitudinal study design was used to generate data on healthcare waste composition and generation rate and develop predictive models. The MLR analysis was applied to each type of hospital (private, teaching, and public). The study found that the mean generation rates in all hospitals in kg/bed/day for general, infectious, pharmaceutical, sharps, pathological and radioactive healthcare waste were 1.14, 0.74, 0.27, 0.21, 0.09 and 0.02, respectively. The study found that inpatients and outpatients were significant factors in MW generation. A strong linear correlation (r) was found between waste generation and the number of inpatients ($r = 0.965$), but a weak correlation with the number of outpatients ($r = 0.424$).

Wei and others (2021) carried out a study to estimate the generation of MW and pollutants in China from 2002 to 2018 using medical statistical data on a provincial scale. Moreover, to forecast the MW trend in China until 2030, a combination of the time series model Autoregressive Integrated Moving Average (ARIMA) and environmental pressure model (STIRPAT) was used. The factors associated with MW production were therefore identified. The study found that even if there is no pandemic, MW production would still increase by more than 50% by 2030 compared with 2018 due to the vast population. The factors that were found to be causes of explosive growth in MW were the number of people seeking medical treatment, GDP, popularization of medical insurance, inpatients of large hospitals, and population. Moreover, one of the key findings was that in some regions in China, mercury (Hg) emitted from MW was more than that from discharged wastewater.

Singh et al.(2022) identified the factors associated with MW generation in 78 countries with transitional economies using meta-analysis from 2000 to 2020. Five factors, namely, human development index (HDI), life expectancy (LE), healthcare expenditure (HE) per capita of GDP, and environmental performance index (EPI) were studied. For data analysis and correlations, Pearson and Spearman coefficients were used. The study found that all the considered factors were significant to the generation rate of MW.

Endris and others (2022) assessed the MW generation rate and associated factors with waste generation in medical laboratories of public healthcare facilities in Addis Ababa, Ethiopia. The study used health institution-based cross-sectional data from laboratories of 6 hospitals and 20 health centers within the time frame of July 13, 2020 - September 25, 2020. Different statistical techniques, like Pearson correlation, linear, and logistic regression analysis, were used for data analysis. This study found that the average daily generation rate of MW in the medical laboratories was 4.9 ± 3.13 kg/day per laboratory; specifically, for the hazardous waste, it was 3.86 ± 2.66 kg/day, and for the sharp waste, it was 1.10 ± 0.853 kg/day. Another study conducted in Adama, Ethiopia, found that the average daily generation per health facility was 4.46 ± 0.45 kg/day (Hayleeyesus & Cherinete, 2016). The reason behind the difference in the generation rate between the two studies could be that medical laboratories produce a higher quantity of weight-bearing biological waste, like tubes, glasses, sharps, and others (Endris et al., 2022). Moreover, the study found a significant association between the hazardous MW generation rate and the number of patients receiving medical laboratory services per day.

2.6 Prediction of MW Generation and Factors Using Machine Learning.

Direct sampling can be used to measure MW generation rates; however, not all hospitals have enough resources to build a complete database (M Abbasi et al., 2013; Sengupta & Agrahari, 2017). Several methods have been used to predict MW generation rates, including sample surveys, data mining, and models based on influential factors. These models include statistical or conventional methods that are focused mostly on deterministic methods or trend analysis regardless of the dynamic properties of the MW generation (Sengupta & Agrahari, 2017). Consequently, advanced methods are required for data modelling of complex systems, which have acceptable performance in predicting dynamic systems behavior, to build a non-linear relationship between inputs and outputs (Golbaz et al., 2019).

Artificial intelligence (AI) has gained significant prominence and popularity in the past few years due to its exceptional flexibility and demonstrated capabilities in predictive tasks. Generally, the application of AI models in healthcare waste is not as widespread as in other environmental fields. Most of the studies are concentrated on municipal solid waste issues (M Abbasi et al., 2013; Maryam Abbasi & El Hanandeh, 2016; Ali Abdoli et al., 2012; Noori et al., 2009), while the articles tackle the healthcare waste issues are limited (Altin et al., 2023; Erdebilli & Devrim-İçtenbaş, 2022; Hao et al., 2021).

In Bahrain, artificial intelligence (AI) was applied to different types of waste like predicting domestic, commercial and construction and demolition (C&D) (Coskuner et al., 2021), municipal solid waste generation (Jassim et al., 2022), and forecasting daily domestic waste (Jassim et al., 2023). However, there is no application of AI in estimating or forecasting MW and associated factors in Bahrain or even GCC.

It was stated that conventional forecasting techniques are not ideal for accurate prediction of MW generation when there is a scarcity of data or short datasets (Karpušenkaitė et al., 2016). Moreover, Jahandideh et al. (2009) found that the traditional methods of forecasting MW performed poorly; on the contrary, the machine learning (ML) method performed more accurately. ML is a branch of AI and computer science that uses data and algorithms to progressively simulate human learning processes to enhance accuracy over time (IBM, 2023). With an increased number of predictors, traditional regression methods are not enough to accurately predict the MW generation. In contrast, advanced techniques, which utilize more complex and sophisticated algorithms, demonstrate superior and robust results in predicting the amount of MW (Altin et al., 2023). Therefore, more advanced methods like ML algorithms were employed in this study.

Data scientists have highlighted that a universally optimal algorithm for solving all problems does not exist. The algorithm selected is contingent on the nature of the problem, the number of features involved, and the most appropriate model type (Mahesh, 2020). It is evident that ML can be applied to small datasets, and it has revealed the significant growth of the research community focused on addressing the challenges posed by small dataset problems through ML (Kokol et al., 2022). Gheyas & Smith (2010) applied an ML algorithm and demonstrated its practical nature by showcasing its capability to achieve successful predictions even with incomplete or small datasets. For instance, Karpušenkaitė et al. (2016) used ML to analyze short and extra-short datasets that contained 20, 10 and 6 observations. A thorough literature review on predicting MW generation and associated factors has been conducted below; a summary is given in Appendix 1.

Jahandideh et al. (2009) predicted the generation of different types of MW, sharp, infectious, general, and total, in selected hospitals in Fars province, Iran. The study applied artificial neural networks (ANNs) and MLR methods and used a 5-

fold cross-validation procedure to verify the performance of the models. The studied factors were the type of hospital (governmental, private, educational, and non-educational), bed occupancy and hospital capacity (number of beds). The study found that based on root mean squared error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2), the developed model using MLR was poor. The MLR found hospital capacity and bed occupancy to be effective factors. On the other hand, the performance measure of ANNs was high ($R^2 = 0.99$), confirming the good fit of the data. The study mentioned that the success of this approach could be attributed to the non-linear nature of ANNs in solving problems, which makes it possible to relate independent variables to the dependent variable in a non-linear manner. The study concluded that the results obtained through the ANN model are very promising and can play an important role in the development of a better, cost-effective strategy for waste management that can be adapted in the future.

A study aimed to develop a model to predict the amount of healthcare waste in 50 hospitals in Iran (Arabgol & Ko, 2013). The study applied three models based on MLR, ANN, and a combination of ANN and genetic algorithm (ANN-GA). The factors involved were the hospital type, capacity, and bed occupancy. In the study, GA was applied to find the optimal initial weights in the ANN to improve the performance of ANN for prediction. The performances of the three models were evaluated by mean squared error (MSE), and the results were 28.8659, 1930 and 2.9563 for MLR, ANN, and ANN-GA, respectively; therefore, ANN-GA achieved the lowest error. The results showed that GA significantly impacts optimizing initial weights and improving the performance of ANN.

A study conducted by Karpušenkaitė et al. (2016) aimed to develop models to forecast MW generation in Lithuania using short and extra-short datasets: one dataset based on 2012-2013 regional annual data; the second dataset based on 2004–2013 annual national data (long annual data); third dataset based on 2008-2013

annual national data (short annual data) (with 20, 10 and 6 observations). The study used ANN, MLR, partial least squares, support vector machines and four non-parametric regression methods. It studied different factors, such as visits at hospitals, retired residents, new-born, the number of children in the region, average life expectancy, number of beds, patients, bed days and the number of day cases in healthcare facilities, average time spent in the hospital, cases of AIDS, HIV and cancer. Based on RMSE, MAE, and R^2 , the best and most promising results in the regional data case were demonstrated by generalized additive ($R^2 = 0.905$), in the long annual data case, the smoothing splines models ($R^2 = 0.986$) and the short annual data case was the multilayer feedforward artificial neural networks ($R^2 = 0.61103$).

A study (Adamović et al., 2018) developed a model to predict annual hazardous healthcare waste quantities. The study used a general regression neural network (GRNN), a form of ANN model. The model was trained with the biannual data from 28 European Union (EU) countries for the period 2004-2012 and tested with the data from 2014. Different economic, social, industrial and sustainability indicators were used as input variables (16 variables). The model performance was evaluated using R^2 , RMSE, MAE, and the mean absolute percentage error (MAPE). The optimal model was designated using sensitivity analysis and correlation analysis. The results revealed that the predicting capability of the model is high as the prediction was with errors not greater than 25%.

Thakur & Ramesh (2018) studied the production rates of the MW compositions (yellow, red and blue waste) and the associated significant factors on cross-sectional data for May 2015 from 75 hospitals in Uttarakhand, India. The study used MLR and ANN techniques, and the type of hospital and bed occupancy were considered as the studied factors. Also, seasonal variation in the generated MW was investigated on longitudinal data for 2 years (2013 and 2014) using polynomial

regression analysis. The MLR method found both factors as significant contributing towards MW generation. Based on used performance criteria (RMSE, MAE and R^2), the ANN model was much better than MLR. Moreover, the polynomial regression analysis found that the amount of MW was affected by the year's seasons.

Golbaz, Nabizadeh, & Sajadi (2019) carried out a study to estimate MW and associated factors using MLR in addition to several Neuron- and Kernel-based ML methods. The studied factors were the number of wards, active and occupied beds, staff, inpatients, and ownership type and activity years of the hospital. As a result of the study, the neuron- and kernel-based ML methods performed satisfactorily, but Kernel-based models (average MSE = 0.003-0.008 and average R^2 = 0.82–0.86) have performed better results than Neuron-based models (average MSE = 0.009-0.023 and average R^2 = 0.68-0.74). The results also showed that the number of staff and ownership of the hospital were the most significant variables for predicting the rate of MW generation.

A study (Ceylan et al., 2020) aimed to predict MW generation in Istanbul, Turkey, using ML techniques. The authors collected data from three hospitals and used three models: Support Vector Regression (SVR), Grey Model (GM) and ARIMA. The results showed that the ARIMA model had the highest accuracy with RMSE (763.6852), mean absolute deviation MAD (588.4712), MAPE (11.7595) and R^2 (0.9888), followed by the SVR and GM (1,1) models. The study suggested that these models can predict MW generation in hospitals in other cities to help improve waste management planning.

Erdebilli & Devrim-İçtenbaş (2022) developed an ensemble voting regression algorithm through ML algorithms, for instance, random forests (RFs), adaptive boosting (AdaBoost), and gradient boosting machines (GBMs) to predict the MW for Istanbul, in Turkey using official yearly data. The variables studied were the amount of MW, number of hospitals, beds, crude birth rate (CBR), and GDP. The

results revealed that RF performed best in line with MAE, RMSE, MAPE, and R^2 values. Then, these base models were used to construct the proposed ensemble voting regression (VR) model utilizing weighted averages according to the base models' performances. As a result, compared with the three baseline models, the recommended model performed the best and had the lowest RMSE (843.70).

Rashid and other authors (2022) forecasted the MW generation for two years, from 2021 to 2022, in Hospital Taiping, Perak. The study used the Non-linear Autoregressive (NAR) Neural Network method based on monthly data of MW generated from 2018 until 2020, comprising 36 datasets, and R^2 was used for the model performance evaluation. The total MW was predicted for 2020 and 2021 as 397,510.564 kg and 326,608.8845 kg, respectively. The results showed that the NAR Neural Network method is reliable and could effectively forecast MW generation for an efficient waste management plan.

A study (Altin et al., 2023) predicted the amount of MW using Deep Learning and Kernel-based SVM methods for a private hospital in Antalya, Turkey. Maxout activation function for the Deep Learning method and Epanechnikov function for Kernel-based SVM were employed. The model consists of different inputs such as the number of surgeries, inpatients, outpatients, intensive care days, and intensive care patients. In addition, the proposed models' performance was evaluated based on R^2 , RMSE, and MAE. The results showed that both methods were successful in terms of evaluation criteria, but it was observed that the Deep Learning method ($R^2 = 0.466$, RMSE = 0.094, and MAE = 0.079) was more successful than Kernel-based SVM ($R^2 = 0.221$, RMSE = 0.264, and MAE = 0.202). The study concluded that Deep Learning algorithms and Kernel-based SVM could successfully interpret the relationship between model inputs and MW production and efficiently plan MW management.

2.7 Google Trend Tool to Measure Public Interest in MW.

Interest in public health and environmental themes is vital. Public awareness, engagement, and endorsement are necessary to support environmental management plans and strategies, particularly in the long term (Ficetola, 2013). The internet plays a progressively vital role in popular science and science communication. Thus, Google search patterns could be considered a source of information about general interests (McCallum & Bury, 2013; Wilde & Pope, 2013; A. C. Yang et al., 2010). Currently, search patterns can be measured by Google using the tool “Google Trends”. This tool measures how repeatedly a term is searched in Google compared to the total number of searches performed on Google.

In this regard, the potential of the internet was used by most countries as well as the WHO to enhance awareness and educational programs on COVID-19, which consequently could affect the MW generation. Surveying the relative search volumes (RSV) has been considered a method to gain information about public interests, and Google Trends is one of the most commonly used tools for this purpose (Arora et al., 2019; Effenberger et al., 2020). Google Trends has proven to be a versatile tool with applications across various domains, including public health and the environment (Kurniawan et al., 2023). One notable example of the utility of this tool can be found during the COVID-19 pandemic, where it was used to gauge public interest and awareness regarding the disease. Lacitignola & Saccomandi (2021) employed Google Trends to investigate the potential impact of public interest on disease spread in Europe. They looked at the trend of the RSV for the keyword search query ‘Coronavirus’ over a specific period of time. By analyzing the correlation between COVID-19 transmission rates and search queries, researchers found the importance of the role of public awareness in controlling the pandemic.

Google Trends is a tool that Google introduced to the public in May 2006 to support studying trends founded on searches to Google Search (Rech, 2007). Google

Trends provides search volumes that reveal the relative popularity of a search term within a designated region and time (any time between 2004 and the present) (Google, 2022). This analysis allows the relative popularity of specific search terms in a particular category, place, and time range, providing how the terms are popular at a particular time point. The relative popularity is known as a Relative Search Volume (RSV), producing an index with a scale of 0–100 (100 representing the highest relative popularity) (Havelka et al., 2020; Y. Peng et al., 2020). Google Trends tool has been used for environmental and health research (Effenberger et al., 2020; Havelka et al., 2020; Jarić et al., 2020; Lacitignola & Saccomandi, 2021; Y. Peng et al., 2020). The trends and patterns of Google search queries can be investigated through Google Trends (Arora et al., 2019).

Google Trends has been extensively used in environmental research, offering valuable insights into public interest and trends related to various environmental issues (Twentynow, 2022). For instance, Haider (2016) focused on using Google Trends to examine municipal waste sorting for recycling in Sweden, delving into the online search dynamics regarding waste sorting practices. This investigation illuminated shifts in attitudes and policy developments in waste management. However, the use of Google Trends has not been extended to the domain of MW, although its utility in other environmental and waste management research (Ficetola, 2013).

It was found that awareness plays a significant role in influencing an individual's behavior and ability to make decisions (Casali et al., 2013). For instance, there is a significant correlation between the awareness generated by the environmental crisis and the behavior of individuals when it comes to the separation of MW (F. Chen et al., 2021). Thus, this work provides a platform for dealing with such an abnormal waste generation during a pandemic.

2.8 Theoretical Framework and Hypothesis Development for Investigating Health Workers' MW Segregation Behavior

MW is classified into different types depending on the source and risk factors linked to their storage, handling, and ultimate disposal, as explained in section (1.2.2). It is vital to use rigorous segregation approaches to reduce the quantities of generated hazardous MW (Al-Omran, Abahussain, et al., 2023) and to minimize emissions (Alvim-Ferraz & Afonso, 2005) and only incinerate wastes that are designated by the law for incineration. It was found by Alvim-Ferraz & Afonso (2005) that the amount of waste that has to be incinerated can be reduced by 80% if a rigorous segregation program is implemented. As a result of a reduction in the MW quantity that is incinerated, there will be a reduction in the amount of pollutants emitted; for instance: dioxins, 99.5%; particulate matter, 98%; Arsenic, Cadmium, Chromium, Manganese and Nickle 90%, 92%, 84%, 77% and 92%, respectively; SO₂ and NO₂, 93%; CO and Hydrochloric Acid, more than 99%; and Mercury and Lead practically eliminated (Alvim-Ferraz & Afonso, 2005).

Correct segregation of MW is the responsibility of the individual who generates each waste item, irrespective of their position in that facility. The healthcare facility's management is responsible for ensuring the proper segregation and that all staff comply with the correct procedures (Chartier, 2014).

Therefore, it's important to investigate the health workers' behaviour toward MW segregation in their workplace.

2.8.1 Norm Activation Model (NAM)

The NAM, developed by (Schwartz, 1973), basically focuses on investigating pro-environmental and altruistic behaviors. Pro-environmental behavior is portrayed

as pro-social behavior as it has beneficial effects on others; it involves behaviors that decrease a person's harmful impact on ecosystems shared by diverse human and non-human inhabitants (Steg & De Groot, 2010). In the NAM model, intention/behavior is a function of personal norms (PN) that are measured by awareness of consequence (AC) and ascription of responsibility (AR) (Schwartz, 1977). The term AC refers to a person's consciousness relative to the potential outcomes that may result from their behavior, whether positive or negative. The AR refers to whether the individual will be responsible for the corresponding act. The PN is the belief in whether the behavior is morally acceptable, driving one's own choices and actions accordingly (Rezaei et al., 2019).

The NAM has been used widely to study pro-environmental behaviours (Han, 2014, 2015; Vaske et al., 2015), transport studies (Bamberg et al., 2007), and energy studies (Van der Werff & Steg, 2015; B. Zhang et al., 2013; Y. Zhang et al., 2013). These studies have proved the potency and appropriateness of NAM in pro-environmental behaviour investigation. For instance, based on the NAM framework, Wang et al. (2019) examined the waste segregation intention of residents in China. The data was collected through a questionnaire survey, and structure equation modelling (SEM) was used for data analysis. The study proved that the resident's awareness of consequences is significantly and positively related to the ascription of responsibility, and there are positive and significant relationships between both of them and personal norms. Also, it found a significant relationship between Personal norms and waste segregation intention.

The following hypostases are proposed in the present study, as shown in Figure 2.2:

Hypothesis 1 (H_1): The AC of MW segregation has a significant influence on AR.

Hypothesis 2 (H_2): The AR has a significant influence on health workers' PN.

Hypothesis 3 (H₃): The AC toward MW segregation has a significant influence on the PN of health workers.

Hypothesis 4 (H₄): The PN of health workers has a significant influence on their intention to segregate MW.

Hypothesis 5 (H₅): The PN of health workers has a significant influence on their MW segregation behaviour.

2.8.2 Theory of Planned Behavior (TPB)

TPB was developed by Ajzen (1991), derived from the Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1988), and has been proven as a robust framework and effective in accurate prediction, and extensively used for examining behaviors across different research fields as a highly popular socio-psychological theory (Arkorful, Hammond, et al., 2022; Arkorful, Lugu, et al., 2022; Armitage & Conner, 2001). Three main components make up the TPB: attitude toward behavior, subjective norm (SN), and Perceived behavior control (PBC) (Klöckner, 2013). A person's attitude refers to the degree to which they evaluate a specific behavior positively or negatively, depending on their perception (Abrahamse et al., 2009). SN is the perception of social pressure from other people that makes one behave or not; in other words, it refers to the degree to which an individual perceives how much others approve or disapprove of a particular behavior (J. J. Kim & Hwang, 2020). PBC shows a person's belief that he or she will be able to succeed in a behavior, i.e., one's perception of how easy or difficult it is to perform a particular behavior (J. M.-L. Wu et al., 2017). It also mediates the intention of a person to perform a specific behavior (Gao et al., 2017). The TPB is robust and widely implemented in empirical studies on predicting pro-environmental behavior, including recycling (Botetzagias et al., 2015; M.-F. Chen & Tung, 2010), energy use efficiency (Bhutto et al., 2020;

Gao et al., 2017), and technology adoption for environmentally sustainable development (Sopha & Klöckner, 2011).

Tudor et al. (2007) examined the main factors that associate intended behaviour and actions for sustainable healthcare waste management within a large organisational setting in the UK. The study implemented waste bin analysis and TPB framework through a questionnaire approach to 566 employees in Cornwall National Health Service (NHS), and regression analysis was used for data analysis. The study found the occurrence of an intended behaviour–action gap in the waste management actions of the staff. This gap was caused by the attitude and beliefs about the urgency of waste management as a problem, the advantages of recycling, and whether recycling was a matter of concern for the employees. Moreover, the study proved the benefit of TPB as a robust framework for predicting behaviours in healthcare waste management.

Mouloudj et al. (2023) investigated the factors influencing intentions for medication waste reduction during COVID-19 in Algeria. The study used the TPB framework and incorporated three additional constructs of environmental awareness, moral obligation, and medication waste risk perception. A questionnaire survey was used to collect data from 225 responses. The study found that positive attitudes, moral obligation, SN, environmental awareness, PBC, and greater perceived risks significantly and positively influence the intention to minimise medication waste. Moreover, it was stated by the study that a gap between the intention of the behaviour and the actual behaviour could occur, and future investigation to study this gap was recommended.

It's essential to ensure whether the intention will lead to taking action because, in the fields of social science and psychology studies, there are differences between what individuals intend (intentions) and what is truly done (behavior)(Tudor et al., 2007). Differences between intentions and actions in sustainable waste management

have been debated by several studies in environmental management (McDonald & Ball, 1998; Robinson & Read, 2005; Tonglet et al., 2004; Tucker, 2001). Tudor et al. (2007) found the presence of an intended behavior–action gap in the healthcare waste management behaviors of employees in large organisations within the UK. Further studies were recommended by Mouloudj et al. (2023) to investigate the factors that influence actual pro-environmental behavior.

The following hypotheses are proposed in this study, as shown in Figure 2.2:

Hypothesis 6 (H₆): Health workers' attitudes toward MW segregation have a significant influence on their behaviour intention.

Hypothesis 7 (H₇): Health workers' SN toward MW segregation has a significant influence on their behaviour intention.

Hypothesis 8 (H₈): Health workers' PBC toward MW segregation has a significant influence on their intention.

Hypothesis 9 (H₉): Health workers' intention toward MW segregation has a significant influence on their behaviour.

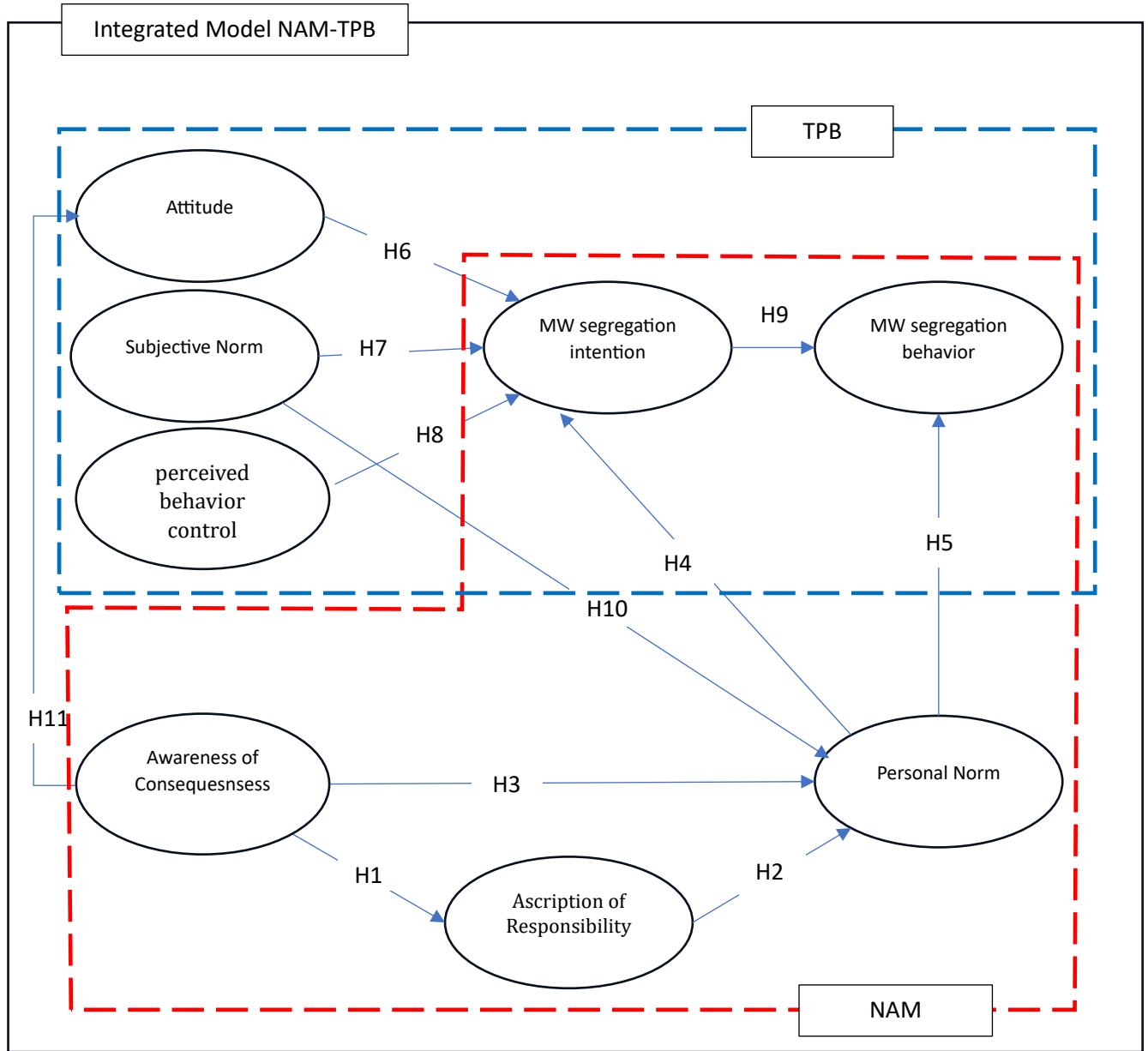


Figure 2.2 Theoretical framework of integrated model.

2.8.3 Integrating TPB and NAM models.

The NAM and TPB are fundamental binary theories that assess and predict individual behavior (Si et al., 2021). The strength of TPB and NAM can be found in their ability to predict and interpret social and psychological factors (Ru et al., 2019; S. Wang et al., 2019). Various studies have proven the predictive potency of integrating these theories (Y. G. Kim et al., 2018; S. Wang et al., 2019; H. Zhang et

al., 2017). Applying these combined theories has been demonstrated in research and practice across various fields, including environmental studies. In recent years, various researchers have applied the TPB in integration with other models or theories for better studying human behavior related to the environment, particularly waste management (Concari et al., 2020; Ding et al., 2023).

Wang et al. (2018) investigated the residents' behavior intentions toward e-waste recycling in Shandong Province, China. The study combined TPB and NAM and analyzed the influence of information publicity through a questionnaire design with 462 responses. The study used SEM for data analysis. The results showed that the behavior intentions toward e-waste recycling are not directly affected by information publicity but indirectly affected by two mediating variables: the recycling attitude and personal norm. The findings of this study support the salience of an expanded model of the NAM and TPB.

Arkorful, Shuliang, & Lugu (2023) investigated household waste separation behavior by combining TPB and NAM in Ghana. Data were obtained from 707 households using the questionnaire survey and analyzed by means of the SEM technique. A number of relationships between constructs were confirmed. The study verified the appropriateness and effectiveness of the integrated model for predicting behavior.

Arkorful, Lugu, & Shuliang (2021) assessed the behavior of mask waste separation in Ghana during the COVID-19 pandemic. The study used an integrated model of the TPB and the NAM. Through a questionnaire survey approach, data was collected from 570 respondents, and the SEM technique was used for the data analysis. The study found significant relationships between the ascription of responsibility and other constructs, except attitude, and relationships between awareness of consequences and other constructs, except attitude. Also, relationships

between subjective norms and the constructs: personal norm, attitude, and perceived behavior control were significant.

The suggested hypotheses in this study are:

Hypothesis 10 (H_{10}): Health workers' SN has a significant influence on their PN.

Hypothesis 11 (H_{11}): Health workers' AC has a significant influence on their attitude toward MW segregation.

All the proposed hypotheses in the integrated model are illustrated in Figure 2.2.

2.9 Chapter Summary

This chapter can be summarized as follows:

- Integrated assessment is considered crucial for addressing any environmental issue. After reviewing the IEA, it has been implemented in different environmental fields including different types of wastes, however, it has not been applied for investigating the MW issues, figuring out the driver forces and pressures and identifying their impacts on the environment and humanity, or studying the MW policies comprehensively. Consequently, this integrated assessment can result in the development of future scenarios, policies, options, and suggestions.
- A detailed and comprehensive literature review related to the predicted factors associated with MW generation is accomplished. The review shows the importance of this work and identifies the scientific gap therein. It revealed that many studies have attempted to identify factors associated with healthcare waste generation in different regions of the world. Besides, different authors

have studied internal and external factors. Nonetheless, no study has been conducted on identifying the factors associated with COVID-19 MW.

- There was a lack of research on the topic of MW estimation in GCC countries in general, where most of the studies in the literature were about the related MW management and challenges related to storage space, transportation logistics, and knowledge and awareness of the medical staff. Despite the COVID-19 pandemic leading to a surge in the quantity of MW, research specifically addressing the estimation of MW during this period in GCC countries has been relatively limited compared to other regions.
- In the literature, there was only one study about MW in Bahrain, conducted more than a decade ago, in 2009. The study focused mostly on the healthcare waste management status in the Kingdom.
- The study conducted in Bahrain showed that the hazardous MW generation rates were 0.038 kg/patient/day for a small hospital with 10 beds, and 1.177 kg/patient/day for a vast complex hospital with 882 beds. 74% of the public health services come from the large facility SMC. Each person in the country produced an annual average of 1.45 kg of hazardous healthcare waste.
- Knowing the extent of people's interest and whether there is a movement regarding the problem of increasing MW generation in the abnormal situation of the COVID-19 pandemic is a key step. This is to draw people's attention to this problem, especially the decision-makers, to keep all the dealing hands vigilant to cope with the situation.
- Statistical methods have been used to predict MW amounts and identify significant factors related to the generation of MW. By reviewing the statistical techniques and models, it was found that most of the studies used multiple linear regression. Other studies used time series forecasting, like the

ARIMA model. Others used the STIRPAT model, a combination of a statistical modelling framework and environmental and sustainability studies.

- The application of AI in predicting the amount of MW had a prominent role in proving the high level of accuracy. It can explore the significant features that lead to MW generation. One study used an ensemble model that encompasses three different algorithms: RF, AdaBoost and GBM.
- To predict the MW generation and determine the significant factors, it is essential to focus on the public and private healthcare sectors, thus leading to plan and managing the MW effectively.
- Numerous studies have laid important groundwork, confirming the suitability of integrating TPB and NAM theories for behavior analysis. Nevertheless, there is a lack of literature regarding the behavior of health workers related to MW segregation.

Chapter 3

Methodology

3.1 Introduction

This chapter presents the methodology used in this work, the data collection methods, analytical techniques, and tools. Integrated Environmental Assessment as a tool for assessing the MW issue, estimation of MW during the COVID-19 Pandemic in Bahrain and other selected GCC countries, Google trends, estimating MW and associated factors during COVID-19 and the normal situation using ML, and assessing MW segregation behavior of health worker all are presented in section (3.2). The tools used to perform the data analysis and the ML experiments are given in section (3.3). Finally, the data collection and source of this study are discussed in section (3.4).

3.2 Methodologies

This study used a mixed method approach, a comprehensive research strategy combining quantitative and qualitative research methods. Qualitative research methods, such as semi-structured interviews with some of the key stakeholders, were employed to gather rich, context-specific data that delved into the intricacies of the MW topic. Quantitative methods like experiments, surveys, and statistical analysis were applied, which added rigor and provided statistical evidence.

Using this approach, the study aimed to take advantage of quantitative and qualitative research strengths, which led to a more well-rounded and comprehensive understanding of the research questions. Therefore, a holistic view that combines the depth of qualitative insights and the breadth of quantitative data is fostered, which

enhances both the overall robustness and validity of research findings (Creswell et al., 2003).

3.2.1 Integrated Environmental Assessment (IEA)

The rise in MW amount and mismanagement are growing issues worldwide. Population growth causes an increase in the demand for medical services thus producing MW in bulk (Marinković et al., 2008) and many other driving forces and pressure for these issues. To study these drivers and pressures and investigate their impact and the associated policies, the DPSIR (drivers, pressures, state, impact and response) framework was used.

Policies must be reviewed, revised or approved to deal with MW as this waste poses a high risk to the environment and human health as well. Therefore, effective disposal and treatment should be adopted, and all countries and communities must be well-equipped for any unwanted situation in the future (Ilyas et al., 2020).

The IEA methodology was adopted in this research; it could answer the five questions shown in Figure 3.1 using the DPSIR framework, policy analysis, including policy type, policy instruments and effectiveness, and finally, the future scenarios and policy options (UNEP, 2019).

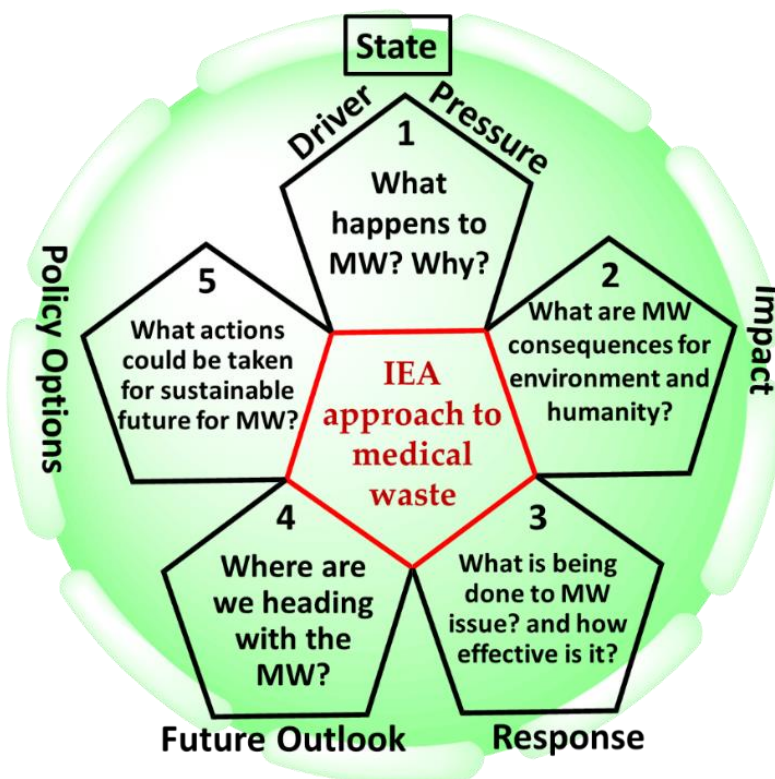


Figure 3.1 Integrated Environmental Assessment-IEA approach to medical waste (Al-Omran, Abahussain, et al., 2023).

3.2.2 Estimation of MW During COVID-19 Pandemic in Bahrain

The amount of waste generated during the pandemic period in the Kingdom of Bahrain resulted from different sources and activities were estimated: waste produced by COVID-19 cases, COVID-19 diagnostic tests, vaccination, and PPE used in healthcare facilities. The weights were measured using an analytical balance scale.

Besides the pandemic, the waste being generated is of great concern to environmental scientists. Several groups have highlighted the high risk of a pandemic in various parts of the world. The Asian Development Bank (ADB, 2020) proposed an equation (Eq. 3.1) to estimate the MW produced by COVID-19 infected cases in Asian countries and numerous studies have applied this equation (Lunag et al., 2023; Purnomo et al., 2021). The equation (Eq. 3.1) was applied in this study to

estimate COVID-19 medical waste (CMW) generated from the infected persons in Bahrain since the pandemic started, i.e., from February 24, 2020, until May 31, 2021.

$$CMW \text{ of infected cases (kg/d)} = \text{Number of infected persons} \times 3.4 \quad (\text{Eq. 3.1})$$

COVID-19 medical waste (CMW) in this study refers to MW that was generated during the COVID-19 pandemic.

Trend line refers to a best-fit line, and it is used to characterise a set of data's behavior to determine a particular pattern. Moreover, the trend line is an analytical tool often employed with a two-dimensional graph of ordered pairs. The trend line can predict future data points (Study.com, 2021). Trend line analysis was used to predict the number of newly infected people and the generated amount of CMW in Bahrain.

The following equation Eq. 3.2 was used to estimate the number of daily facemasks in this study, as proposed by Nzediegwu & Chang (2020):

$$\text{Total daily facemasks} = P \times UP (\%) \times FM.A (\%) \times DFM / 10,000 \quad \text{Eq. 3.2}$$

P is population, UP is urban population, $FM.A$ is facemask acceptance rate, DFM is average daily facemasks per capita.

By following the literature (Nzediegwu & Chang, 2020) and due to the government of Bahrain's strict implementation of facemask policies, it was assumed that the facemask acceptance rate is 80%. Based on the literature (H.-l. Wu et al., 2020), the assumption that everyone in the general population uses one face mask daily was considered. It is worth mentioning that the term 'urban population' refers to the number of people living in an area that is considered an urban area by the national statistical offices. This calculation is based on the urbanization ratios from the United Nations World Urbanization Prospects as well as population estimates from the World Bank (The World Bank, 2022a).

The mass of all PPEs used in the five healthcare centers was determined for representative samples using an analytical balance. Posteriorly, the daily weight of PPEs in each center was calculated by Eq. 3.3.

$$\text{Daily PPE's weight (kg/d) per center} = W_{PPE} \times T_{workers} \quad \text{Eq. 3.3}$$

Where W_{PPE} is the average PPE's weight per worker, $T_{workers}$ is the total number of workers

The vaccination set, including a syringe, glass vial, and alcohol swab, was weighed to calculate the waste generated from vaccination. The total waste weight generated from all the vaccinated people was calculated using Eq. 3.4.

$$\text{Total waste weight of vaccination in kg} = W_{vaccine\ set} \times N_{vp} \quad \text{Eq. 3.4}$$

Where $W_{vaccine\ set}$ is the weight of the vaccine set, and N_{vp} is the number of vaccinated people.

To calculate the weight of waste generated from COVID-19 tests, the items of the test kit comprising a nasopharyngeal swab and a bottle of a chemical preservative were weighed. The total waste weight generated from all the COVID-19 tests performed was determined using the equation Eq. 3.5.

$$\text{Total waste weight of COVID-19 tests in kg} = W_{test\ kit} \times N_{tests} \quad \text{Eq 3.5}$$

Where $W_{test\ kit}$ is the weight of the COVID-19 diagnostic test kit, and N_{tests} is the total number of tests performed

3.2.3 Estimation of Medical Waste During COVID-19 in Other GCC Countries

The quantities of generated MW due to COVID-19 infection were estimated in other GCC countries including Bahrain; CMW generated from infected cases,

daily facemasks, vaccination, and COVID-19 diagnostic tests. The quantities were measured using the same methodology applied in Bahrain, explained in the previous section (3.2.2).

Advanced time series forecasting techniques were employed to forecast the amount of CMW generated by infected cases, using the Autoregressive Integrated Moving Average (ARIMA) model. ARIMA has been used widely in COVID-19 epidemic analysis (Cihan, 2021; Maheshwari et al., 2020).

ARIMA model was developed by Box and Jenkins (1976), and it is an autoregressive time series method that predicts future short-time values by analyzing historical data time series. It is a combination of Autoregressive (AR), which illustrates the relationship between present and past values, and Moving Average (MA), which reveals the present value's association with past residuals (Alabdulrazzaq et al., 2021; Owusu-Sekyere et al., 2013).

Knowing the quantities of MW generated in a pandemic could be helpful for the planning and designing of future facilities and MW management. In the event of any pandemic, it would be critical for all involved to remain vigilant in order to cope with the situation, which could create a platform to deal with the abnormal generation of MW during such events. Therefore, it's imperative to investigate the public interest in medical waste matters, especially during abnormal situations, and this work could draw people's attention to the problem. The public interest in the issue of MW was compared and analyzed with the generated CMW quantities in GCC using the Google Trend tool. Google Trends was used to access data on internet user search activities in the search queries in GCC for the search keywords; 'medical waste', 'Facemask', 'COVID-19 vaccine', and 'COVID-19 testing'.

3.2.4 Factors Associated with COVID-19 Waste Generation

According to the literature and scientific database, during COVID-19, studies were carried out about MW generation, treatment, and management, in addition to identifying generally associated factors with the generation rate. But no study exists exploring COVID-19 related factors to the increasing MW generation. Therefore, to make up for this deficiency and take the necessary measures to address the medical waste threat arising from future public health emergencies, this work is carried out using COVID-19-related public medical statistics for the potential factors.

To have an effective MW management system, it's imperative to care about the quantities of generated MW and the influencing factors. Since the COVID-19 pandemic started in Bahrain, the government has intensified its efforts to preserve the people's health and safety and raise its preparedness level through a wide range of decisions, preventive measures, and precautionary measures. These have contributed significantly to reducing the impact of the virus. These efforts align with the Government's Action Plan (2019-2022), which seeks to promote sustainability and keep pace with developments regulating various sectors (Portal, 2022a).

3.2.4.1 Selected indices and hypothesis development

The factors associated with COVID-19 waste (CW) generation were explored. The CW in this study refers to the waste generated in different healthcare facilities that deal with COVID-19 diseases in Bahrain, for instance, assigned words in SMC for treating COVID-19 cases, vaccination centers, testing centers, including the airport, causeway, and drive-through centres and others. CW is collected and treated by BWTC. The potential factors related to COVID-19 that are described below were selected to investigate the main factors associated with CW generation.

The presence of potential correlations between the CW generation and selected factors in Bahrain was examined. After conducting an intensive literature review, the

following hypotheses were put forth, along with explaining the five predictors used in this investigation:

New cases: new cases are the number of daily infected people by COVID-19. The MW generated during the pandemic is related to the number of infected cases as investigated by the ADB (ADB, 2020). Many studies in Asian countries estimated the quantities of MW through the number of COVID-19 cases (Al-Omran et al., 2021; Al-Omran, Khan, & Perna, 2023; Purnomo et al., 2021).

Hypothesis 12 (H_{12}). The number of new COVID-19 cases is significantly related to the CW generation.

New Vaccination: In Bahrain, the proportion of people who received COVID-19 vaccination with at least one dose is 84% till September 17, 2022 (Our World in Data, 2022c). Here, the daily accumulated number of vaccinations was obtained from the database, and then the number of vaccinations for each month was calculated separately, which is denoted here as a new vaccination. It was reported that, with the increase in vaccination campaigns and the acceleration in COVID-19 vaccine development, there had been an extensive surge in the amount of plastic, rubber and glass resulting from vaccination activities (Phadke et al., 2021).

Hypothesis 13 (H_{13}). The number of vaccinations is significantly related to the CW generation.

New deaths: As mentioned by WHO, the dignity of the dead body with suspected or confirmed COVID-19 should be respected by all measures. For instance, the body of a person who died from coronavirus should be hastily disposed of (WHO, 2020a). The safety of those who interact with dead bodies is dangerous. It was clearly guided by the Inter-Agency Standing Committee (IASC); it's imperative to ensure that the infection prevention and control (IPC) standard precautions are applied by the

people who interact with the dead body, i.e., the team preparing the body for healthcare or burial or cremation or mortuary staff. Including use of the appropriate PPE (medical mask, gown and gloves as well as eye protection, like goggles or face shield), in addition to hand hygiene before and after interacting with the patient's body and the environment (WHO, 2020a; Yaacoub et al., 2020). Therefore, with the increasing number of COVID-19-related deaths, CW undoubtedly increases. It was found that the COVID-19 death rate is considered a source of increasing the amount of waste generation (Chowdhury et al., 2022).

Hypothesis 14 (H_{14}). The number of new COVID-19 related deaths is significantly related to the CW generation.

New PCR tests: Since the pandemic's prevalence, governments and health officials worldwide have sought to combat COVID-19 and have introduced mandatory preventive measures, i.e., screening tests against coronavirus (Bashir et al., 2020). As a result, the MW generation rate, including diagnostic tests, has increased all around the world, which threatens the environment and public health (Al-Omran et al., 2021; Teymourian et al., 2021). Bahrain was keen to intensify the diagnosis of the coronavirus to limit the coronavirus spread. Therefore, medical test facilities for COVID-19 were provided at several points, for example, government and private hospitals, Bahrain International Exhibition and Convention Center in halls and drive-through facilities, and on arrival from abroad at Bahrain International Airport (MOH, 2021a).

Hypothesis 15 (H_{15}). The number of COVID-19 tests is significantly related to the CW generation.

Stringency Index: The stringency index is calculated as the mean score of the nine metrics: school closures, cancellation of public events, workplace closures, restrictions on public gatherings, stay-at-home requirements, closures of public

transport, public information campaigns, international travel controls and restrictions on internal movements. The index takes a value between 0 and 100, where a higher score (i.e., 100) shows a stricter response. This index is developed by the Oxford Coronavirus Government Response Tracker (OxCGRT) project, and it designates the strictness of government policies toward combating the pandemic. The index scores data were obtained daily, and then in this study, the average for each month was taken to associate with monthly COVID-19 waste. The stringency index is tested as a moderator for the relationship between the significant predictor and the CW generation; therefore, the hypothesis put forth as follows;

Hypothesis 16 (H_{16}): The stringency index significantly moderates the relationship between the significant predictor and the CW generation.

The above factors are assessed in this work as major sources of increasing quantities of CW in Bahrain.

3.2.4.2 Structural Equation Modelling (SEM) and Statistical Analysis

Firstly, graphical representations were employed to inspect the patterns of the predicted variables by visualizing the trend of the potential factors and comparing them with the CW generation. Also, a heatmap matrix was figured out to analyze the relationship between the examined indicators and CW production to figure out the influencing factors of CW.

SEM is a method used to estimate, represent, and test a theoretical network of generally linear relations among variables that might be either directly observable or unobservable and only be measured imperfectly. This method is a generalization of both factor analysis and regression, and it mainly encompasses the methods of linear modelling as "special cases" (Shi et al., 2018). In this work, the SEM was employed using Analysis of Moment Structures (AMOS) software to verify the relationship between CW quantities and the selected exploratory variables. The SEM can

effectively deal with the structural relationship among multiple variables, integrate the factors and path analysis methods, and overcome the collinearity among independent variables. Thus, the SEM technique effectively verifies the causal relationship between variables (Shi et al., 2018).

SEM is mainly applied to check the validity of a certain model rather than to determine a suitable model. Thus, it is likely a confirmatory method rather than exploratory. However, the SEM technique often comprises a certain degree of exploratory analysis (Dragan & Akhtar-Danesh, 2007). The SEM has been widely implemented to analyze the complex relationship between socio-economic and environmental indicators (da Rosa et al., 2021; Rathore & Sarmah, 2021). Therefore, this study set up SEM to explain the interaction among the selected indicators. The goodness-of-fit indices of the model resulting from SEM were tested; the common threshold included the chi-square standardized to the degree of freedom ($\chi^2/df < 3$), relative index of fit (RFI > 0.9), normed fit index (NFI > 0.9), comparative fit index (CFI > 0.9), root mean square error of approximation (RMSEA < 0.08), and root mean square residual (RMR < 0.08) (Schreiber et al., 2006; L. Shen et al., 2019).

After finding the significant factors, the effects of COVID-19 policies ("stringency index") as a moderator for the relationship between the only substantial factors and CW were tested. Thus, the moderator variable "stringency index" was entered into the model, and the visualization technique was used to illustrate the moderator's effect further.

3.2.5 Estimating MW and Associated Factors in Normal Situations Using Machine Learning

3.2.5.1 Datasets and Selected Variables

Two hospitals, one governmental and one private hospital, were selected to investigate factors associated with MW in normal situations.

Salmaniya Medical Complex (SMC) is selected for this study because it is the largest public healthcare facility in the Kingdom of Bahrain and provides all kinds of healthcare needs for Bahrain's citizens and residents. It also serves as a teaching and research center for healthcare professionals (MOH, 2023). The SMC has been providing medical care to the people of Bahrain since 1959 and is the most visited medical facility in the country. With a full range of services and specialized departments, SMC was relaunched in 1978 and continues to meet the healthcare needs of citizens and residents (Portal, 2022b). It was chosen as a representative government healthcare facility. The first dataset was set up for SMC (the government hospital), consisting of the generated MW quantities in kg as the predicted variable, and the number of inpatients, outpatients, surgeries and hospital capacity (beds) are the predictor variables. Only recently has a hazardous waste collection system and health data recording been created in SMC. Therefore, the study's access to more extensive data and sets of relevant data for its research has been somewhat limited. It's noteworthy that, during the COVID-19 pandemic, SMC has emerged as a key healthcare facility in Bahrain, responsible for diagnosing and treating COVID-19 cases. Consequently, the quantity of MW generated from COVID-19-related activities has witnessed a significant surge. Therefore, the data related to COVID-19 waste was excluded from the dataset in this part to focus on the influenced factors during normal situations and without the impact of abnormal conditions.

A private hospital PH, healthcare facility was selected because it is one of the largest private hospitals in Bahrain. It provides a wide range of medical and surgical services, including neurology, cardiology, orthopedics, and general surgery, among others, so it offers a reasonably wide spectrum of medical services. In addition, the hospital has both local and expatriate patients in its patient population.

The second dataset belongs to the private hospital (PH), containing the amount of MW in kg as a predicted variable, number of inpatients, outpatients,

hospital capacity (beds), surgeries, deliveries, patient days and bed occupancy. Here, the obtained amount of MW represents all classifications of MW in the hospital except the cytotoxic and chemical types. Moreover, the population and the amount of monthly personal loans were added to the model of the two hospitals as studied features as control variables. The control variable does not have a direct effect on the outcome but is controlled because it has the potential to change the final results (deHaan et al., 2023; Scribbr, 2021).

3.2.5.2 Medical waste Generation rate

The weight (in kg) of MW produced per total bed is a measure of the MW generation rate for a given healthcare facility (Alagha et al., 2018; Sanida et al., 2010). The number of beds is the hospital bed capacity. However, not all the beds might be occupied within a health facility during the day. Typically, the hazardous MW is generated by the occupied beds in a hospital (Komilis et al., 2012; Korkut, 2018). At the same time, it was found that most of the literature for the determination of unit MW generation rates measured by kg per official bed (hospital capacity) as it offers a comparative and standardized metric (Korkut, 2018). In this study, the MW generation rate was calculated in kg/occupied bed/day and kg/bed/day for SMC and the selected private hospital in 2022, where the bed occupancy information for SMC was available only for 2022. The MW generation rate was calculated using equations Eq. (3.6):

$$GR_{\text{occupied-bed/day}} = \frac{MW \text{ in kg}}{\text{Bed Occupancy\%} \times \text{beds} \times \text{Days}} \quad \text{Eq. 3.6}$$

$$GR_{\text{Bed/day}} = \frac{MW \text{ in kg}}{\text{Bed} \times \text{Days}} \quad \text{Eq. 3.7}$$

Where $GR_{\text{occupied-bed/day}}$ is the MW generation rate in kg/occupied bed/day and $GR_{\text{Bed/day}}$ is in kg/bed/day.

3.2.5.3 Machine Learning Algorithms

The concept of ML can be seen as a subset of AI, where computers can learn from information by blending statistical analysis methods and computer science in order to create algorithms that are "statistically proficient" (Gutierrez, 2020). These algorithms can be classified into two main types: supervised and unsupervised. Within supervised learning, two distinct categories exist: classification and regression algorithms. These categories are defined based on the approach they employ to establish relationships between dependent and independent variables. Ensemble techniques involve ML algorithms that leverage several base models to enhance the performance of classification and regression problems as well as feature selection. These techniques combine predictions from individual models to generate more accurate and robust results (Y. Li & Chen, 2020). Based on the learner generation process, ensemble techniques are classified into two types: sequential, denoted by boosting (Y. Li & Chen, 2020), and parallel, denoted by bagging (Breiman, 1996). In the boosting approach, various sets for training with sample size " n " are created from the data using bootstrap sampling, a technique that ensures the independence of these distinct training sets. The final model is then constructed by aggregating the predictions from all individual models (Y. Li & Chen, 2020). The base learners in ensemble models are established independently of each other as they are developed simultaneously. In the sequential ensemble type, multiple learners are constructed in a sequential manner, which enhances the performance of the ultimate model. This sequential construction allows subsequent learners to potentially overcome the limitations or errors of their predecessors, leading to improved overall model performance.

3.2.5.4 Baseline Algorithms

- Random Forest (RF):

The RF is an ML technique that links multiple decision trees to address regression and classification problems. By employing bootstrap sampling, the decision trees are combined, and their collective results, such as majority classification vote and average, are used for regression tasks (Ahmad et al., 2021; Byeon, 2021). The RF is well-suited for handling missing, imbalanced, and multicollinear data, making it a robust approach in such scenarios (Byeon, 2021; Y. Li & Chen, 2020). The analysis using RF consists of two stages. Stage 1: A forest is built by creating multiple decision trees. A sample from the initial training dataset is randomly selected with replacement to create sub-datasets. Regression trees are then constructed based on these smaller sets of data. The number of variables and trees can be adjusted during the training stage. Stage 2: Predictions can be made once the RF model is trained. The input variables are combined for each regression tree, and their predictions are aggregated. Then, the average of the predictions from all the trees is calculated to find the ultimate result (Ahmad et al., 2021).

- Light Gradient Boosting Machine (LightGBM):

The LightGBM is a powerful ML algorithm that falls in a gradient-boosting framework based on a gradient-boosting decision tree (GBDT) (Microsoft, 2023b). It applies gradient-based one-side sampling (GOSS) and exclusive feature bundling (EFB) technologies. LightGBM uses a leafwise tree-splitting method, which sets it apart from the conventional GBM method. This unique method allows LightGBM to construct intricate models that deliver superior accuracy. By employing the GBDT algorithm and the leaf-wise method, LightGBM offers several benefits, including reduced memory consumption and faster training speed (Jinwoong Park et al., 2020). This algorithm offers a range of hyperparameters that can be fine-tuned to optimize its performance. Key hyperparameters such as the number of iterations, learning rate, and number of leaves significantly influence the prediction accuracy. To avoid overfitting, adjustments can be made to the `colsample by tree` and `subsample`

hyperparameters (Ke et al., 2017; Vinayak & Gilad-Bachrach, 2015). It is specifically designed to deliver fast and efficient performance while maintaining high predictive accuracy. LightGBM is widely used for both classification and regression tasks in various domains (Ke et al., 2017).

- Elastic Net (EN):

The EN is a regularization-based feature selection technique commonly used in ML models (Zou & Hastie, 2005). It combines the strengths of two other regularization methods, L1: least absolute shrinkage and selection operator (LASSO) and L2: Ridge regression regularization. EN can handle multicollinearity, which occurs when some predictors correlate strongly (W. Wang et al., 2022). The LASSO regularization can encounter problems of inconsistency and instability in the presence of multicollinearity since it may arbitrarily select one predictor over another. Ridge regularization handles multicollinearity better, but it may retain many irrelevant predictors. EN, on the other hand, addresses these issues by selecting a subset of predictors that are correlated but not redundant. Moreover, the elastic net can reduce overfitting, which occurs when the model extremely fits the training data but shows poor performance on new data. The LASSO and ridge methods could also address overfitting by incorporating regularization, but elastic net can achieve it more effectively by leveraging the advantages of both methods. Therefore, EN optimizes the bias-variance trade-off by balancing underfitting and overfitting (Medium, 2019). Another advantage of the elastic net is its ability to perform feature selection, which involves identifying the most important predictors for the predicted variable. While LASSO can also perform feature selection by assigning zero to some coefficients, it may miss some relevant predictors when faced with many predictors. In contrast, Ridge regression cannot perform feature selection as it retains all predictors but applies shrinkage. EN addresses this issue by simultaneously

performing feature selection and setting certain coefficients to zero while retaining other significant predictors (Zou & Hastie, 2005).

- Extreme Gradient Boosting (XGBoost):

The XGBoost is a popular gradient-boosting algorithm for classification and regression tasks. While XGBoost is commonly known for its effectiveness in classification problems, it can also be applied to regression problems. It is an algorithm that employs scalable tree boosting and is specifically designed to handle sparsity in data (Nalluri et al., 2020). It is established upon the principles of gradient boosting, integrating concepts from optimization and ML domains (Lai et al., 2020; S. Li & Zhang, 2020). The predictive model is trained in an additive manner in this algorithm. For prediction of i_{th} data instance and at t_{th} iteration, f_t is added to minimize the objective function (Eq. 3.8):

$$L(t) = \sum_{i=1}^n \frac{l}{(y_i \hat{y}_i^{(t-1)} + f_t(x_i))} + \Omega(f_t) \quad (\text{Eq. 3.8})$$

Where l is a differentiable convex loss function that measures the difference between the target y_i and the prediction $\hat{y}_i$, Ω penalizes the complexity of the XGBoost model, and x_i is the input (Chakraborty et al., 2023; Nalluri et al., 2020).

- Extreme Random Trees (ERT):

The ERT regression was proposed by (Geurts et al., 2006); it is an ensemble learning method that relates the concepts of decision trees and random forests. It is a variation of the random forest algorithm and is particularly effective for handling high-dimensional data with noisy or incomplete features. It is an algorithm that constructs an ensemble of un-pruned decision trees in a top-down fashion. The approach involves random cut-point selection for node splitting, rather than using bootstrap replicas, and utilizes the entire learning sample to grow the trees (Heddam, 2021). Moreover, this algorithm substantially reduces the prediction model's variance,

which helps prevent overfitting, improves generalization performance, and slightly increases the model's bias, which may introduce a small trade-off between bias and variance. This algorithm achieves these benefits with low computational costs compared to other ensemble methods (Basith et al., 2018). Mathematically, this algorithm composes a set of decision trees that uses the entire training dataset independently during the training process; these trees could be built as either decision or regression trees (Nattee et al., 2017).

3.2.5.5 Voting Regressor (VR)

A voting ensemble is an approach in an ML ensemble that uses multiple models instead of a single model to enhance the overall performance of a system. This methodology can be used in classification and regression problems by aggregating the predictions of multiple models. In the case of regression problems, ensembles known as VRs are used, where the ultimate estimate is obtained by averaging the estimations of all the individual models (Kilimci, 2022). Weighted voting (WV) and average voting (AV) are the two methods for awarding votes in VRs. For AV, the weights of all models in the ensemble are equivalent and equal to 1. However, it assumes all models to be equally effective, which is often not the case, especially when different ML algorithms are employed and is considered its limitation. While WV assigns a weight coefficient to each model in the ensemble, these weights can be either floating-point numbers between 0 and 1, with their sum equal to 1, or integers starting at 1, indicating the number of votes assigned to each respective ensemble model (Shahhosseini et al., 2022).

3.2.5.6 Process of Proposed Model

Two ensemble voting regression models were developed in this work that used 3 RF and one LightGBM for the SMC dataset. And 3 RF, 1 EN, 1 XGBoost and 2 ERT for the PH dataset. The proposed model's superiority stemmed from integrating multiple ML algorithms, which collectively endowed it with the capability to

accurately predict the quantities of MW in both datasets. The workflow of developing the best ML model is demonstrated below in Figure 3.2.

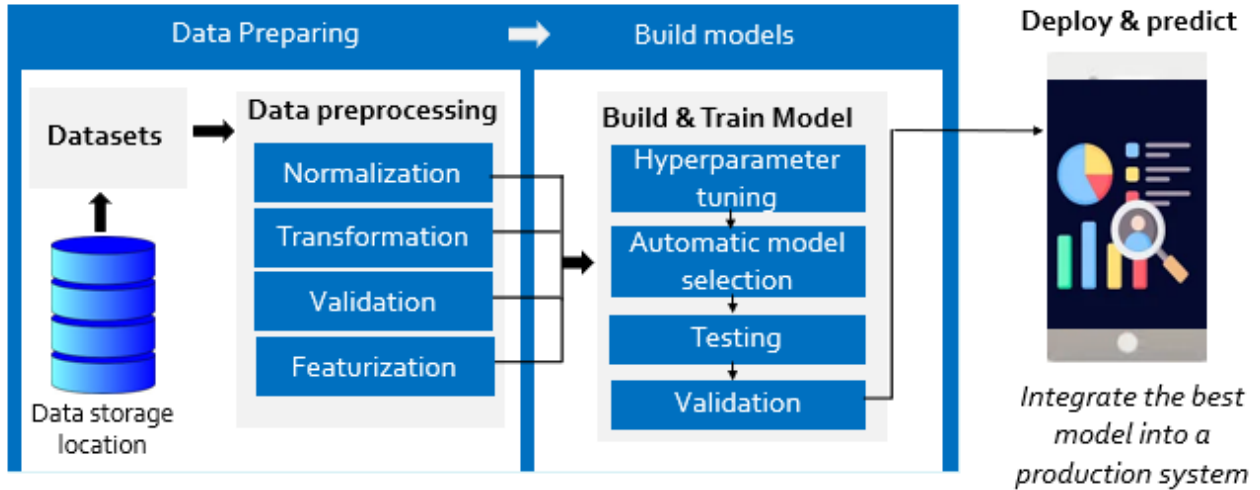


Figure 3.2 Workflow of proposed ML model.

3.2.5.6.1 Phase 1: Preparing the Data

Official data was obtained from the two selected hospitals and the public domains; the selected features were described in section 3.2.5.1, and two distinct datasets were created. The input variables (features) were carefully selected to encompass the potential factors that could impact the quantity of MW for each type of the selected hospital. The independent variables (features) were selected based on an overview of effective parameters in MW production from a literature review (Appendix 1) and interviews with hospital administrators and academics. Data preprocessing was carried out, an important stage in ML modelling. Real-world data often exhibit inaccuracy, inconsistency, and incompleteness, which could cause erroneous results. Data preprocessing plays a vital role in addressing these issues and ensuring the reliability of the findings (Ramírez-Gallego et al., 2017). Data preprocessing involves important steps prior to modelling, such as cleansing, instance selection, normalization, transformation, feature extraction, and feature selection (X. C. Nguyen et al., 2021).

In the two datasets, there were minimal missing data points. Therefore, two methods were used to handle these missing values, omitting rows and estimating values using a forecasting approach to ensure accurate decision-making (Kwak & Kim, 2017). The population data were converted from yearly to monthly by spreading the annual data over the 12 months and then smoothing it by taking 12 moving averages. A moving average is a technique that calculates the average of a set of data points over a sliding time window. By smoothing the data in this way, any short-term fluctuations or noise can be reduced, making it easier to identify long-term trends or patterns (FasterCapital, 2023).

In this study, the variables were initially normalized to a range of values between 0.0 and 1.0 to facilitate their processing in a standardized manner. The normalized indicators were then assigned as both independent and dependent variables in the analysis (Altin et al., 2023). This way of normalization would help in comparing the performances of the models (Carbonell et al., 1983). The datasets were split into training and testing sets, with 75% of the samples allocated for training purposes and 25% for testing.

3.2.5.6.2 Phase 2: Building the Model

In the training stage, the parameters (hyperparameters) of the utilized algorithms for the two models were set by default (Microsoft, 2023a). The corresponding algorithms were incorporated to build the two ensemble VRs using the default weighted averages. Thereafter, the trained two ensemble VR models for the two datasets were fitted. Lastly, the performances of the two proposed models were assessed using different metrics, R^2 , MAE, mean squared error (MSE), and RMSE, as detailed hereunder.

3.2.5.7 Performance Criteria

The models' performances for each method and the relevance of the characteristics resulting from the test data analysis were evaluated using different measures. To measure the ML models' performances, four metrics, coefficient of determination (R^2), root mean squared error (RMSE), mean absolute error (MAE), and mean squared error (MSE), were used, as shown in Eq. 9 – Eq. 12 (Erdebilli & Devrim-İçtenbaş, 2022; Golbaz et al., 2019; Karpušenkaitė et al., 2016; Rashid et al., 2022).

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - x_i)^2}{\sum_{i=1}^n (y_i - \bar{x}_i)^2} \quad (\text{Eq. 3.9})$$

$$RMSE = \sqrt{\sum_{i=1}^n \frac{(y_i - x_i)^2}{n}} \quad (\text{Eq. 3.10})$$

$$MAE = \frac{\sum_{i=1}^n |y_i - x_i|}{n} \quad (\text{Eq. 3.11})$$

$$MSE = \frac{\sum_{i=1}^n (y_i - x_i)^2}{n} \quad (\text{Eq. 3.12})$$

where, y_i represents the actual value for the i^{th} observation, x_i represents the predicted value, n represents the number of observations, and $\bar{x}_i$ represents the average of predicted values. Models with higher R^2 values and lower RMSE, MAE and MSE were more successful than others (X. C. Nguyen et al., 2021).

3.2.6 MW Segregation Behavior among Health Workers

3.2.6.1 Partial Least Square Structural Equation Modelling (PLS-SEM)

An integrated model composed of the TPB and the NAM was proposed to investigate the MW segregation behavior of health workers. The PLS-SEM technique was used for data analysis and hypothesis testing. The PLS-SEM can examine a series of relationships, direct and indirect, within a model at the same

time, it evaluates association between latent and observed variables (Arkorful et al., 2020; Joe F Hair et al., 2011). In this study, PLS-SEM was selected because it is widely used in behavioral studies as it can analyze constructs of multiple items. Moreover, it does not require the items to be multivariate normal distributed. Compared to the other covariance-based SEM (CB-SEM) techniques, a large sample size is not required for PLS, with more accurate prediction results that could be achieved with a limited sample size (Qureshi & Compeau, 2009; Wynne, 1998). In addition, the PLS-SEM is appropriate for analyzing complex relationships without necessitating strong theoretical confirmation (Chin et al., 2003).

3.2.6.2 Scale Development

A survey approach was used to collect data and investigate health workers' behavior toward MW segregation. Prior to collecting data, a pilot test was conducted to examine the constructs and their respective items. The pilot test improves clarity and ensures the constructs' robustness and efficiency in gaining consistent responses by restructuring the questions to deepen their content validity, understanding, quality, and relevance within the study context (Arkorful et al., 2021).

The questionnaire underwent validation by a panel of public health experts and academics, including two academics from the University of Bahrain (UOB), and two experts from a government hospital, one from the Infectious Diseases Department and another from the Infection Control Department. Additionally, input was obtained from an expert in the Infection Control Department in a private hospital, as well as a statistician with significant research and interest in the applied framework. Finally, the questionnaire was reviewed and approved by the research committee of the University of Bahrain.

The questionnaire was also exposed to the Reliability test, which assesses the consistency or dependability of the measurement tool (Chapelle, 1998). Cronbach's

alpha was employed using IBM-SPSS to test the reliability, and values greater than 0.7 were deemed acceptable (Arkorful et al., 2020).

The questionnaire was pilot-tested among 28 respondents from the target population. These steps further enhanced the clarity of study items to make them comprehensive, ensuring relevant and appropriate items within the scope of the study.

3.2.6.3 Measurement of Constructs

Multiple-item scales to measure the variables were employed. The items were adapted from previously validated and reliable sources (Arkorful et al., 2021; Letho et al., 2021) and refined to fit the study's objective. Responses were collected using a five-point Likert scale, ranging from 'strongly disagree' (1) to 'strongly agree' (5). The 5-point scale was chosen to enhance clarity and understanding (Arkorful et al., 2020; Dawes, 2008).

The variables include "Awareness of consequences", "Ascription of responsibility", "Personal norm", "Attitude", "Subjective norm", "Perceived behavior control", "Intention", and "Behavior", Appendix 2 illustrates the constructs along with measurement items. Demographic characteristics were also included in the questionnaire.

3.3 Research Tools

The Microsoft 365 Excel package was used in data analysis. Also, the IBM SPSS Statistics Version 23 software was used for performing ARIMA and further statistical analysis. IBM SPSS - AMOS 22 software was used for implementing analysis and SEM. HEATMAP dendrogram for clustering correlation analysis was visualised in R software.

Microsoft Azure Machine Learning Studio is the platform chosen to develop a tool and perform experiments (<https://studio.azureml.net>) for predicting and

identifying the significant features of MW generation. It is a cloud-based machine learning service that provides the ability to publish experimental results on the web. Moreover, SmartPLS 4.0 software was used to perform the PLS-SEM technique for analyzing the behavior of health workers toward MW segregation.

3.4 Data Collection

Multiple datasets were collected to fulfil the objectives of this work; Figure 3.3 demonstrates the workflow of the processes and data collection.

3.4.1 IEA

For performing the IEA for the MW issue in Bahrain, data on the MW quantities in tons from 2010 to 2020 were collected from Bahrain's open data portal (Information & eGovernment Authority, 2022). Data on the number of violations of MW management in healthcare facilities were collected from the annual reports issued by NHRA (NHRA, 2021b). The collected data were used to demonstrate the increasing quantities of MW and the number of medical waste violations.

For policy analysis in IEA, the relevant legislation, in addition to the regional and international conventions and agreements pertinent to MW in the country, were collected and analyzed.

3.4.2 CMW Estimation in Bahrain and Other Selected GCC

Data were collected to estimate the MW generated during the COVID-19 pandemic in Bahrain and the other selected GCC countries. Data on COVID-19 new daily cases, the number of vaccinations, and diagnostic tests in Bahrain were obtained from "Our World in Data" (Our World in Data, 2022a) up to May 31, 2021. In addition, online/call interviews were conducted with several staff members working in five dedicated healthcare facilities in Bahrain during COVID-19. Information about the quantities of each type of PPE they were using during their duties was collected. The selected healthcare facilities were the Exhibition center,

Bahrain International Hospital (BIH), Kanoo Center, 5th and 6th floors (6 wards on each floor) in SMC and Hereditary Blood Disorder Center (HBDC).

Besides, data on new daily infected cases, the number of given vaccines, and the total number of COVID-19 tests performed in the GCC countries up to March 26, 2022, were collected from the website "Our world in data" (Our World in Data, 2021b), (Our World in Data, 2022b), and (Our World in Data, 2021c). The collected data in this part was from the beginning of the pandemic, specifically, January 29, 2020, in the Emirates; February 24, 2020, in Bahrain, Kuwait and Oman; March 2, 2020, in Saudi Arabia, until March 26, 2022. It is worth mentioning that, on March 28, 2022, wearing a facemask became optional in both indoor and outdoor areas in accordance with precautionary measures in most of the selected countries (MOH, 2022c). Moreover, data from the public domain, the website "world meters" (Worldmeter, 2021a, 2021b), were collected for the population size and the rate of urban population for Bahrain and other selected GCC countries. Furthermore, the Google Trends tool (www.google.com/trends) (GoogleTrend, 2022) was used to collect data on internet user search activities in GCC for the specified search queries. The retrieved data on internet search queries were on a weekly basis, and it was from the first week that the pandemic started in each selected country until week 20-26 in March 2022.

3.4.3 Associated Factors in MW Generation During COVID-19

The factors associated with COVID-19 waste generation were investigated from February 2020 until May 2022. So, data about monthly quantities of CW was obtained directly from the treatment company BWTC. The explanatory data for this part (new cases, deaths, vaccinations, diagnostic tests, stringency index) were obtained on a daily basis from the public domain (Our World in Data, 2021b), and then they were converted to monthly to be competent with CW quantities. They were

converted by computing the summation, except the stringency index was computed by the average. In addition, data about emissions resulting from the MW incineration was also obtained from BWTC.

Furthermore, a semi-structured interview was conducted with the manager of BWTC to collect information about the MW treatment techniques. The company collects and treats MW generated by governmental and private hospitals and healthcare facilities.

3.4.4 Medical Waste Generation and Associated Factors Using ML

Two datasets containing data about the quantities of MW and data about tested features were obtained from the two hospitals; the first was from SMC, which was monthly from January 2019 to February 2023, and the second was from PH, which was monthly from January 2018 to Nov 2022. In addition, data about the population was collected from the word bank (The Word Bank, 2023), and the amount of monthly personal loans (in Bahraini Denars, BHD) was obtained from the Central Bank of Bahrain (CBB, 2023).

3.4.5 Health Workers' Behavior in MW Segregation

A questionnaire survey approach was utilized to collect data (Appendix 2); there were 144 respondents. This investigation's sample population was health workers in the governmental and private hospitals in Bahrain. An online questionnaire version was distributed from June 15, 2023, to September 15, 2023. The questionnaire was built in compliance with the principles and recommendations of the ICC/Esomar International Code on Market Opinion and Social Research and Data Analytics (ESOMAR, 2016).

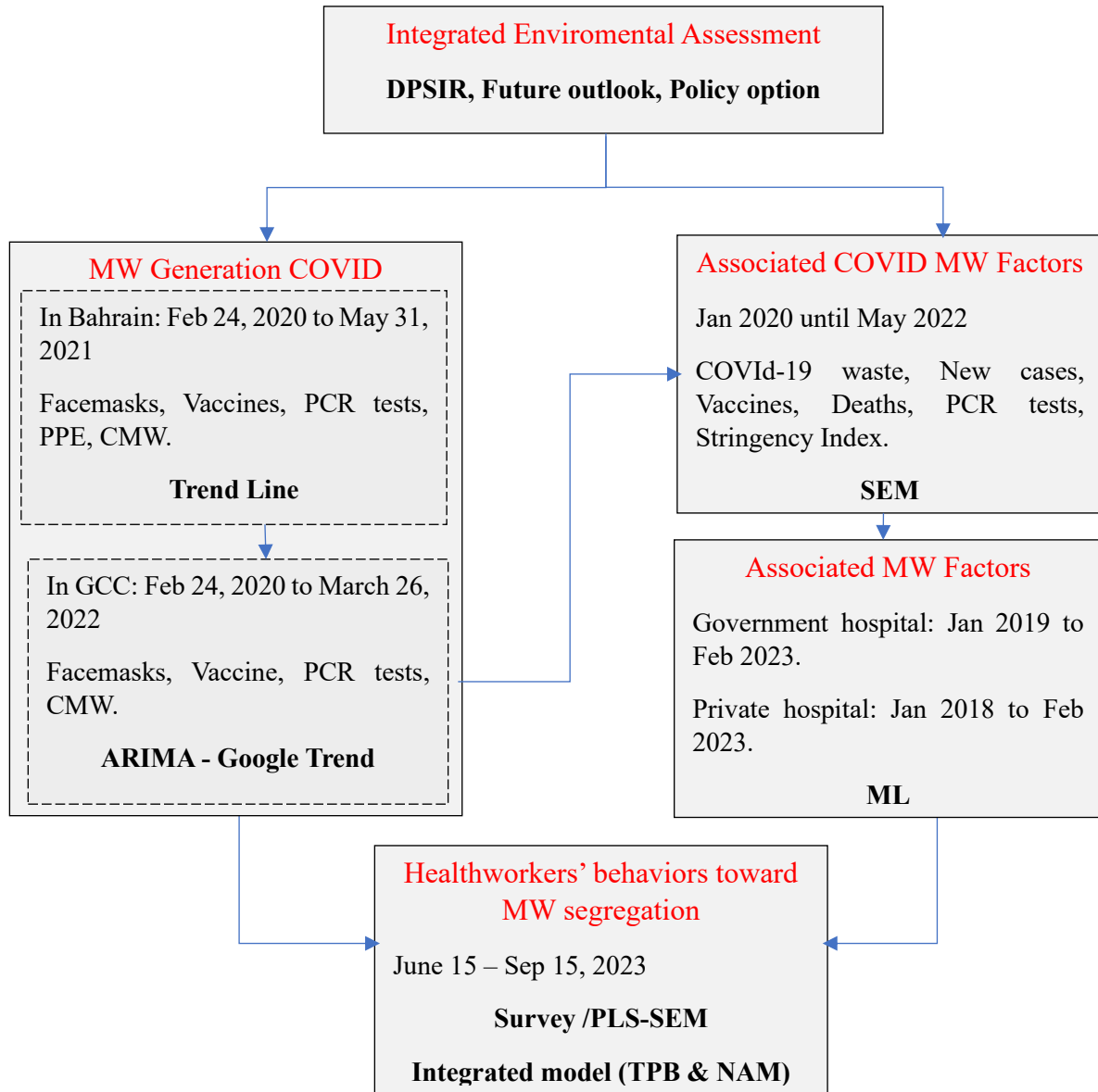


Figure 3.3 Data collection workflow

Chapter 4

Results and Discussion

4.1 Introduction

This chapter is dedicated to presenting and discussing the obtained results and interpretations. The assessment of MW using the IEA method is presented in section 4.2. The estimation of MW during COVID-19 in Bahrain and other selected GCC countries is explained in sections 4.3 and 4.4. Identifying the main significant factors associated with MW during the pandemic is discussed in section 4.5. Predicting and finding the main significant features associated with MW in normal situations using ML models is discussed in section 4.6. The investigation of health workers' behavior toward MW segregation is analyzed in section 4.7. Finally, the results of the study are summarized in section 4.8, highlighting the key findings and outcomes obtained from the analysis.

4.2 Integrated Environmental Assessment (IEA)

This part of the study answers the five IEA questions (Figure 3.1) related to the two issues of MW in Bahrain: increased MW quantity and its mismanagement.

4.2.1 What is happening to medical waste in Bahrain "State"?, and Why "Drivers" and "Pressure"?

To answer this question, firstly, the collected data from Bahrain's open data portal was plotted to figure out the trend (behavior over time graph) of the generated MW in Bahrain from 2010 to 2020, as shown in Figure 4.1. The figure demonstrates the increasing quantity of MW in Bahrain.

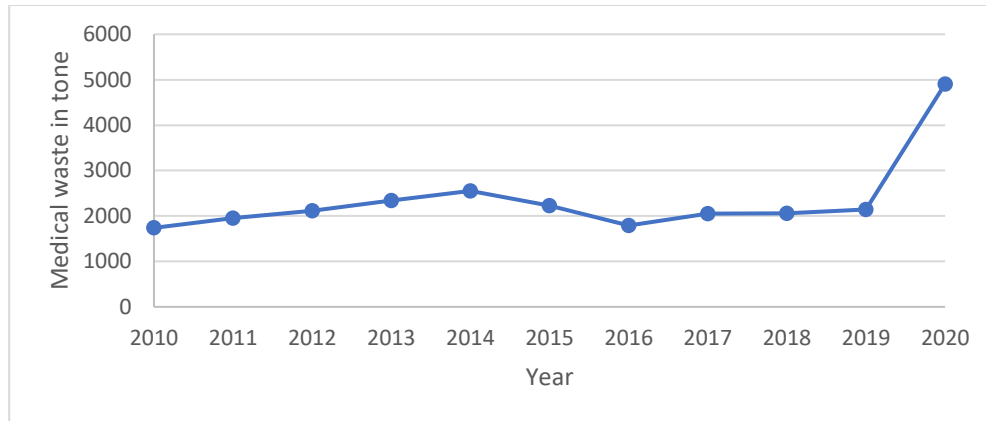


Figure 4.1 Medical waste quantities in tons generated from 2010 to 2020 in Bahrain.

An evident, sharp increase of more than twofold in MW in 2020 can be observed in Figure 4.1. The rise in 2020 was more than double, and it was stated that the main reason behind that increase is the COVID-19 pandemic (Information & eGovernment Authority, 2021). Moreover, the Awali incinerator, which handles this type of waste, reported an approximately 50% increase in hazardous MW during the pandemic (DERASAT, 2021). It is almost the same case with some other countries; for instance, one of the provinces of Turkey witnessed an increase in the amount of MW due to the COVID-19 pandemic, reaching 48% on average (Hanedar et al., 2022).

Proceeding precisely to the quantity of MW generated during the pandemic, the CMW is increasing with the number of infected people; the quantity of CMW approached 11,128 kg (11.128 tons), with 3,273 infected cases on May 29, 2021 (the highest number of daily new cases in the study period) (Al-Omran et al., 2021). Focusing more on the MW quantities generated during the pandemic, it was reported that the waste generated from the facemasks was around 35.5 kg/day; PPEs used in healthcare facilities was 1,864 kg/day; and the accumulated quantities of waste generated from vaccination and PCR test until June 1, 2021, were approximately 16,633.5 kg and 53,551 kg, respectively (Al-Omran et al., 2021), further details are explained in section 4.3.

Several drivers could lead to the aforementioned MW issues. For the first issue, the increasing quantities of MW every year, the main driver is population growth in the country. Population growth leads to more medical services and consumption of medical supplies. Where the population in Bahrain in 2022 increased to 1,797,844, with a population growth rate of 3.68% in 2020 (Worldometer, 2022). Another driver could be the free treatment and medication for Bahraini citizens and partially for immigrants (WHO-Bahrain, 2022).

Economic development could also be considered a significant driver. Attracting workers from abroad leads to an increase in medical services (TOURISM, 2021). The medical tourism sector contributes to increasing economic diversification. It was mentioned that health tourism offers multiple opportunities for the Kingdom of Bahrain, promoting its exports and diversifying its economic activities (ZAWYA, 2021). Making Bahrain an attractive destination for medical tourism leads to an increase in the number of tourists, attracting many workers and establishing more institutions and hospitals. As a result, the country's private healthcare sector has considerably grown. The number of private healthcare facilities has increased from 500 in 2018 to 800 in 2019 (Economic Development Board Bahrain, 2019; FCCIB, 2021), and the growth rate in health facilities from 2017 to 2020 reached 18% (Bahrain News Agency, 2021b), leading to more health services, thus, a high amount of MW.

Medical technology is another driver, where high technology would lead to advanced medical services and consequently to more MW generation (Wei et al., 2021). The Ministry of Health (MOH) in the Kingdom of Bahrain is keen to work according to a unified governmental system based on the commitment to the Economic Vision 2030. The vision aims to keep pace with the technologies of the industrial revolution. Indeed, the MOH has been able to keep pace with these global developments and develop its health and treatment services through a serious follow-

up to the latest developments in the medical device industry and its quest toward providing modern technologies to improve and raise the level of quality of treatment service for patients (MOH, 2022d).

Additionally, a lack of public awareness is considered a strong driver for increasing MW. For instance, understanding the importance of the COVID-19 vaccine and its effectiveness in protecting against diseases. Likewise, the awareness of the importance of adhering to precautionary measures and social distancing at the beginning of the pandemic. Additionally, awareness about the importance of nutrition and following healthy behaviors could reduce MW quantities by decreasing exposure to related diseases (Al-Omran, Abahussain, et al., 2023).

Moreover, the absence of MW segregation and mixing of the generated waste of the health institute is an essential driver. It was reported that there are violations related to MW segregation in different health facilities in Bahrain (Figure 4.2) (NHRA, 2021b).

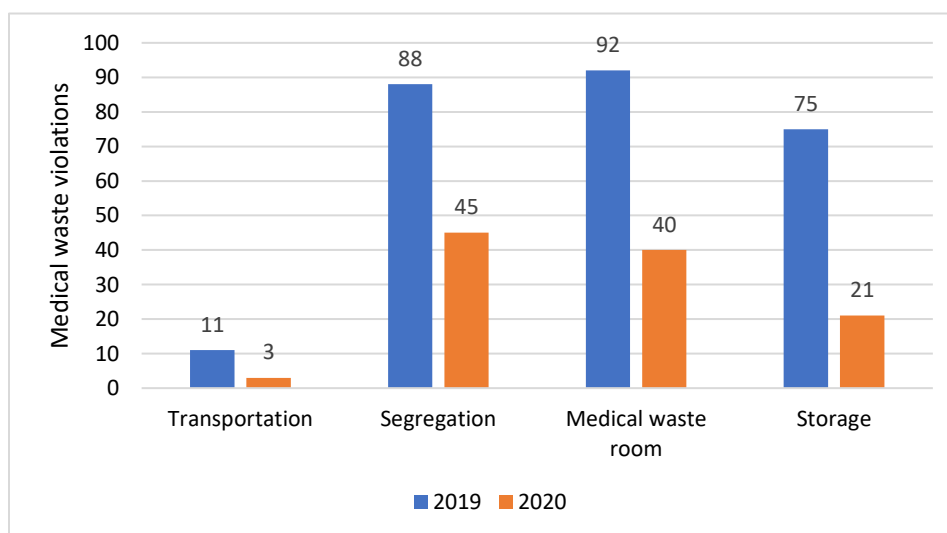


Figure 4.2 Number of medical waste violations for 2019 and 2020, source of data: (NHRA, 2021b).

The second issue is MW mismanagement. NHRA (2021b) reported violations in 2019 and 2020, mainly in MW rooms, segregation, storage, and transportation

(Figure 4.2), which implies a serious issue in disposing and managing the produced MW. It can be observed that the number of violations in 2020 is much lower than in 2019, where it decreased by nearly more than 50% (Figure 4.2). However, this reduction is not because of the better management process. The reason could be the cutting or reduction of the number of visits to health facilities due to the quarantine during the COVID-19 pandemic (NHRA, 2020). Moreover, as mentioned during the interview with the responsible office bearers of BWTC for the MW treatment methods, the incineration method is used for treating MW. And it is well known that this method emits CO₂ and other unwanted gases (Al-Omran et al., 2021).

The most significant driver for this issue of MW management is the lack of monitoring of the practices of workers in the medical sector, as well as the lack of the polluter pays principle (PPP), which is the public enforcement of environmental laws and regulations. Therefore, it is a considerable driver for having an issue in managing the MW in health facilities as well as MW treatment centers (Al-Omran, Abahussain, et al., 2023). The driving forces, pressures, and the role of the state of MW issues in Bahrain are illustrated in Figure 4.3.

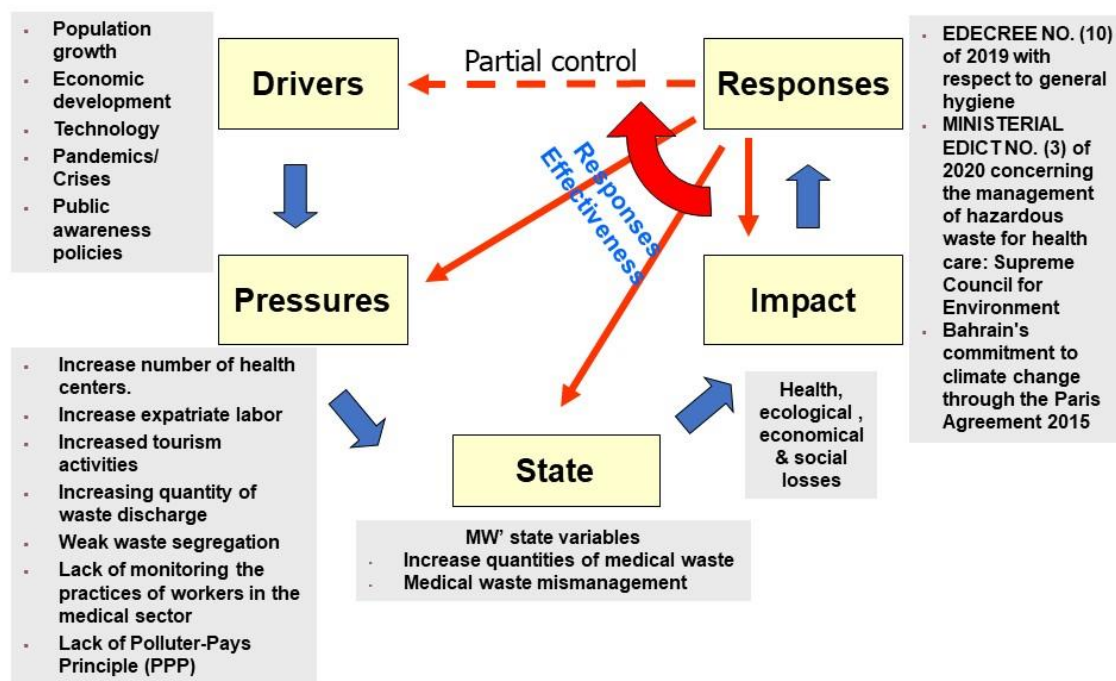


Figure 4.3 The DPSIR framework of MW in the Kingdom of Bahrain.

4.2.2 What are the consequences of medical waste for the environment and humanity? (Impact)

The MW issues could lead to negative impacts on human health and the environment. One of the most significant adverse impacts is spreading the virus and increasing diseases and infections. Many cases of acute hepatitis B (HBV) and C (HCV) infections in healthcare workers were reported (Chartier, 2014). WHO stated that more than two million healthcare workers sustain percutaneous injuries from infected sharps each year (Chartier, 2014). There are severe risks of disease transmission to waste pickers, cleaners, health workers, patients, and the community in general. Likewise, the improper management of MW could increase the spread of infections in the same way, particularly in the case of COVID-19 (J. Peng et al., 2020). It was indicated that the main sources of COVID-19 MW were hospitalized patients, people in isolation at home, and those in quarantine, and the amount of MW has increased during the emergency of the COVID-19 pandemic (Bucătaru et al.,

2021). The MW generated by the pandemic poses a high risk to human health. A study identified that the PPEs used by medical staff could lead to indirect infections without contact with infected patients (Rhee, 2020), and it's the same case in Bahrain (Al-Omran, Abahussain, et al., 2023).

Environmental risk is another significant impact of inappropriate MW management and disposal. The incineration method is used for MW treatment in Bahrain, which can lead to harmful effects, such as causing high levels of dioxin emissions (Prem Ananth et al., 2010). It was reported that the incineration of biomedical waste contains polycyclic aromatic hydrocarbons (PAHs) and a high concentration of heavy metals resulting in unfavorable amounts of hazardous materials, thus causing to pollute the surface and groundwater (Heera et al., 2014). Furthermore, the incineration method produces ash residues, which cause to change the soil quality near waste dumping sites (Manzoor & Sharma, 2019). Moreover, the MW issues cause financial challenges in managing, storing, transporting, and subsequent treatment associated with MW (Al-Omran, Abahussain, et al., 2023).

4.2.3 What is being done to medical waste, and how effective is it?

(Response)

A few significant laws and policies have been adopted in Bahrain recently. On May 30, 2019, the LEGISLATIVE DECREE NO. (10) of 2019 (Legislation & Legal Opinion Commission, 2020) concerning general hygiene was issued. It was the first decree that directly addressed MW. It includes different kinds of MW under "special waste", which is defined as "any waste resulting from various healthcare activities in all its forms, nursing, curative and diagnostic, in hospitals and health centers, including laboratories, research centers, radiology, pharmacies, dental treatment and physiotherapy".

The Legislative Decree includes two articles on MW. Article 5 obligates MW producers to take all necessary measures to separate MW from other wastes by

following the requirements and specifications established for the preservation, collection and transportation of such type of waste stated by the executive regulations of this law. Article 8 prevents transferring MW, whatever its source is, from the site of its lifting to the treatment site, except through companies and institutions licensed and classified for this purpose, following the controls determined by the executive regulations of this law.

Moreover, anyone who violates the provisions of this decree articles related to other types of waste shall be penalized between BHD 50-300 (BHD 1 = \$2.65). On the other hand, in violation of the provisions of articles related to MW (Articles 5, 8), a BHD 500-1000 fine shall be imposed on the violator. It is noticed that this Legislative Decree imposes penalties on environmental violations by producers of MW more stringently than producers of other waste (non-MW) due to the seriousness and danger of MW.

On December 31, 2020, MINISTERIAL EDICT NO. (3) of 2020 (Legislation & Legal Opinion Commission, 2021) concerning hazardous waste management for healthcare was issued. It includes 36 articles about healthcare waste management. This law aims to regulate the process of managing hazardous waste for healthcare safely and sustainably to control the waste and prevent its spread, guaranteeing the preservation of health and the environment. This EDICT is applied to every producer, carrier or treatment unit whenever the activity practised by any of them is related entirely or partially to the management of hazardous waste for healthcare (more details about the two policies are summarized in Appendix 3).

The policies and regulations related to MW in Bahrain, including decrees, laws, international conventions, initiatives, and guidelines, were collected and then analyzed by checking whether they address drivers, pressures, state or impact. The results of policies analysis are summarized in Table 4.1. Note that all collected policies and regulations used/analysed are briefly described in Appendix 4.

Table 4.1 The policy analysis of medical waste (driver D, pressure P, state S and impact I).

Issue	D/P	S	I
Increase quantities of medical waste	DECREE NO. (10) of 2019 (Legislative, Proactive, Economic, +++) MINISTERIAL EDICT NO. (3) of 2020 (Regulatory, Reactive, +++)		Law No. 39 of 2005 of Stockholm Convention (Legislative, Reactive, +++) WHO Guiding Principles (Institutional, Reactive, ++)
Medical waste mismanagement	MINISTERIAL EDICT NO. (3) of 2020 (Regulatory, Reactive, Enhance +)	DECREE NO. (10) of 2019 (Legislative, Proactive, Economic, +++)	MINISTERIAL EDICT NO. (3) of 2020 (Regulatory, Reactive, Enhance, ++) Royal Decree 75 of 2016 on ratifying the Paris Agreement (Regulatory, Reactive, ++) Law No. 39 of 2005 of Stockholm Convention (Regulative, Reactive, ++) Decree No. (26) of 2001 ratifying the Regional Protocol (Regulatory, Reactive, 0) WHO Guiding Principles (Institutional, Reactive, Enhance, ++)

Note: strongly positively effective (+++), positively effective (++), neutral (0).

As shown in the policy analysis in Table 4.1, the policy instruments used to govern and manage MW are regulatory, economic, and institutional. Some of the policies were proactive, and others were reactive. The reactive approach is based on responding to events after they have already happened. However, the proactive approach focuses on eliminating and preventing problems before they have a chance to appear. Most of the policies aim to enhance the environment (Enhance). Some are strongly positively effective (+++), and one policy is neutral (0). It can also be noted that most policies address the negative impacts. In contrast, no policy tackles the state of increasing MW quantities; also, there is a lack of policies tackling the drivers and pressures of both issues.

Economic instruments are considered an effective policy tool in minimizing, preventing, and managing waste. Moreover, the charges and fees are deemed economic instruments that can be used to recover the waste management costs and

support the user PPP, ensuring the financial sustainability of waste management services. The Rio Declaration and Agenda 21 of the SDGs and UNEP_GEO reports, especially GEO5 (2012) and GEO6 (2019), emphasized the importance of economic instruments for environmental policy. Economic instruments embody a tool for national authorities to support the internalization of environmental costs and efficiently employ the PPP (Panaiotov, 1994). In addition, the economic instruments could help encourage the behavior changes necessary to achieve waste policy objectives—for instance, waste reduction or investment in technology for improved waste treatment (OECD, 2019).

4.2.4 Where are we heading with the MW? (Future Outlook)

Policy analysis of MW management reveals that the current policies are insufficient to moderate the pressures and drivers, diminish the two main issues (MW quantity and management) and mitigate their adverse impacts. For example, although there are policies on segregating MW at the generation source, they are not yet implemented in many health centres, as shown in Figure 4.2.

Two future scenarios (Scenarios for Outlooks) were predicted for determining strategic solutions to help the policy/decision-makers achieve sustainability in Bahrain, as summarized in Table 4.2. The first scenario is a business-as-usual (BAU) prediction, corresponding to the current situation with no policy reforms or more government intervention. As a result, there will be a continuous increase in the generation rate. The second scenario, the sustainability scenario, assumes that the policy/decision-maker would be stricter in segregating the MW at the generation source to reduce the generated waste. This is to minimize the adverse human health, environmental and economic impacts. It was found that 15–20% of the total healthcare waste is hazardous, which is contaminated with pathogens and treated by a particular treatment technique, and 80–85% is non-hazardous waste (Bahrain News Agency, 2021). Moreover, it was found that if a rigorous segregation program

is implemented, the amount of waste that should be incinerated can be reduced by 80% (Alvim-Ferraz & Afonso, 2005). Therefore, a large proportion of them could be recycled. Thus, some types of MW can be recycled with proper separation, thus encouraging investment in recycling MW that is suitable for recycling, such as plastic. The MW provides an opportunity for the circular economy, especially in the private sector (Tirkolaee et al., 2022).

Although the top priority of any health facility is delivering high-quality care, complete waste minimization and recycling programs could be adjusted to save financial and environmental resources. In addition, any health institute can take steps to activate the circular economy model; these steps are: establishing a "green team" (to ensure implementation of strategies of circular economy), measuring waste production, segregation, waste minimization, safe reuse, recycling and reprocessing (Voudrias, 2018). Emerging a circular economy is a bridge for sustainable waste management and a way to a sustainable future. However, many countries need to adopt a series of policy instruments to manage waste effectively (OECD, 2019). The sustainability scenario focuses on implementing policies and regulations to reduce the quantities of MW and improve disposal and treatment methods. It is expected to apply alternative technologies rather than the incineration method. For example, the US EPA proposed alternative technologies for the disposal and treatment of MW: steam sterilization (autoclaving), thermal treatment (microwave technologies), thermochemical systems, and electropyrolysis (EPA, 2022a).

Table 4.2 Proposed scenarios for medical waste management.

Scenarios	Actions	Assumptions
Business as usual–BAU	Conventional	All medical waste is mixed together and treated by the incineration method. The quantity of medical waste is increasing.
Sustainability Scenario		
a. Reduction in medical waste quantities.	Segregate the types of medical waste. Focus on segregation of the hazardous from non-hazardous waste from the source.	Around 80% of medical waste would be recyclable. 20% would be treated by incineration.
b. Efficient medical waste management.	Use alternative treatment technologies.	Less quantity of medical waste. Greenhouse gasses (GHG) would be reduced.

4.2.5 What actions could be taken for MW for a more sustainable future? (Policy options)

Increasing MW quantities and mismanaging its disposal and treatment are long-term problems. Therefore, these issues need root solutions to the drivers and pressures. Additionally, these issues need instruments such as forming policies for MW producers and treatment units, reforming some regulations, and encouraging or discouraging specific behaviors and actions through introducing initiatives, incentives, or disincentives. Focusing more on implementing strict policies regarding efficient MW management is crucial. However, as indicated previously, the number of violations regarding the MW room, storage, segregation, and transportation for 2020 is much less than in 2019 (NHRA, 2021a). That reduction is

because the visits to health institutions were stopped during the pandemic, and only the authorities asked for pictures; therefore, in this case, the truth is less. As actions to be taken, the law should be implemented in its true spirit more firmly, and a rise in monetary penalties against violations can also have a positive impact. Moreover, the violators' license must be permanently withdrawn when the offence is repeated, and final or temporary closure depends on the circumstances. Furthermore, EDICT 3/2020 must be activated regarding the necessity for healthcare facilities to nominate an employee responsible for waste management and to form a working group to achieve the highest level of waste management. Furthermore, each work team member must abide by the responsibilities specified in the EDICT, their commitment to the standards specified for storing hazardous waste within the facilities, and the period that must remain in the storage site before transferring it to the treatment unit.

Under the Bloodborne Pathogens Standards, the US Occupational Health and Safety Administration (OSHA) regulates the safety of MW in the workplace. The OSHA requires that all personnel handling MW be trained annually concerning the proper storage, handling, labelling and transportation of the waste. The standard also obliges healthcare facilities with occupational exposure to infectious substances to submit an annual exposure control plan that outlines all assessment procedures, potential risks, and a schedule detailing how the facility will remain compliant (Medical Waste Pros, 2021). As policy options, this study proposes a policy to require all health facilities to provide annual training for staff, including hospital administrators, doctors, nurses, paramedical staff, cleaners, porters, waste handlers, and others. In addition, it is recommended to consider the WHO healthcare waste training modules (WHO, 2021b).

For proper MW treatment, it is also proposed to provide guidelines for the treatment units on alternative technologies for MW treatment and select the best technique depending on the MW type. Before 1997, the incineration method was

applied to more than 90% of potentially infectious MW. In August of 1997, EPA issued regulations setting strict emission standards for incinerators of MW due to substantial concerns about poor air quality affecting human health (Phillips & Moya, 2013). The EPA's Air Quality Planning and Standards Department is still reviewing and revising Hospital Medical Infectious Waste Incinerator (HMIWI) standards (EPA, 2022a).

4.3 Estimation of COVID-19 MW in Bahrain

4.3.1 Estimation of CMW by Infected Cases

The number of newly confirmed cases since the first case in Bahrain on February 24, 2020, till May 31, 2021, are plotted using Microsoft Excel in Figure 4.4. The curve is affected by two components of the time series analysis: the cyclic and irregular components. In time series analysis, the cyclic component is defined as the periodic changes or regular fluctuations around the trend, forming a series of expansion and contraction phases (OECD, 2007). The countries in the world have been hit by several waves of the coronavirus (Vahabi et al., 2021), and the Kingdom of Bahrain is one of them. The country was highly affected by the coronavirus waves, which formalized a cyclic pattern of high and low slopes in the curve. The other component that causes the variation and irregular movements in the curve of the confirmed cases is the irregular component, and its sudden changes occur in a time series that are unlikely to be repeated (OECD, 2007). Here, the leading factors for the irregular component could be the vaccination of the public and the lockdown imposed to curb the spread (Al-Omran et al., 2021).

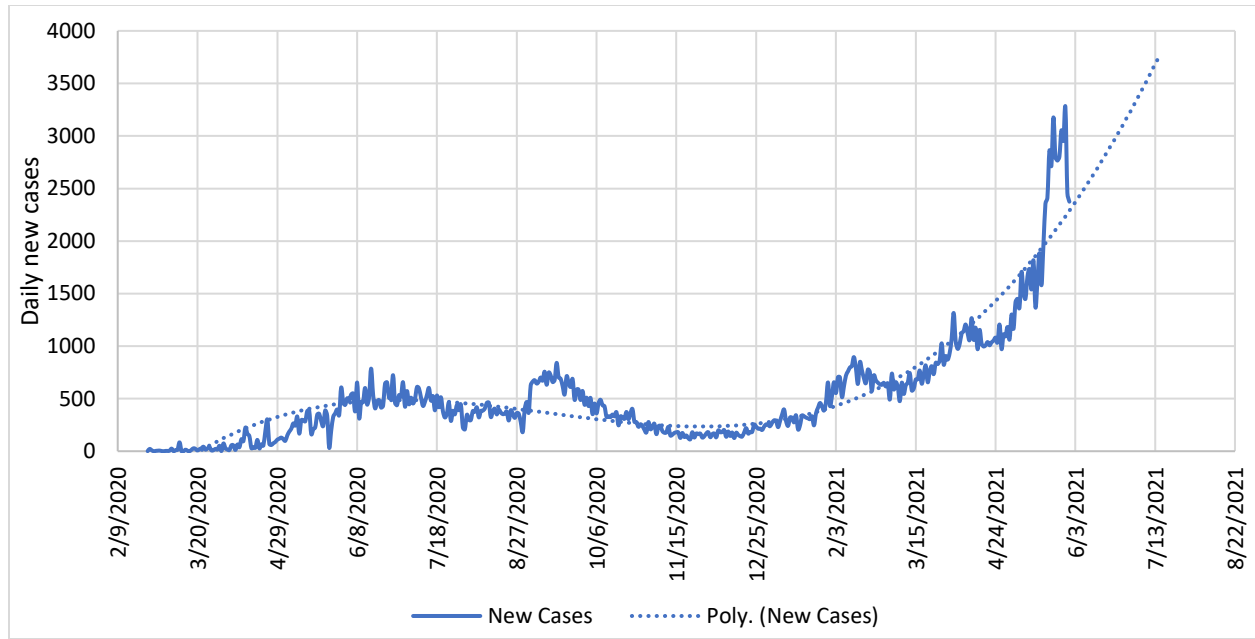


Figure 4.4 The number of new daily infected persons of COVID-19 in the Kingdom of Bahrain and the forecast of new cases.

Their best-fit line was found using the derived polynomial functions (3rd order) with R^2 equals 0.8549; this indicates a good fit-line and reliable model for a future forecast. Where R^2 measures the "goodness of fit" and represents a value between 0.0 and 1.0 (Wei et al., 2021). The cubic equation used to estimate the number of newly infected cases is found in Eq. 4.1:

$$y = 0.0001x^3 - 19.417x^2 + 856018x - 1E^{+10} \quad \text{Eq. (4.1)}$$

Where, y refers to the number of newly infected cases and x refers to the date (number of days).

It is worth mentioning that this study assumed the current situation to remain the same, for instance, without anymore/advanced precautionary measures. Therefore, the best-fit line reveals that the expected number of newly infected cases will increase after May 2021 and reach around 3,700 cases by the middle of July 2021. However, this could not happen because of the two abovementioned factors (cyclic

and irregular components); for instance, a new wave of the deadly COVID-19 could hit the country. Vaccination is a vital factor, and the daily rate of COVID-19 vaccines is increasing in Bahrain (REUTERS, 2021). Up to May 28, 2021, the number of COVID-19 vaccine doses administered was 1.67 million (Our World in Data, 2021a). Another critical factor is the precautionary measure, i.e., the imposition of lockdown. As found in the literature, the lockdown has had a great impact in decreasing the number of infected persons in Bahrain, and it was reported that implementing the lockdown, closing stores, businesses and restricting social gatherings in April 2020 led to a drastic drop in the infected people by 64% (AlSayegh & Iqbal, 2021). The government of Bahrain imposed a lockdown on May 27, 2021, to limit the spread of the coronavirus (MOH, 2021b), which could affect the estimated number of cases.

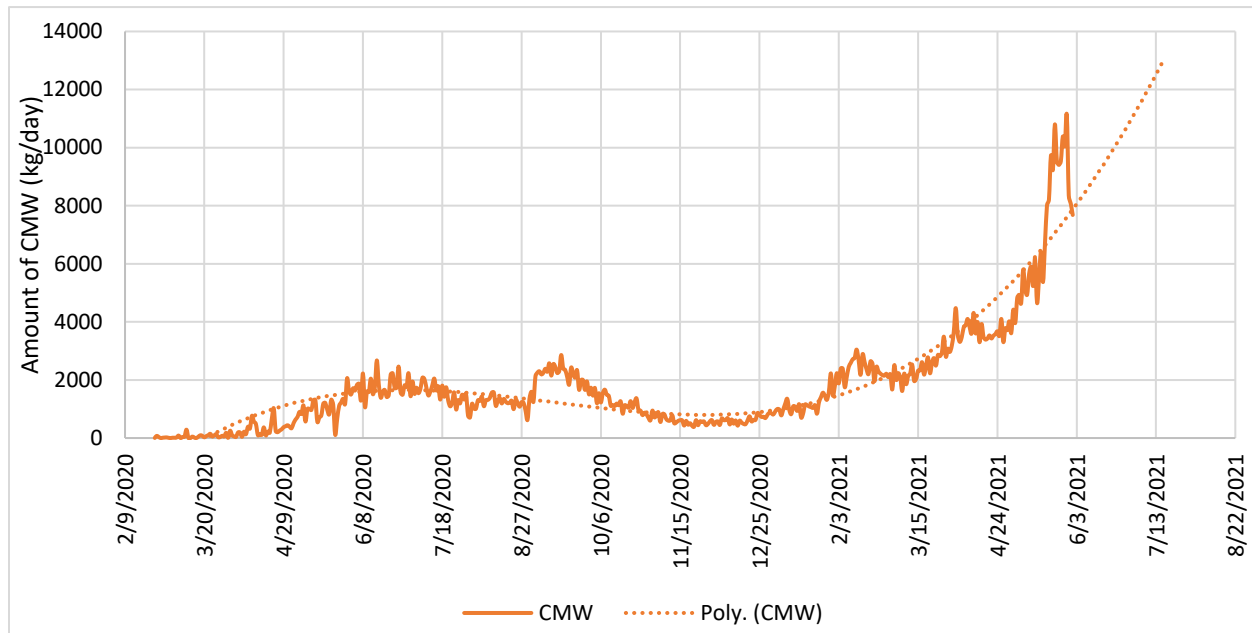


Figure 4.5 The calculated amount and expected CMW generated from infected cases (kg/day).

Consequently, CMW generated by infected cases was expected to increase as well. The calculated CMW using Eq. 3.1 was plotted to figure out the anticipated quantity of CMW, as shown in Figure 4.5. Their best-fit line was found using the

derived polynomial functions (3rd order) with R^2 equals 0.8582, meaning it is a good fit-line and reliable model for a future forecast (Wei et al., 2021). The amount of CMW is expected to increase to 13,000 kg/day by the middle of July 2021. The cubic equation used to estimate the amount of CMW was found in Eq 4.2:

$$y = 0.0005x^3 - 65.939x^2 + 3E - 4E^{+10} \quad \text{Eq (4.2)}$$

Where, y refers to the amount of CMW generated by the infected cases and x is the date (number of days).

4.3.2 Estimation of the Daily Disposable Facemask of the General Population

The rapid spread of the COVID-19 virus has prompted people to wear masks daily as a precautionary measure. In this regard, the government of Bahrain has adopted strict measures to make it compulsory during outdoor activities. A disposable medical mask (surgical mask) is primarily designed and used to protect healthcare workers from hazards during medical activities. However, the medical facemask was extensively worn by most citizens during the outbreak of infectious diseases, for instance, SARS in 2003, PDM H1N1 in 2009, and then COVID-19, as recommended by the authorities (Elachola et al., 2020). It is believed that the facemask could reduce the risk of transmission from one individual to another. According to a study (Eikenberry et al., 2020), facemasks can reduce the rate of disease transmission, resulting in the prevention of disease to a healthy person and the protection of asymptomatic transmission. Moreover, the WHO has stated that, in response to the current COVID-19 virus, the global requirement for facemasks is approximately 89 million per month (WHO, 2021a). As of February 2020, the daily production capacity in China has been raised to about 15 million pieces of facemasks (Xinhuanet, 2020). The global market for facemasks (including respiratory and

surgical) was expected to increase from about 14.6 billion in 2019 to 33.4 billion in 2023, with an annual increase of about 23% (Market Research, 2020).

The weight of the surgical facemask was measured using a precision digital scale to be 2.85 g, and the calculated total number of facemasks used by the general population of Bahrain at 80% acceptance during the pandemic using Eq 3.2 was 1,244,903 facemasks/day (population = 1,742,586, urban population % = 89.3% (Worldmeter, 2021b)). Therefore, the total weight of the facemask used by the general population in Bahrain in one day is $2.85\text{g} \times 1,244,903$ facemask, which equals $3,547,973.55\text{ g} = 3,547.974\text{ kg/day}$ ($12,950.108\text{ kg/year}$).

4.3.3 The PPE Used by the Medical Staff Per Day.

The coronavirus spreads by direct contact and aerosols. For ensuring routine droplets/aerosols barrier precautions, generally proper infection prevention practice, environmental hygiene and minimizing the risk of infection when treating COVID-19 patients were measured. The healthcare workers are required to use protective gear such as facemasks, goggles, PPE suits, face shields, shoe covers, etc.; after their use, decontamination and discarding were strictly directed to be safe (Adams & Walls, 2020). These protective gears were essential as they play a vital and influential role in controlling transmission.

Most PPEs are mainly organic polymeric material; sustainable plastic and its waste pose risks to biota and environmental segments. Mismanaging the waste not only threatens human beings but also puts a greater burden on the environment, which is already inundated by the current amount of plastic waste generated daily from non-medical sources (Purnomo et al., 2021). The component of respiratory masks N95 is polypropylene (PP), the surgical mask is PP, and the textile and fabric mask is cotton. The main components of face shields are polyethylene terephthalate (PET), Polycarbonate (PC), and/or polyvinylchloride (PVC). Goggles are made up of PC, and the protective gowns contain PP, polyester (PE), or polyethylene (PE).

The coveralls (white and blue suites) comprise mainly of high-density polyethylene (HDPE), while the main components of latex gloves are natural rubber, vinyl gloves are PVC, nitrile gloves are acrylonitrile and butadiene, neoprene gloves are carbon, chlorine, sulfur, and hydrogen containing material.

In Table 4.3, the COVID-19 centers were arranged by nature of patients, i.e., case severity of the patients. The exhibition centre was designated to receive all suspected persons, Bahrain International Hospital (BIH) received the mild cases, Kanoo center, 5th and 6th floors (6 words on each floor) in SMC received the severe cases, and HBDC reserved critical cases (Intensive Care Unit - ICU).

Table 4.3 The number of PPE items used by front liners in designated five healthcare facilities of COVID-19 per worker per day.

PPE name	Exhibition center	BIH*	Kanoo center	5 th and 6 th floors in SMC	HBDC**	Weight of PPE item (g)
Surgical facemask	2	4	4	5	5	2.85
Facemask N-95	1	1	1	1	1	10.46
Face shield	1	1	1	1	1	33.56
White suit	1	1	1	1	1	360
Gown	2	10	15	25	25	60.8
Goggle glass	1	1	1	1	1	34.35
Gloves (pairs)	40	25	25	30	30	20.06
Shoes cover	2	10	25	30	30	27.7
PPE's weight per worker (g): <i>Sum (no. of item × weight)</i>	1423.47	1836.27	2555.77	3405.42	3405.42	-

*BIH- Bahrain International Hospital, **HBDC- Hereditary Blood Disorder Center.

The data in Table 4.3 were used to calculate the total weights of PPEs in kg per day using Eq. 3.3 for each centre, as summarized in Table 4.4. It reveals that the total weight of PPE waste was 1849 kg/day. The highest amount of PPE waste was generated by SMC (1243 kg/day) amongst the five selected centres. The Kanoo Centre generated the lowest amount of waste (51 kg/day). The variation in the amount of waste generated in the five centers could be due to the difference in the number of patients attending the center and in the number of health workers.

Table 4.4 Total PPE weight in kg/day for the five healthcare facilities of COVID-19.

	Exhibition center	BIH	Kanoo Center	5 th and 6 th floors in SMC	HBDC
Number of workers/day	240	42	20	365	40
*PPE kg/day per center	341.6328	77.12334	51.115	1242.9783	136.2168
Total weight of PPE kg/day = 1,849.067					

**PPE kg/day per center = PPE's weight per worker (from Table 4.3) × Number of workers.*

4.3.4 Waste Generated from COVID-19 Vaccination.

The vaccination drive against COVID-19 started around the globe at the beginning of 2021. The vaccine production was increased to meet demands, achieve the general population's desired immunization levels against COVID-19, and meet global needs. Governments worldwide tried to vaccinate as many people as possible to eliminate the coronavirus pandemic. However, that could lead to negative environmental consequences (POLITICO, 2021). The vaccination campaign could cause another concern in raising the waste, which is added to the waste produced by single-use PPEs to protect medical staff and general people from the virus. With the

acceleration of vaccine development during the pandemic and the immunization campaign growth, a substantial surge in plastic, rubber, and glass resulting from vaccine bottles was anticipated (Phadke et al., 2021). It was noted that this resulting burden was enormous, especially in the poor, low-income areas, which do not have significant waste management resources, with adverse environmental and financial impacts in the short and long term (UCLA, 2014).

In Bahrain, the MOH has provided various vaccines and urged people to take them as the national campaign for vaccination against COVID-19 continued, with the aim of preserving the health and safety of citizens and residents by raising and strengthening immunity through vaccinations to provide the highest levels of health security in Bahrain (MOH, 2021e). There was a high turnout of citizens and residents to take the coronavirus vaccination, and the intake rapidly increased, as demonstrated in Figure 4.6. By April 14, 2021, the number of vaccination doses administered reached 1,008,746.

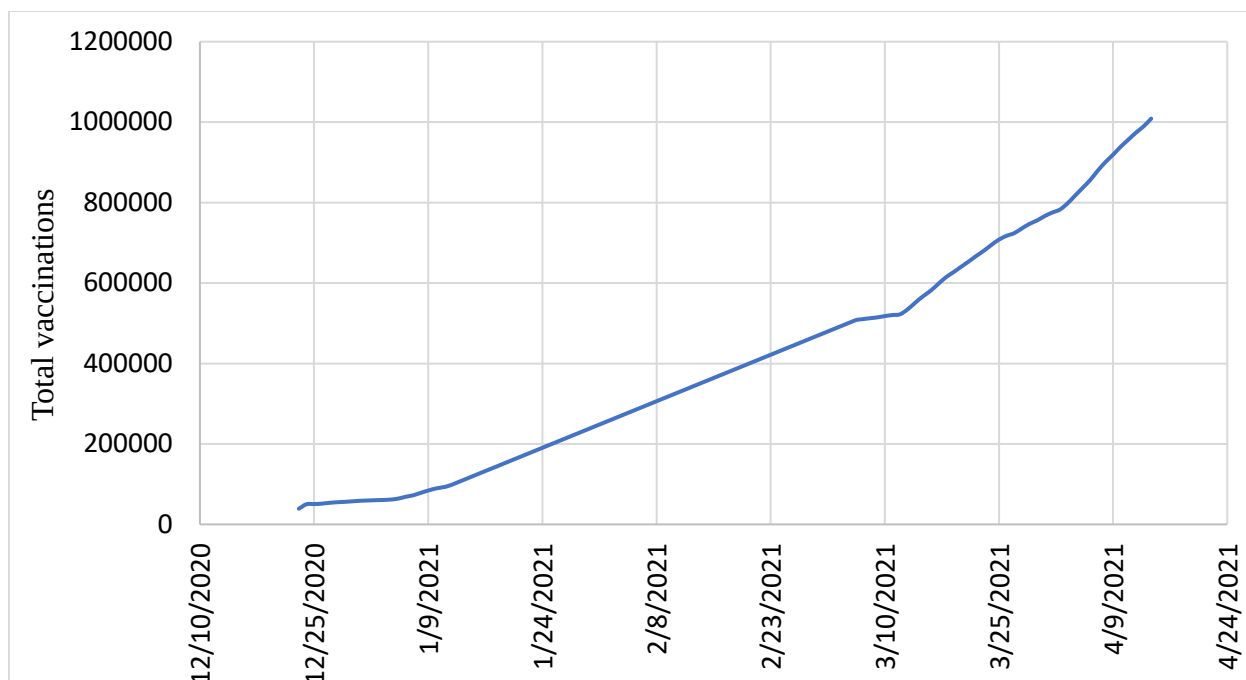


Figure 4.6 Total COVID-19 vaccinated individuals in Bahrain till April 14, 2021; Source of data (Our World in Data, 2022a), available vaccines are AstraZeneca, Pfizer, Sinopharm and Sputnik.

The vaccination drive was at its best, and by May 11, 2021, the number of vaccinated individuals who took two doses was 602,390, and 813,728 vaccinated individuals with the first dose (MOH, 2021d). The time interval between 1st and 2nd dose is 3 weeks (21 days); it was estimated that the given number of the individual took their 2nd mandatory dose within the stipulated time (This number is also included in calculations as discussed below).

Table 4.5 shows all the necessary and required items during an individual's vaccination for a single dose. The data depicted in the table was used to calculate the total weight of the waste produced from vaccination using Eq. 3.4. The total weight of waste generated from the vaccine until May 11, 2021, was determined to be 16,632.505 g, and was estimated to reach 23,337,624.64 g, equal to 23,337.62 kg after taking the second does as shown in Table 4.6.

Table 4.5 The weight of waste items for one dose of vaccination.

Tool	Weight (g)
Syringe	5.82
Glass vial	1.59
Alcohol swab	0.83
Total	8.24

Table 4.6 Total calculated waste generated by vaccination till May 11, 2021.

Number of vaccines (a)	Does (b)	Weight (g) = $8.24 \times (a) \times (b)$
602,390	2	9,927,387.2 g
813,728	1	6,705,118.72 g
813,728	2 nd Mandatory dose within 21 days from the date of their 1 st dose	6,705,118.72 g
Total weight in (g)		23,337,624.64 g

4.3.5 Estimation of Waste Generated from COVID-19 Tests.

In March 2020, the Global Emergency Committee and the WHO called for early detection in order to prevent the virus from spreading among people (Sohrabi et al., 2020). To detect the coronavirus, a swab is used to collect a sample from the mouth, nose or lungs, which is kept in chemical preservatives in a plastic tube. Then, the sample is analyzed and extracted by polymerase chain reaction (PCR), precisely, Real-Time PCR (RT-PCR). The PCR test is applied by collecting a quick sample from the throat or nasopharynx using a long cotton swab into the throat or nostril (Times, 2021). This procedure uses single-use plastics, which are 100% disposable (Tang et al., 2020). The scientific community, in particular, was concerned about the environmental impacts related to the pandemic of COVID-19, like sustainable medical plastic waste. As of August 2020, all COVID-19 tests used RT-PCR generated 15,439.59 tons of plastic waste globally. Approximately 97% of the plastic

residues from coronavirus diagnostic tests are incinerated because they are dangerous to human beings (Celis et al., 2021). Still, during the incineration, toxic chemicals such as emission of dioxins, furans, and particulate matter (WHO, 2018), come out and are released into the air. Also, the study evidenced that, in the short term, it is necessary to reduce plastic waste and intensify efforts to improve controls on gas emissions resulting from incineration, especially in deficit countries. There is a need to consider biomedical manufacturing in the long term, which should be biodegradable and contain no toxic chemicals when burned (Celis et al., 2021).

The Kingdom of Bahrain was committed to introducing modern technologies in the field of diagnosis and treatment to limit the spread of the coronavirus. The country facilitated the methods of examinations and made them accessible to everyone. Moreover, Bahrain provided a medical test facility for COVID-19 at several different points, such as the Bahrain International Exhibition and Convention Center in halls and drive-through facilities, government and private hospitals, and at Bahrain International Airport on arrival from abroad. The MOH made it easier for citizens and residents to be accessed in all regions of the country through random campaigns. These centres relied on PCR to detect coronavirus, which is one of the most commonly practiced tests conducted by hospitals and laboratories to determine the presence of the viral strain or otherwise in the human body. The test is conducted by taking a quick sample from the nasopharynx or throat via a long cotton swab into the nostril or throat (Times, 2021).

The total number of PCR tests performed in Bahrain from March 3, 2020, to May 11, 2021, is shown in Figure 4.7. At the time of the study, the number of COVID-19 tests was increasing daily, where the accumulated number of PCR tests approached 4,273,842 tests on May 11, 2021. This increase led to a rise in medical plastic waste, which is expected to affect the environment negatively.

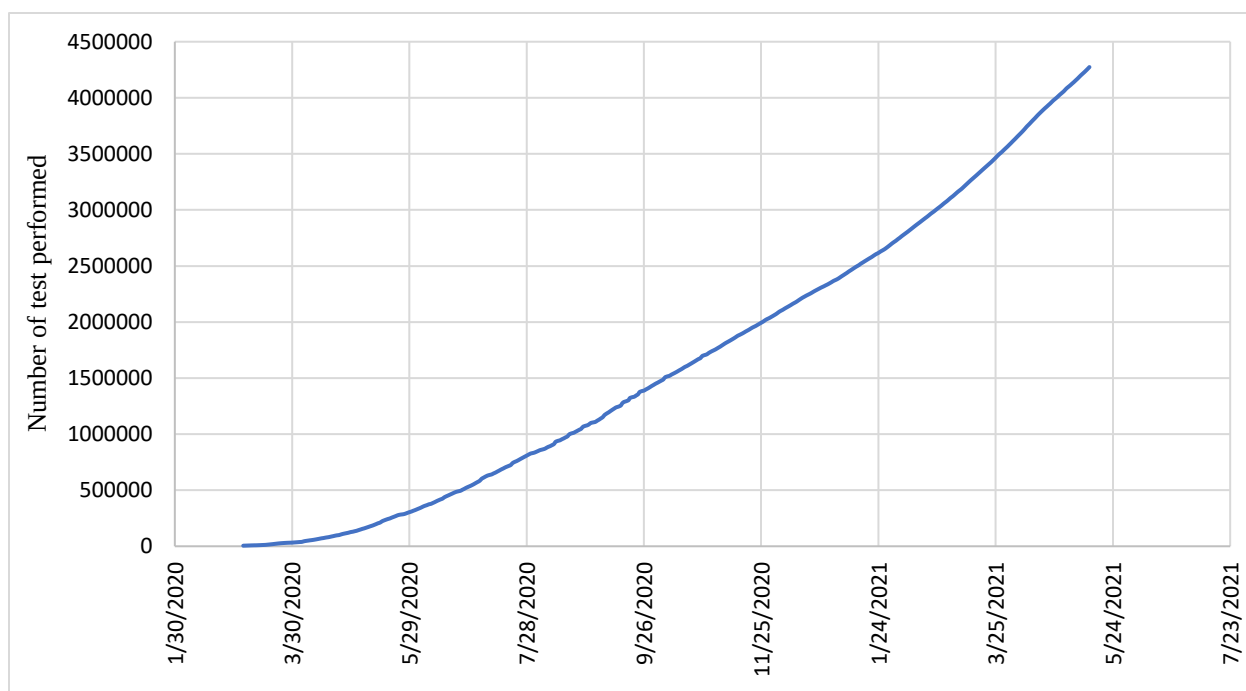


Figure 4.7 The total COVID-19 tests performed in Bahrain till May 11, 2021. Source of data (Our World in Data, 2022a).

Table 4.7 The weight of COVID-19 test items.

Tool	Weight (g)
Nasopharyngeal swab	1.23
Bottle of chemical preservative	11.30
Total weight for one test	12.53

The weight for one COVID-19 test is 12.53 g (Table 4.7), and it was used to calculate the total weight of waste generated from diagnostic tests using Eq. 3.5. Therefore, the waste generated from PCR tests until May 11, 2021 (during the study period) equals $12.53 \times 4,273,842 = 53,551,240.26 \text{ g} = 53,551.240 \text{ kg}$.

Lastly, all the solid MW generated during COVID-19, from March 2020 to May 2021, is summarized in Table 4.8.

Table 4.8 Summary of solid MW generated during one year of the COVID-19 pandemic in Bahrain.

Total waste generated from COVID-19-related activities in Bahrain	Weight
Predicted CMW by July 13, 2021	13,000 kg/day
Facemasks used by the general population	3,547.974 kg/day
PPEs used by medical staff in 5 centers	1849 kg/day
Number of vaccinations, by May 11, 2021	23,337.62 kg
COVID-19 tests, by May 11, 2021	53,551.240 kg

4.3.6 Efficient Management and Treatment of CMW

MW management is a serious threat, particularly in developing countries. The major portion of the COVID-19 related MW is plastic, which needs to be processed for sustainable resource recovery and recycling. The prevailing pandemic situation invites all countries to use collective wisdom and adopt environmentally sustainable management of waste during and after the pandemic (N. Singh et al., 2022). There are concerns about treating CMW before disposal, particularly in developing countries, to curb the spread. Like other associated issues with the virus, the CMW seriously threatens the environment and scientific community. There are several techniques already in the field to cope with MW in a proper way. Incineration is practically applicable, but it emits CO₂ and other unwanted gases; in contrast, the most feasible option that deals with recycling the material, a scientifically acceptable and recommended practice, is chemical treatment and conversion of the waste into useful materials (Figure 4.8). Pyrolysis among chemical treatments is preferred because useful products are obtained due to the process, and ultimately, a small amount at the end is retained for landfill. So far, the technique is efficient, requires the least landfill capacity, is economically viable and publicly accepted. Since the chemical composition of the CMW is the same as normal waste, the main ingredients are polyethylene, polypropylene, polystyrene, polyethylene terephthalate and nylon

(Dharmaraj et al., 2021), which are convertible into useful products. The processes require elevated temperatures ranging from 300-581°C to afford liquid oil and gases (sanitized refused derived fuels (SRDF)) for energy production, where SRDF is a cleaner-burning fuel made by processing and removing contaminants from MW (Purnomo et al., 2021). Gasification and pyrolysis are promising as these techniques lead to useful fuel products and lesser environmental impact. Insufficient operating temperature limits carbonization for processing the CMW, which must be ensured during the process (Purnomo et al., 2021). The CMW is a challenge for the scientific community; it needs to be disinfected before processing for any secondary products. Policies need to be revised or approved to cope with CMW and any possible pandemic situation in future. Efficient treatment is required to be plasticized, and the community shall be ready to deal with any untoward situation in future (Ilyas et al., 2020). Positive features of pyrolysis are that waste is completely decomposed and enough energy is produced, but high investment cost and temperature demand are still to be intelligently answered. Before treating the CMW, certain steps must be taken to reduce the adverse effects (Vanapalli et al., 2021; Zand & Heir, 2021).

The COVID-19 pandemic calls for speedy and precise decisions and enhancing the capacity building for MW management in future abnormal situations. Some steps are necessary to be taken during/before processing the CMW. For instance, the risk of infection and transmission to sanitation workers shall be reduced by scientific sanitization of CMW and the use of sealed bags for safe disposal. A transition towards environmentally friendly materials such as bioplastic must be worked out extensively for normal use and fighting any possible pandemics in future.

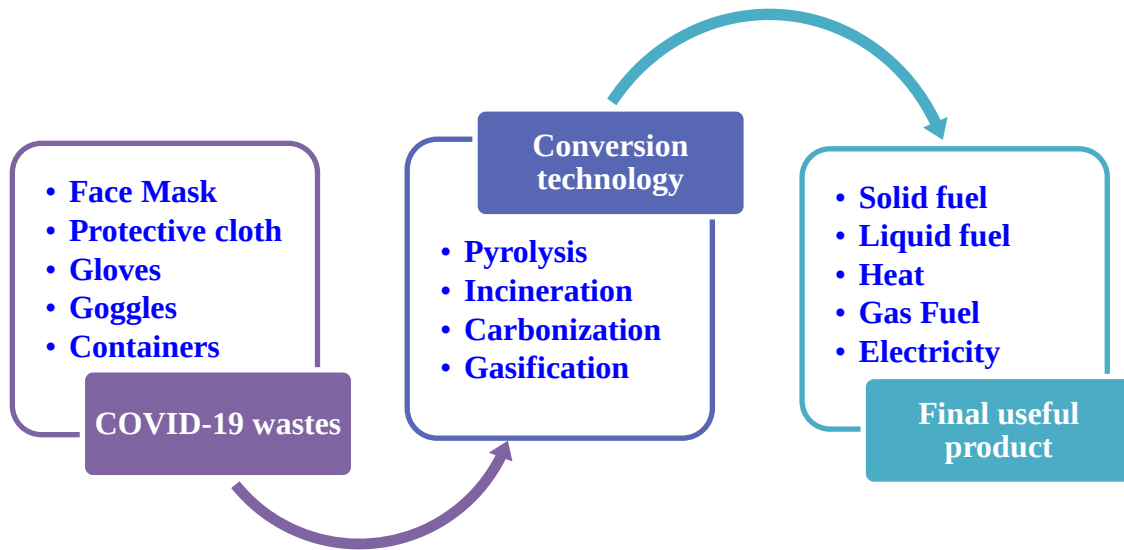


Figure 4.8 Possible schematic explanation of medical waste management, adapted from (Al-Omran et al., 2021)

4.4 Estimation of MW During COVID-19 in GCC countries

In this section, the amounts of MW generated during the COVID-19 pandemic from different sources in the selected GCC countries were estimated. The considered sources were facemasks worn by the public, diagnostic testing PCR and vaccination, in addition to the CMW generated by infected cases.

4.4.1 Estimation of Daily Protective Disposable Facemask

The coronavirus spread led the GCC countries to take strict measures towards facemasks to be worn in public places and during outdoor activities as a precautionary measure. The GCC governments issued laws to impose penalties and fines on violators for not wearing a facemask (EUTERS, 2020; GulfInsider, 2020; Jazette, 2020; OmanObserver, 2021; U.S Embassy in Bahrain, 2021; UAE, 2021), which prompted people to wear facemasks daily during all outdoor activities. Accordingly, the use of facemasks was increasing day by day in GCC countries in the then prevailing situation. Since the consumption of facemasks is directly related to a country's population, it was therefore important to know the total population of

these countries. The calculated number of facemasks in GCC countries using Eq. 3.2 is presented in Table 4.9 (arranged based on countries' population size).

Table 4.9 Estimated daily facemasks usage in the GCC countries.

Country Name	Population	Urban population (% of total population)	*Total daily facemasks (pieces)	Total facemask for 365 days
Saudi Arabia	35,193,520	84.065	23,668,346	8,638,946,316
UAE	9,974,219	86.4	6,894,180	2,516,375,763
Oman	5,197,118	87	3,617,194	1,320,275,857
Kuwait	4,314,813	100	3,451,850	1,259,925,396
Bahrain	1,742,586	89.3	1,244,903	454,389,755
GRAND TOTAL	59,337,355	--	38,876,473	14,189,913,087

**Total daily facemasks = population × urban population (%) × facemask acceptance rate (%) × average daily facemasks per capita/10,000, @ 80% acceptance rate and 1 daily facemask per capita. Source of population and urban population data: (Worldmeter, 2021b).*

The calculated total facemasks on a daily and yearly basis for the selected countries, and as expected, increased with the increased population. Table 4.9 indicates that among the selected countries, the most significant number of facemasks used by the public is found in Saudi Arabia, with more than 8638 million per year. Saudi Arabia has the highest population size of more than 35 million, followed by the UAE, Oman, Kuwait, and Bahrain, with annual quantities of facemasks around 2516, 1320, 1259, and 454 million facemasks per year, respectively. The total calculated weights of facemasks in kg/day in each country are graphically represented in Figure 4.9 (weight of one facemask=2.85 g (0.00285 kg) as found in section 4.3.3). The total weight of waste generated from facemasks in GCC is around 110,798 kg/day. It can be noted that the facemask's weight in Saudi Arabia was the highest, where it reaches around 67,455 kg/day, followed by the UAE

(19,648 kg/day), Oman (10,309 kg/day), Kuwait (9,838 kg/day), and Bahrain (3,548 kg/day).

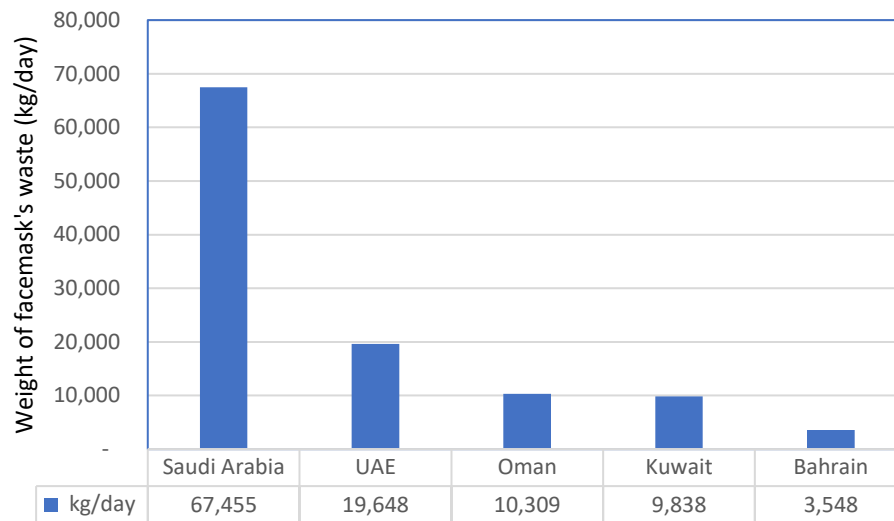


Figure 4.9 Weights of daily facemasks usage in GCC countries till March 26, 2022.

4.4.2 Estimation of MW Generated From COVID-19 Vaccination.

Large national campaigns for COVID-19 vaccination have begun, and they continue to preserve people's health by raising their immunity to afford the highest levels of health security (Kuwait Government, 2021; MOH, 2021c). In the GCC countries, governments provided various types of vaccines and encouraged people to get vaccinated. Until March 26, 2022, the number of fully vaccinated people, including the booster doses, continuously increased in the GCC countries, as depicted in Figure 4.10.

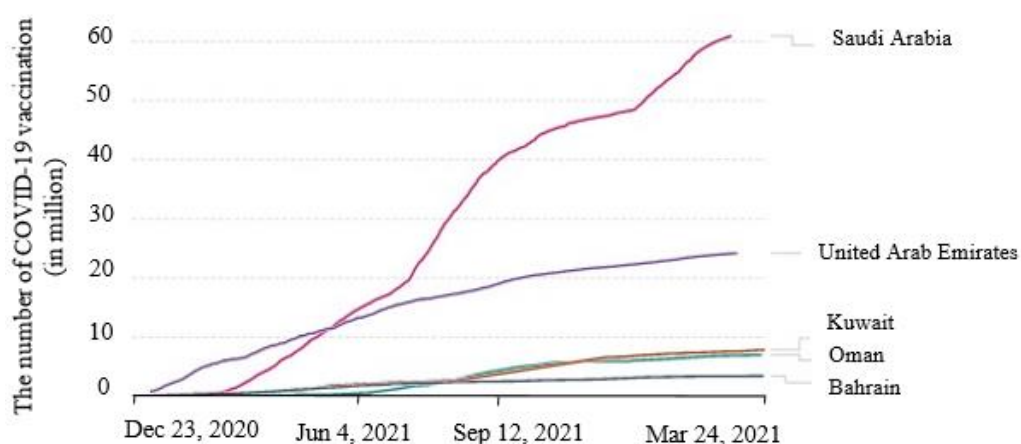


Figure 4.10 The COVID-19 vaccine doses administered in GCC countries, including boosters.
Source: (Our World in Data, 2022b)

As mentioned in section 4.3.4, the total weight of necessary items for an individual's vaccination for one dose is 8.24 g (0.00824 kg). Based on that and the accumulated number of vaccinated people, the total weights of the generated waste from vaccination in the selected countries were calculated as detailed in Table 4.10. The total number of given vaccines with two doses and the booster was 103.35 million, generating 2,554,812 kg (2,554.812 tons) of waste in the selected GCC countries until March 26, 2022 (regardless of the latest data availability date). It can be noticed that Saudi Arabia produced the highest accumulated amount of waste concerning vaccination, which reached 1,506,684 kg.

Table 4.10 The calculated waste generated from COVID-19 vaccination for two doses, including booster dose.

Country Name	Vaccinated individuals (million)*	Total vaccine waste (kg)
Saudi Arabia	60.95 (February 28, 2022)	1,506,684
UAE	24.18 (March 4, 2022)	597,729.6
Oman	6.99 (March 22, 2022)	172,792.8
Kuwait	7.81 (March 24, 2022)	193,063.2
Bahrain	3.42 (March 23, 2022)	84,542.4

Country Name	Vaccinated individuals (million)*	Total vaccine waste (kg)
GRAND TOTAL	103.35	2,554,812

Total vaccine weight (kg) = 3 x number of vaccinated individuals x 0.00824 kg

*Data retrieved on March 26, 2022, from: <https://ourworldindata.org/grapher/cumulative-covid-vaccinations?country=BHR~SAU~OMN~KWT~ARE>

4.4.3 Estimation of MW Generated From COVID-19 Diagnostic Tests.

During the pandemic, the GCC countries were keen to use the latest technologies to diagnose and treat the coronavirus to limit its spread, facilitate examination methods, and make them available to everyone. Therefore, the GCC governments provided different COVID-19 test facilities at several points in the respective country, making them accessible to all citizens and residents in all regions through random campaigns and centers (Government of Saudi Arabia, 2021; Netherlands, 2021). These centers mostly used PCR tests for coronavirus detection, which was the most popular and reliable test globally. However, increased plastic MW was expected with continuing the diagnostic tests, leading to adverse environmental effects.

As mentioned in section 4.3.5, the weight of the test kit used per individual was measured as 12.52 g (0.01252 kg). Consequently, the total weights of waste generated from COVID-19 tests in the selected countries using Eq. 3.5 are calculated in

Table 4.11. The table reveals that the diagnostic tests performed in GCC countries till March 26, 2022 (regardless of the latest data availability dates) were 207.33 million, generating around 2,595,772 kg (2,595.772 tons) of waste. The highest quantity of this type of waste is generated in the UAE (1,835,432 kg = 1,835.432 tons).

Table 4.11 Weights of waste generated by COVID-19 test in GCC countries, till March 26, 2022.

Country Name	Total number of COVID-19 tests performed (million)*	Total weight of PCR tests' waste (kg)
UAE	146.60	1,835,432
Saudi Arabia	41.48	519,329.6
Oman	1.99 (March 12, 2022)	24,914.8
Bahrain	9.5 (March 25, 2022)	118,940
Kuwait	7.76 (March 12, 2022)	97,155.2
GRAND TOTAL	207.33	2,595,772

Total weight of COVID-19 tests = number of COVID-19 tests performed x 0.01252

*Data retrieved on March 26, 2022, from: <https://ourworldindata.org/grapher/full-list-total-tests-for-covid-19?time=earliest..latest&country=BHR~SAU~KWT~ARE>

4.4.4 Estimation of COVID-19 MW by Infected Cases in GCC

The CMW generated from the infected cases in the selected counties in GCC were calculated using Eq. 3.1. The total number of newly confirmed cases and the corresponding calculated amount of CMW in kg/day in GCC countries are visualized in Figure 4.11. The series of new daily COVID-19 cases and CMW in the graph fluctuate; peaks and valleys are continuously seen, with the values going up and down. The number of daily cases in the GCC countries declined to 1064, contributing to around 3,618 kg on March 26, 2022 (Figure 4.11). The ARIMA analysis for the quantities of CMW is performed and presented in Figure 4.12. It reveals that the predicted daily amount of CMW by the end of 2022, on December 31, 2022, could reach 1,179.52 kg, 240.55 kg, 1,953.13 kg, 0 kg, 294.05 kg for UAE, Saudi Arabia, Bahrain, Kuwait, and Oman, respectively. The worst cases also were predicted to be 14,309.09 kg, 30,618.30 kg, 26,441.61 kg, 21,869.06 kg, and

11,630.05 for UAE, Saudi Arabia, Bahrain, Kuwait, and Oman, with a 95% confidence interval (C.I).

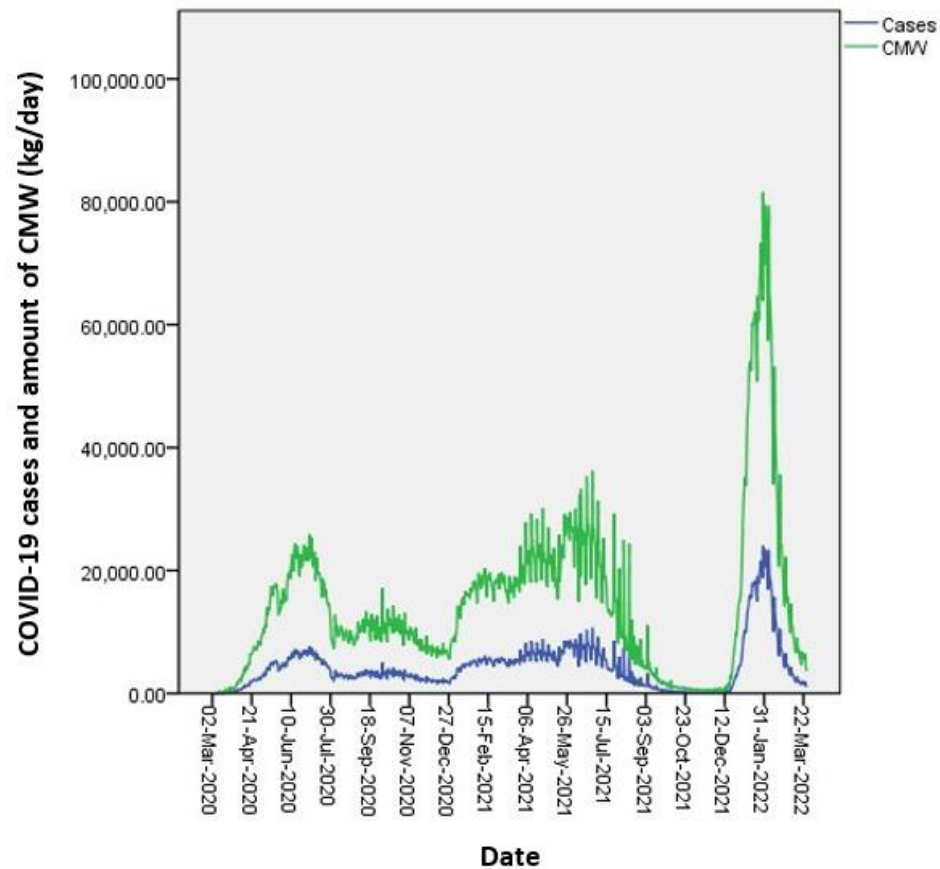


Figure 4.11 Graphical representation of the number of daily COVID-19 cases and calculated CMW generated from infected cases in kg/day in GCC countries until March 26, 2022.

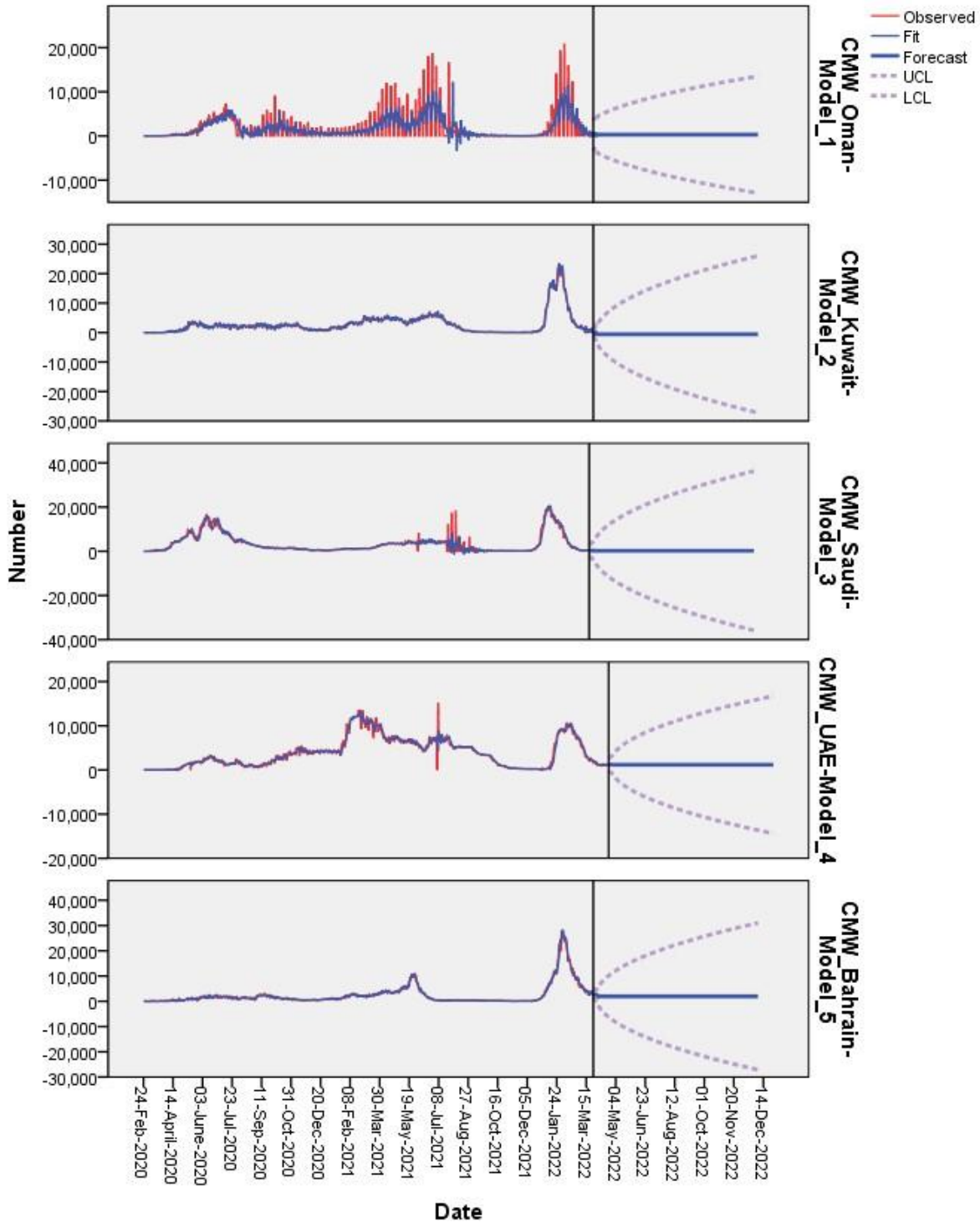


Figure 4.12 Observed and forecasted amount of CMW generated from infected cases in kg/day with 95% C.I. until December 31, 2022

Generally, the amount of CMW in all countries decreased, as evident from Figure 4.12. But in Oman, the amount of CMW was fluctuating, and it was changing

dramatically on a daily basis. Mostly, it's clear that there is strict implementation of policies to curb the virus spread in GCC countries, such as travel restrictions and lockdowns within the specific country. Because of these policies, there were significant reductions in COVID-19 cases and the amount of CMW. Moreover, the number of cases is inversely associated with the number of vaccinated individuals. As can be noticed, vaccination plays a pivotal role in reducing the cases and, in turn, reducing the amount of MW that is generated by the virus. Several studies investigated the effect of vaccination on the spread of coronavirus and indicated that vaccination could substantially impact mitigating COVID-19 outbreaks (Moghadas et al., 2021; Scobie et al., 2021). As shown in Figure 4.14, the vaccination covered most of the population; it is evident that several of these countries have been declared "green" to resume normal activities in a stepwise/gradual manner.

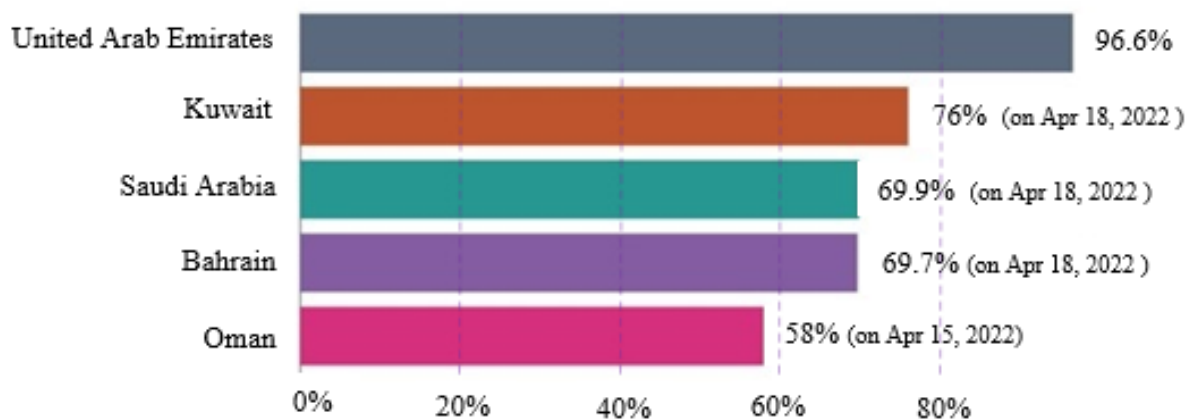


Figure 4.13 Share of the population fully vaccinated against COVID-19 until March 26, 2022, adapted from (Our World in Data, 2022d).

All the calculated solid MW produced during COVID-19 in the GCC countries until March 26, 2022, is summarized in Table 4.12. The weight of used surgical facemasks was 110,797.952 kg/day. The weights of waste produced by vaccination and PCR tests were around 2,554,812 kg and 2,595,772 kg, respectively.

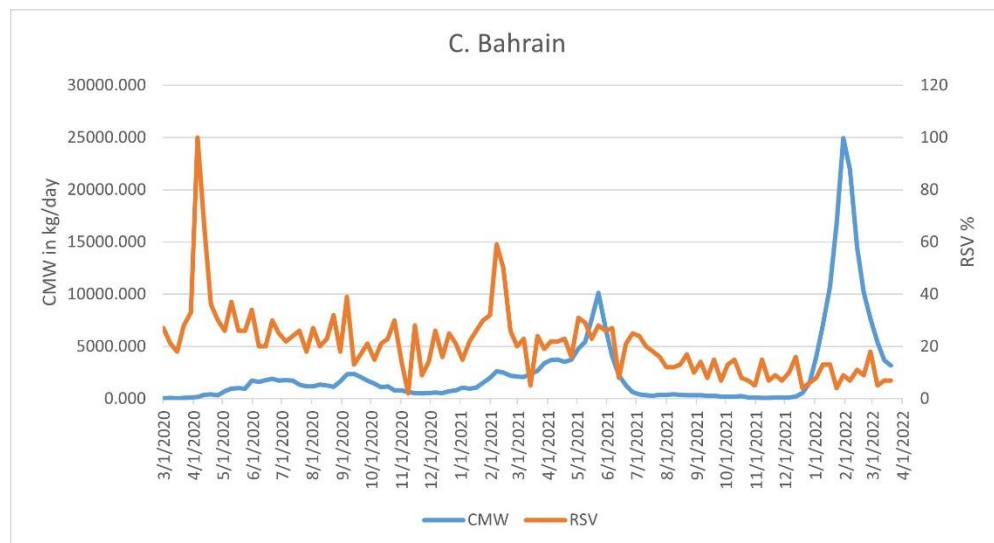
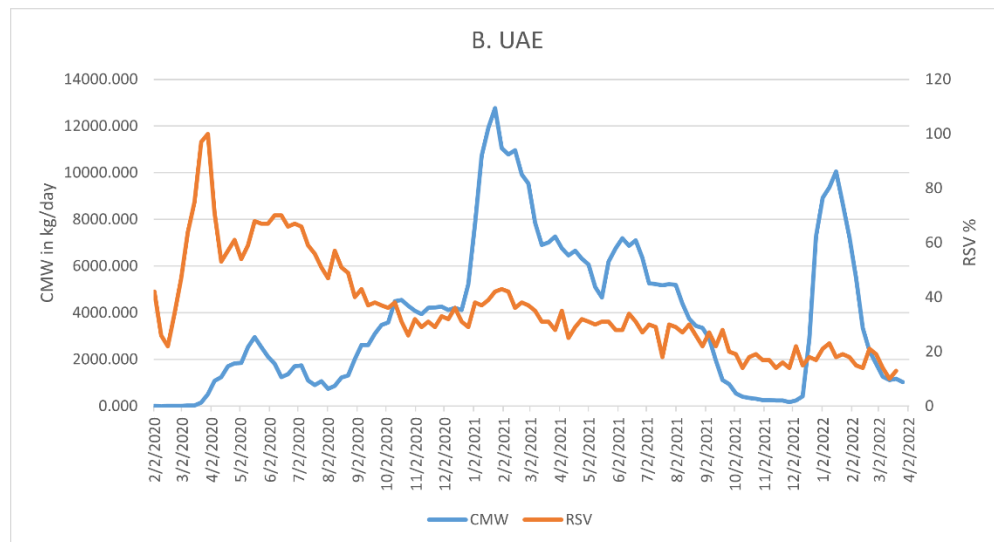
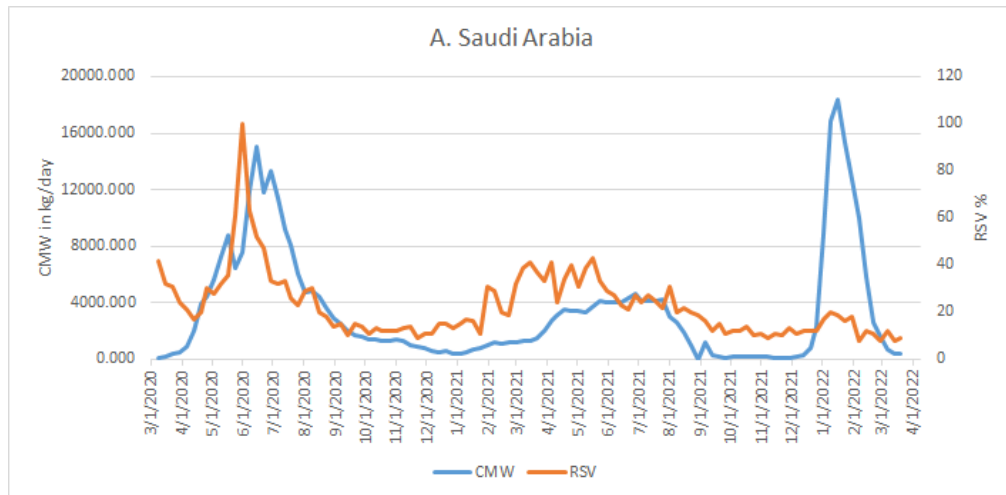
Table 4.12 Summary of generated MW in kg during COVID-19 in GCC countries by March 26, 2022.

Country	Facemask (kg/day)	Vaccination	PCR tests	Predicted CMW (till December 31, 2022)
Saudi Arabia	67,454.786	1,506,684.00 (February 28, 2022)	519329.6	240.55
UAE	19,648.414	597,729.60 (March 4, 2022)	1,835,432	1179.52
Oman	10,309.003	172,792.80 (March 22, 2022)	24,914.8 (March 12, 2022)	294.05
Kuwait	9,837.774	193,063.20 (March 24, 2022)	97,155.20 (March 12, 2022)	0
Bahrain	3,547.975	84,542.40 (March 23, 2022)	118,940 (March 25, 2022)	1953.13
TOTAL	110,797.952	2,554,812.0	2,595,772	3,667.25

Note: the date varies depending on the availability of data.

4.4.5 Relative Search Volume Interest in Medical Waste in GCC Countries (Google Trend)

The GCC countries have witnessed vast and varying amounts of MW during the pandemic since February 2020. This study demonstrates that in some conditions, awareness, and public interest in the issue of MW can be associated with the generated CMW quantities. A Google Trends analysis was performed using the terms ('Medical waste' + 'Facemask'+ 'COVID-19 Vaccine'+ 'COVID-19 testing') as a search query and compared it with the calculated weekly average CMW trends. The trends and patterns of Google search queries could be obtained through the Google Trends data (Arora et al., 2019). Therefore, data from the pandemic's start in each selected country until March 26, 2022, has been obtained and analyzed.



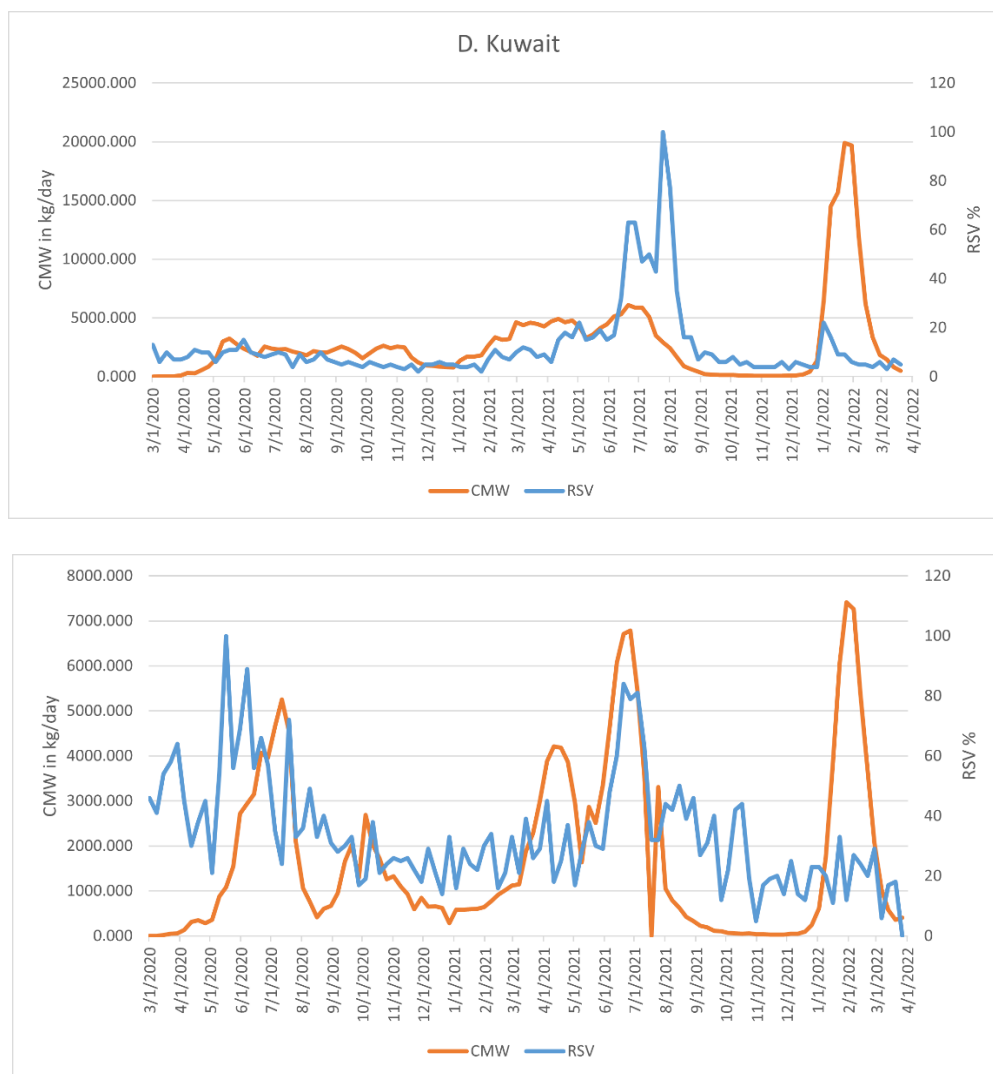


Figure 4.14 Trend of the weekly RSV for the search query 'Medical waste', 'Facemask', 'COVID-19 Vaccine', 'COVID-19 testing' and the calculated COVID-19 MW in kg per day since the pandemic started in the respective country until March 26, 2022.

The trend of the weekly RSV for the mentioned four search query terms in Saudi Arabia is shown in Figure 4.14 A. In the first week of the pandemic in Saudi Arabia, the public interest in the MW issue was moderate, with a popularity of 42% on 8-14 March 2020. After four weeks, the popularity decreased to 17% on 12-18 April 2020. Afterwards, the interest rapidly increased and reached the highest peak with a popularity of 100% between May 31 - June 6 in 2020. After that, the interest level dropped and remained low until the end of 2020. The RSV trend reveals that,

from early 2021, there was a slight oscillation, but mostly, low popularity was observed till the end of this study period, where it reached 9% on 20-26 March 2022. The Google trend in UAE does not differ significantly from that of Saudi Arabia. In the early stages of the pandemic in UAE, the public interest in MW was nearly moderate, with RSV of 42% on 2-8 Feb 2020 (Figure 4.14 B). However, after two weeks, the interest level dropped to 22% on 16-22 Feb. After that, and within the next five weeks, a rapid growth in interest level can be seen, where RSV peaked at 100% from March 29 to April 4. Then, the trend gradually declined until the last week of this study, where RSV reached 13% on 20-26 March 2022. In Bahrain (Figure 4.14 C), the Google trend is also substantially like Saudi Arabia and UAE trends. The first sign of popularity is noticeable in the highest peak, which appears on 5-11 April 2020, with RSV of 100%. A continuous reduction follows this in interest level until the beginning of 2021. On 7-13 Feb 2021, the interest level was slightly raised with RSV of 59%. But again, the interest level fell and remained low until the end of the last week of the study period on 20-26 March 2022.

Based on the Google trend in Kuwait (Figure 4.14 D), it can be observed that when the pandemic started in the country, the interest level was low, with RSV at 13% in the first week of March 2020. Then, the trend of popularity goes almost parallel with the average weekly CMW for more than one year. This is followed up by growth in RSV, reaching 63% in the first peak for the two weeks from June 20 to July 3 in 2021; after four weeks, the interest level rose to the highest peak (100%) in the last week of July 2021. However, afterwards, the interest level fell sharply and remained low till the end of the year 2021. Finally, at the beginning of 2022, it increased slightly to 22%, but it did not last long as it immediately dropped again and remained low till late, with the RSV of 5% on 20-26 March 2022. In Oman (Figure 4.14 E), the first sign of popularity is detected in the small peak of the RSV trend, which is visible between March 29-April 4 in 2020, with RSV of 64%. After

six weeks, on 17-23 May 2020, the interest level rapidly increased until it reached the maximum with RSV of 100%. After that, the trend of the interest fluctuated between highs and lows, and it took the shape of an open upward curve with a slight oscillation for almost one year, i.e. until 20-26 June in 2021, with RSV of 84%. Nevertheless, a drop in the interest level was observed with lots of turmoil until it reached 18% on 20-26 March in 2022.

Overall, at the beginning of the pandemic, there was a high interest in the issue of MW in Saudi Arabia, Bahrain, and the UAE. However, afterwards, there was a change; the interest decreased significantly and remained low until the last week of the study period. The reason behind this change in interest could probably be because, in the beginning, the pandemic was a new emerging situation, and most people were searching for information about the medical waste generated from COVID-19. But later, people may have learned how to live and deal with the situation and its effects due to the prolonged nature of the emergency. Nevertheless, in Kuwait, the medical waste issue's popularity appeared lately, it appeared with the first significant increase in the weekly average CMW when it reached 6,096.686 kg on 20-26 June 2021. Also, it can be observed that, despite the decrease in the amount of CMW, the interest was growing up until a certain point, but after that point, the interest started to fall again. In contrast, the popularity in Oman was somewhat higher than in other countries but continuously fluctuated during the pandemic.

4.5 Factors during the COVID-19 pandemic

Since the outbreak of the pandemic, the Bahrain government has implemented a set of reform measures to respond to the population's demands for medical treatment along with improving the medical system with the intention of responding to public health emergencies (MOH, 2022a).

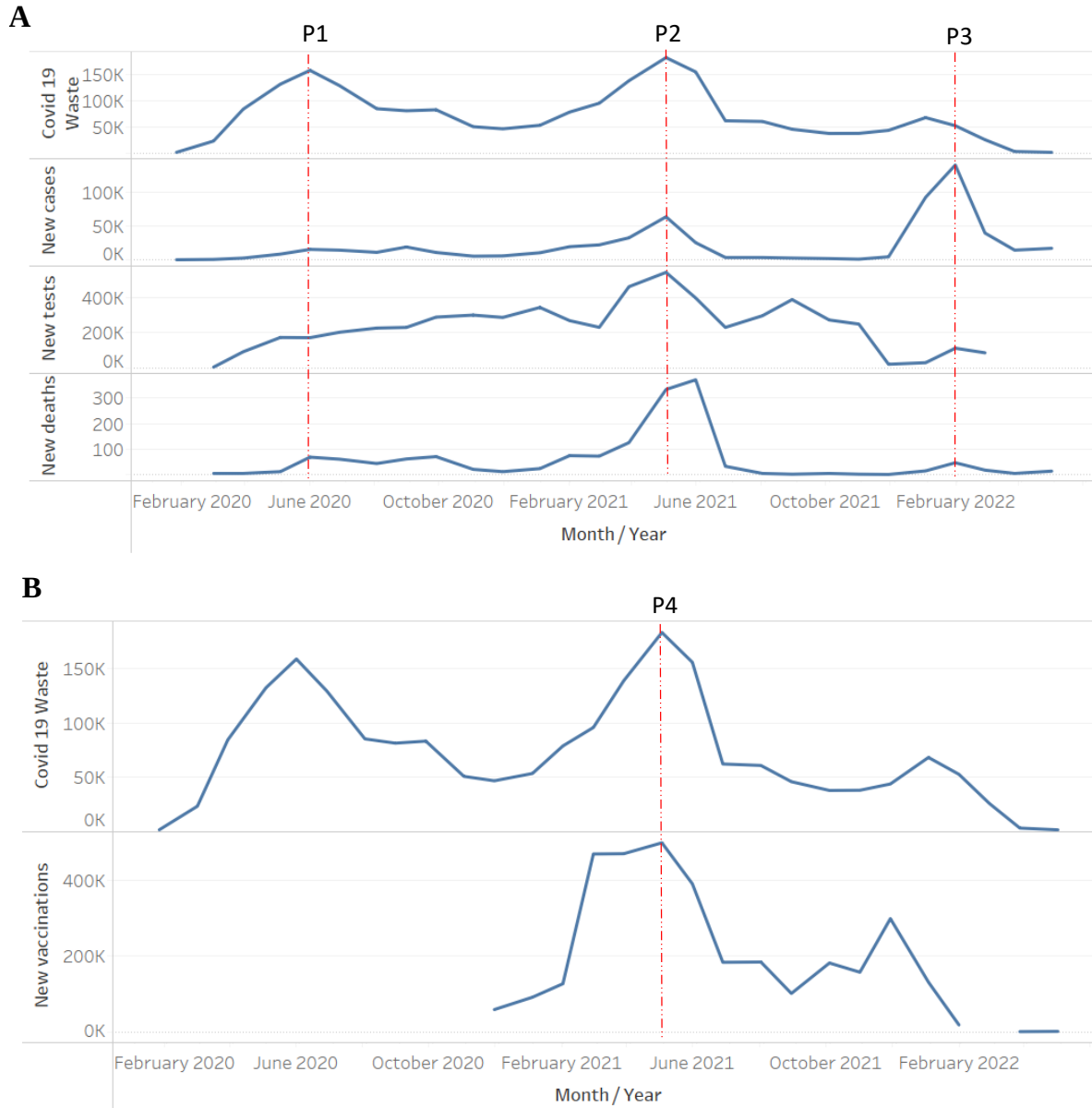


Figure 4.15 A comparison between CW in kg and the four potential factors. (A) CW, new cases, tests, and deaths. (B) CW and new vaccinations, adapted from (Al-Omran, Khan, Perna, et al., 2023).

The first COVID-19 case in Bahrain appeared on February 24, 2020 (Agency, 2020); on March 16, 2020, Bahrain witnessed the first COVID-19-related death. The total number of deaths in Bahrain till the end of September 2022 was 1,520 (MOH, 2022b). As shown in Figure 4.15 A, the first peak of CW can be noticed in June 2020; it reached more than 158,649 kg, although the infected cases, tests and deaths

were still not high at that time (P1). This rise in waste quantity could be because it was at the beginning of the pandemic, and the community was fearful of the coronavirus. Therefore, the government was keen on isolation and quarantine in the health facilities until the beginning of June 2020 (MOH, 2020). But, after that time, the isolation in health facilities was changed to be optional. On June 7, 2020, the MOH started implementing the optional home self-isolation policy for asymptomatic active COVID-19 cases if applicable (MOH, 2020). In the beginning, the doctor examines the health status of the case in the Triaging and Assessment Clinic. Then, if the conditions were met, home isolation was applied with periodic follow-up by representatives of the MOH by phone and also through the software application "Be Aware Bahrain".

Another maximum point for the CW curve in Bahrain was in May 2021 (P2), which reached 183,007 kg. During this month's total, new cases, new COVID-19 tests, and new deaths were also comparatively the highest, reaching 63,597 cases, 547,115 tests, and 334 deaths.

The maximum point for the number of new cases was in February 2022, with 140,308 cases. In the same month, the CW was not high compared to the other months (P3). The amount of CW did not increase in February 2022, although the increasing number of infected people. This CW reduction could be explained by the fact that the severity of the disease decreased due to the decrease in the severity of the virus because of vaccination on the two doses. Also, in that same month, two years after the pandemic, the people coexisted with the virus, which reduced their need for healthcare facilities, and thus, the amount of healthcare waste decreased. It was found that after the first/second doses of vaccination, the number of admissions to the ICU, hospitalizations and in-hospital deaths has decreased (Link-Gelles et al., 2022).

The first dose of the vaccination program started on December 23, 2020, and the second was on March 6, 2021. Figure 4.15 B reveals that the number of vaccinations gradually increased until it reached 497,558 to its maximum point in May 2021. Thus, it can be spotted that the maximum number of introduced vaccinations and the maximum amount of CW were in the same month (P4). Also, it can be observed that, in general, the trend of the vaccination curve is almost similar to the CW curve in the corresponding time. Therefore, vaccination can be associated with the amount of MW generated by COVID-19.

4.5.1 Structural Model and Goodness-of-Fit Statistics

To find out the driving forces of CW production, firstly, the associations among the selected variables needed to be checked. Thus, the HEATMAP dendrogram for clustering correlation analysis was visualized in R software, as shown in Figure 4.16. HEATMAP visually represents data using color gradients to showcase variations or relationships within a two-dimensional matrix (Gu, 2022). Focusing on CW generation, a positive correlation between COVID-19 related waste and the examined factors can be revealed in the respective figure. Additionally, there is a strong relationship between CW and both new vaccinations and deaths.

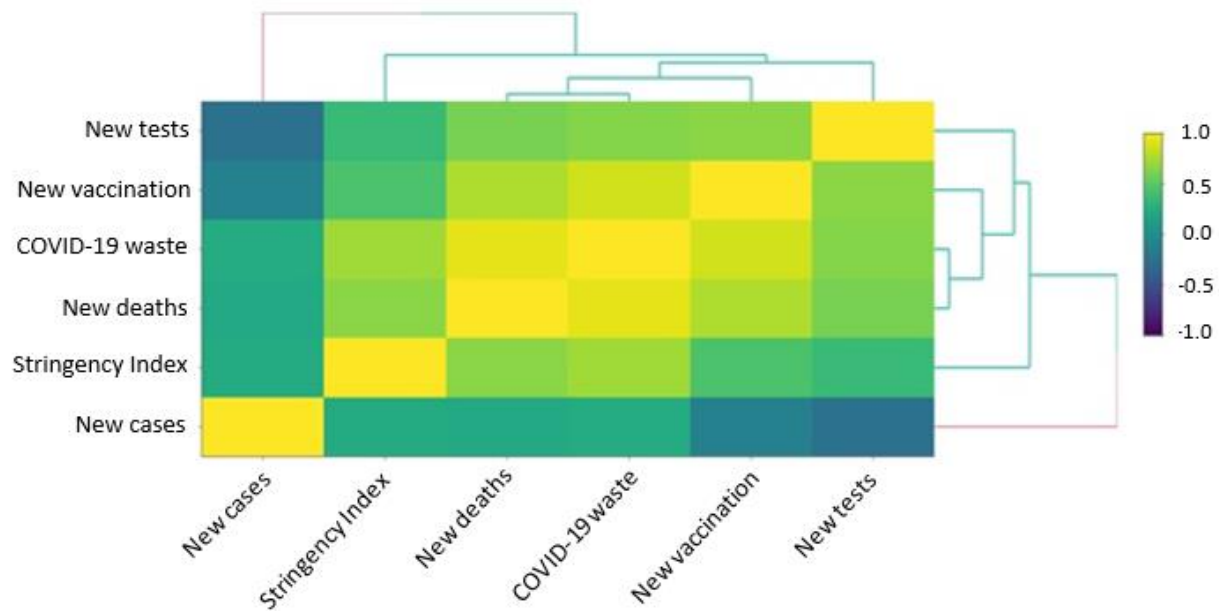


Figure 4.16 The Heatmap correlation matrix for the examined variables.

The structural model was constructed using IBM-AMOS 22.0, as it's well known to represent the model graphically that the rectangles represent the observed variables, and residuals are always unobserved and enclosed by circles or ovals (Figure 4.17). As displayed in Table 4.13, the most common criteria to test the model fit were examined. Firstly, the model fitting produced from the structural analysis did not meet the model fit criteria; for instance, χ^2/df and RFI could not be calculated and $RMSEA = 0.369$, which does not meet cutoff values, indicating the need for the re-specification of the proposed framework. As explained by Charles on applying SEM through many experiments, most models could hardly meet the fitting threshold from the first time due to the data deviation or maybe some problems in the model itself (Charles, 1994). After respecifying the correlation between the observed variables, goodness statistics were examined again on the modified theoretical framework. Subsequently, the values expressed for a better model fit and goodness of fit are as follows: $\chi^2/df = 0.242$, $RFI = 0.948$, $NFI = 0.997$, $CFI = 1.000$, $RMSEA = 0.000$, and $RMR = 0.0334$. Table 4.13 shows that all goodness-of-fit

statistics after re-specification are within the commended limitations, elucidating a good model fit of the proposed model to the data, Figure 4.17 shows the final resulting model.

Table 4.13 Model fit indices of the SEM

Fit Indices	Threshold	Before re-specification	After re-specification
X^2/df	<3	NA	0.242
RFI	>0.9	NA	0.948
NFI	>0.9	1.000	0.997
CFI	>0.9	1.000	1.000
RMSEA	<0.08	0.369	0.000
RMR	<0.08	0.000	.0334

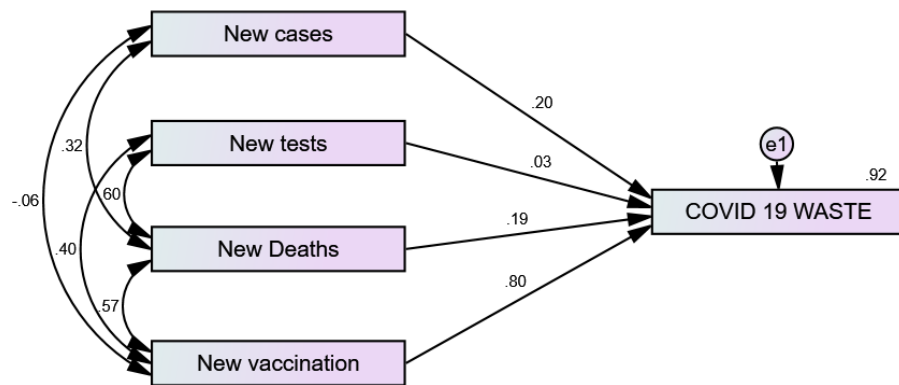


Figure 4.17 Structural Equation modelling for the indicators of the CW amount.

The comprehensive effect of R^2 value is 0.92, which means the model can interpret 92% of the variance in CW generation, as shown in Figure 4.17. As a result, the proposed model can explain each variable well. The results of the hypothesis test are shown in the figure. The standardized path coefficients of the explanatory variables within the two-tailed 95% confidence interval indicate that new cases ($\beta=$

0.20, $p = 0.010$) and vaccination ($\beta = 0.80$, $p < 0.001$) have statistically significant and positive effects on the production of CW. However, the factors, new tests ($\beta = 0.03$, $p = 0.772$) and new deaths ($\beta = 0.19$, $p = 0.093$) are statistically not significant as the p-value is not less than 0.05. The results emphasize that the newly infected cases of COVID-19 and introduced vaccination are the main sources for increasing the quantity of CW.

It can be noticed from the resulting model the most influential factor that causes an increase in CW is vaccination activities, as its coefficient is the highest (0.80). In other words, with the increasing number of people vaccinated, the amount of CW increased significantly. Therefore, the vaccination factor tends to be the main contributor to increasing the quantity of CW.

4.5.2 COVID-19 Policies as a Moderator Factor

To assess the effect of the obtained significant factors on CW with existing COVID-19 government regulations and policies, the variable "stringency index" is entered into the model as a "moderator". The moderator is defined as a variable that interferes with the relationship between an independent variable and its corresponding dependent variable (Awang, 2014). As discovered earlier, out of four factors (COVID-19 cases, tests, deaths and vaccination), only two factors (COVID-19 cases and vaccination) directly influence the quantities of CW that exist and are significant. After that, the "Stringency index" was introduced as a (moderator M) to the model for the relationship between the significant factors (independent variables Xs) and the amount of CW (dependent variable Y). Thus, the causal effects would change by reason of some interaction effect between the significant factor (X), and the moderator variable (M) just entered. Accordingly, the effects of the factor on the amount of CW could either increase or decrease. In other words, the effect of the independent variable on its dependent variable would depend on the level of the moderator variable. For illustration, let M be the moderator variable between the

significant factors and the CW relationship. Then, the moderation role of M is "to alter" the effects of the factor on the amount of CW (Figure 4.18).

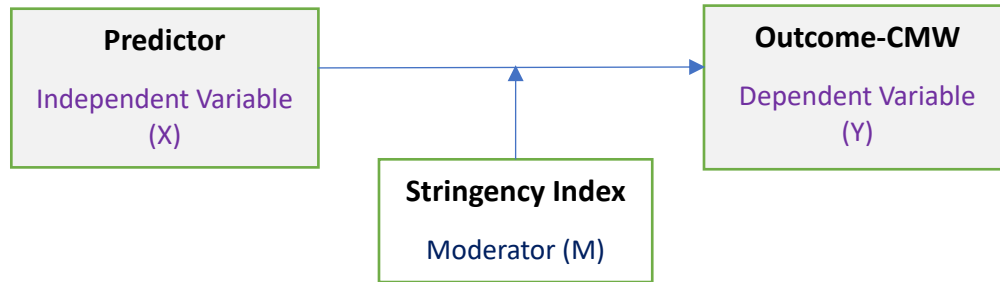


Figure 4.18 The schematic diagram for a model of factors and the outcome variable with a moderator

Here, the outcome can be estimated using Eq. 4.3

$$Y = b_0 + b_1X + b_2M + b_3XM + \varepsilon \quad \text{Eq. (4.3)}$$

Where Y is the predicted amount of CW, X is the predictor, M is the stringency index, and XM is the product of the measured predictor and stringency index. b_0 , b_1 , b_2 and b_3 are the coefficients.

If M moderates X's effect on Y, it is said that X and M interact in their influence on Y. The interaction between the independent variable and moderator variable is tested; if it is not statistically significant, then the stringency index is not a moderator variable; it's only an independent variable. However, if it's statistically significant, then the stringency index will be a significant moderator variable, and thus, moderation is supported (Hayes & Rockwood, 2020). Here, the effect of the stringency index is assessed for each predictor (vaccination and new cases). A third variable was entered into the model, and it was calculated by multiplying the predictor by the stringency index. Thus, hypotheses H_{16a} and H_{16b} were stated.

H_{16a} : The stringency index level moderates the effect of vaccination on the CW generation.

The effect of the number of vaccinations on CW with the presence of a stringency index as a moderator is illustrated in Figure 4.19. The effect of the multiplication of the predictor and moderator (vaccination×stringency) index is statistically significant ($\beta = 0.97$, $p\text{-value} = .005$). It has a positive effect, which means that having more stringency levels, i.e., applying more restrictions related to the vaccination, conducting more vaccination campaigns and being strict with the rules related to vaccination, will lead people to take the vaccine doses. Consequently, increasing the amount of CW. Since the main effect (new vaccination) is not significant ($p\text{-value} = 0.451$) after the stringency entered in the model, then it can be concluded that the moderation type, in this case, is complete moderation (Awang, 2014).

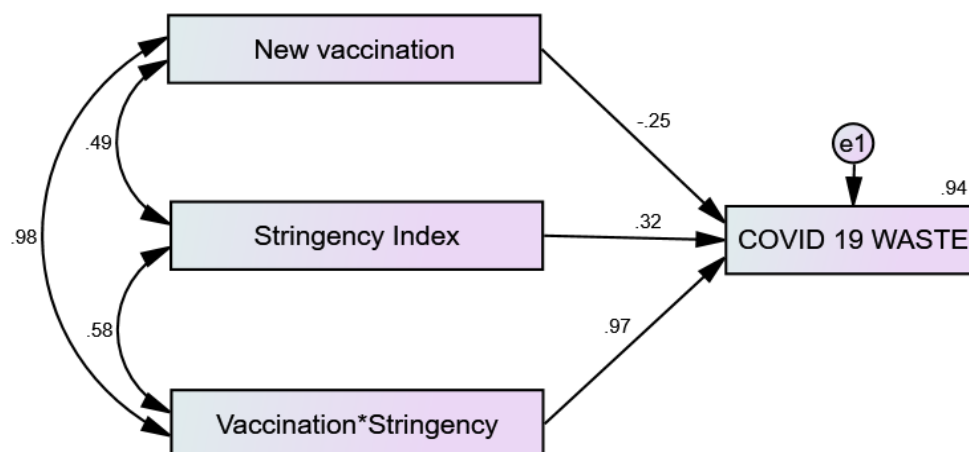


Figure 4.19 Stringency index as moderator for the relationship between vaccination and CMW

To better understand how the stringency index (moderator) changes the causal relationship between the predictors and the amount of CW. It's recommended to visualize and plot the results to support understanding and draw conclusions. It's typically easier to illustrate the nature of moderation analysis using a graph than other methods (Warner, 2012). A common method of illustrating moderation analysis's effects is gradient/slope diagrams (Memon et al., 2019). The low and high values were calculated for the predicted variables and the moderator and then

plotted, as shown in Figure 4.20. The low and high values were below and above the variable's mean.

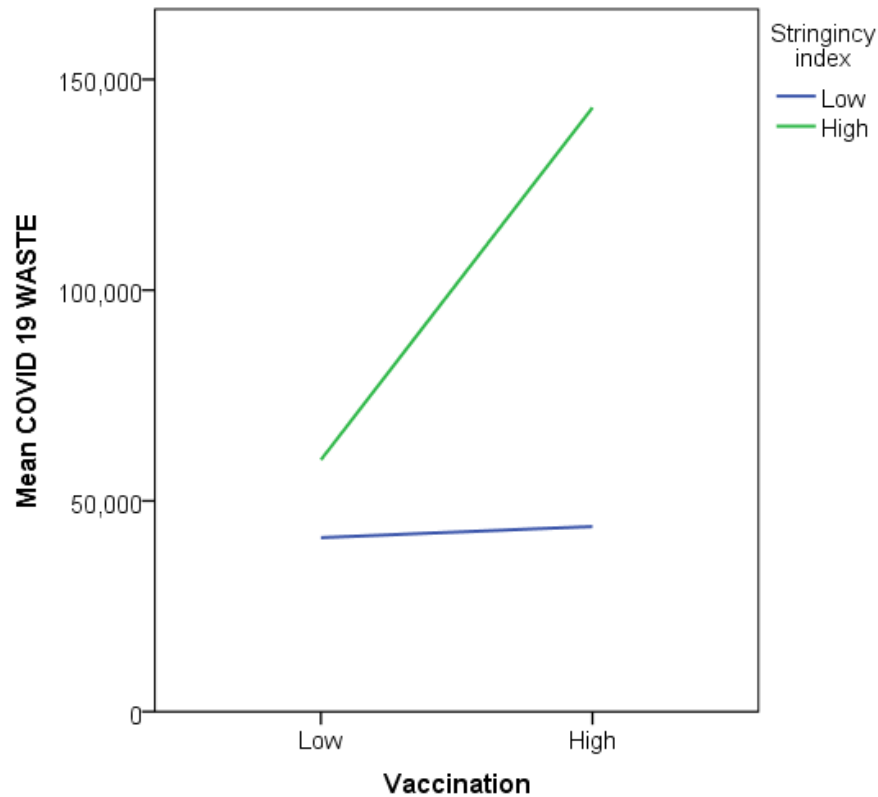


Figure 4.20 The interaction effect of new vaccination and stringency index on the CW generation.

As shown in Figure 4.20, a positive and steeper gradient for the high level of stringency compared to the low level was observed. Thus, the relationship between new vaccination and the amount of CW is stronger for the high stringency index than the low stringency level (McKinley et al., 2018). Results showed that at high levels of stringency, new daily vaccination is a significant, positive predictor of the increasing amount of medical waste during the pandemic. In contrast, at low levels of stringency, the vaccination was only marginally associated with increasing medical waste.

The second hypothesis for assessing the moderation effect was for the relationship between the new cases and the amount of CW, as stated below.

H_{16b}: The stringency index level moderates the relationship between newly infected cases and CW generation.

The effect of the number of newly infected cases on CW generation with the presence of a stringency index is illustrated in Figure 4.21. Here, the effect of the product (new cases×stringency index) is statistically significant ($\beta = 4.60$, p-value less than 0.001). It has a positive effect, in which the stringency index would lead to an increase in the amount of CW. Here, it is pertinent to mention that since the main effect (new cases) is still significant (p-value is less than 0.001) after the stringency entered the model, the moderation type is partial moderation (Awang, 2014).

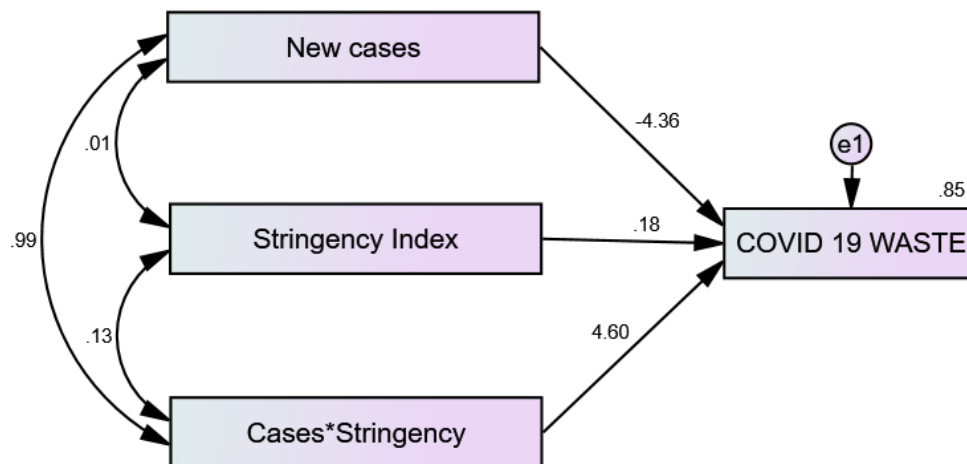


Figure 4.21 Stringency index as moderator for the relationship between COVID-19 new cases and CMW generation.

As shown in Figure 4.22, the line of high stringency is steeper than the low stringency line. Thus, it can be concluded that, in the case of the high stringency index, the relationship between COVID-19 newly infected people and the amount of CW is more potent than in the case of the low stringency level.

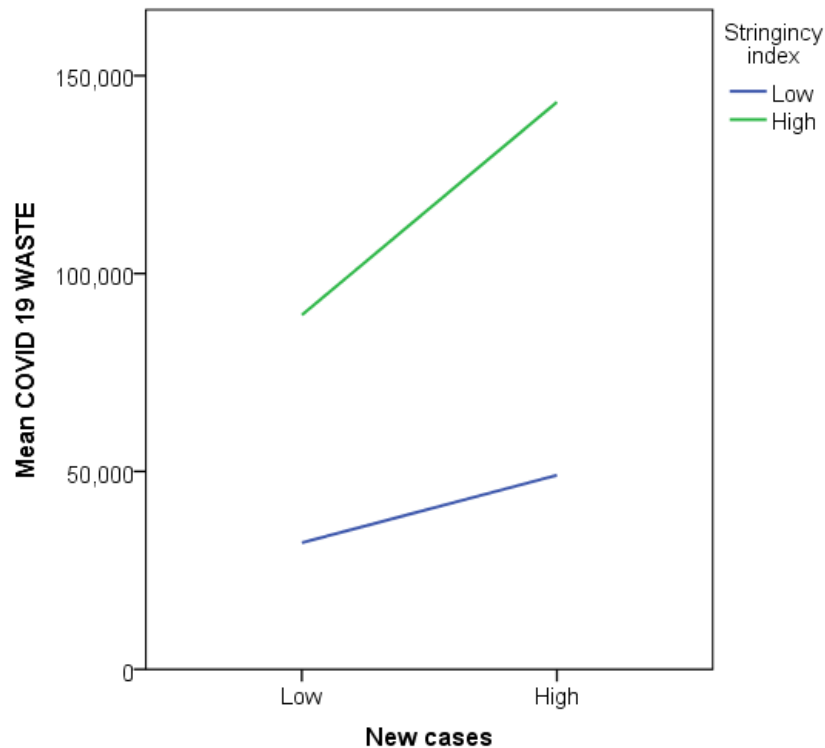


Figure 4.22 The interaction effect of new cases and stringency index on the CW generation.

4.5.3 MW Treatment During COVID-19

The increase in MW in Bahrain during COVID-19 undoubtedly affects disposal and treatment facilities, which might lead to insufficient scientific handling and disposal of the generated waste. The treatment capacity of BWTC for MW incineration is 150 tons/month. However, in some months during the pandemic, the amount of CW and incinerated waste exceeded the company's capacity, as demonstrated in Figure 4.23. It can be noticed that in Jun 2020, May 2021 and Jun 2021, the amount of CW exceeded the company's capacity. In regular time, each incinerator operates for 15 hours/day for 25 days in a month, but on rush days during the pandemic, the operating hours for one incinerator were increased by 5 hours, for instance, 20 instead of 15 hours for two incinerators on alternate days. In that approach, the company dealt with the excess amount of MW and, at the same time,

BWTC diligently maintained the safety measures of the incinerators throughout the peak days of the pandemic (Al-Omran, Khan, Perna, et al., 2023).

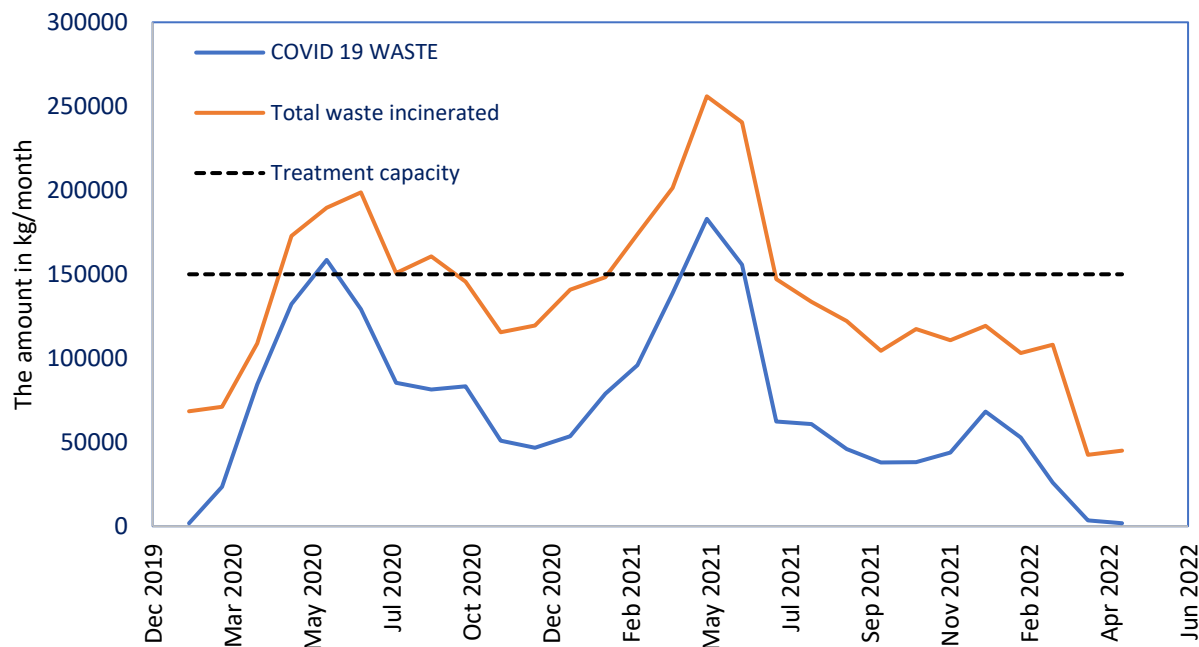


Figure 4.23 The COVID-19 waste, total waste incinerated and treatment capacity of the company in kg/month.

The incineration could diminish the weight of waste by more than 70%, but large quantities of combustion residues remained after incineration, mainly bottom ash, which is the main solid residue from burning MW in incineration facilities, it settles at the bottom of the furnace and is discharged from the moving grate (Zhao et al., 2010). The bottom ash increases as the total incinerated waste increases (Figure 4.24). Since the pandemic started, the maximum amount of resulting bottom ash in BWTC was in May 2021 (35,831 kg) when the total waste incinerated reached 255,963 kg, in which the CW was 183,007 kg, where CW represented 71.5% of the total incinerated amount of waste. During the incineration process, bottom ash, fly ash and air pollution control unit residues, that are the captured pollutants and byproducts removed from exhaust gases by air pollution control equipment in the incinerators, pollutants like heavy metals. A total of 402 tons/year of bottom ash is

disposed of at the Askar landfill, and 22 – 29 tons/ year of air pollution control unit residues (including fly ash) is disposed of at the Hafira landfill (SCE, 2012).

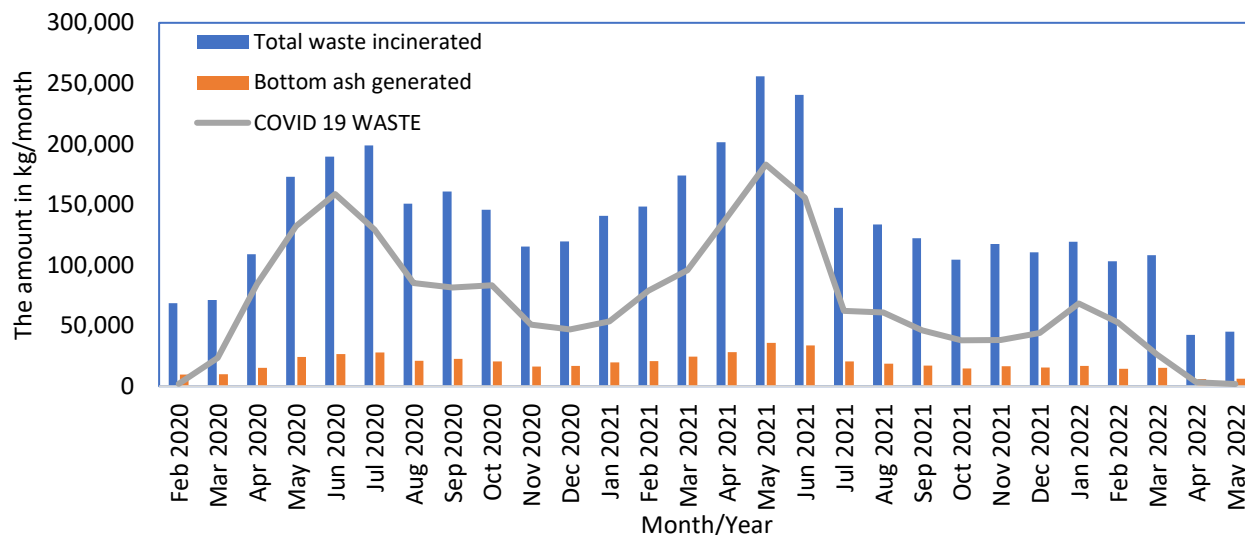


Figure 4.24 The COVID-19 waste generation, total waste incinerated, and the bottom ash generated are all in kg/month from Feb 2020 to May 2022.

Data about emissions have been obtained from BWTC and compiled in Appendix 5. The data on gas emissions is graphically presented in Figure 4.25 and Figure 4.26. The emissions data in the figures reveal that NO_2 is emitted in greater quantities than other gases. The formation of NO_2 is dependent on the nature of the material being incinerated. Most polymeric material contains nitrogen (N) compounds, which afford various oxides upon incineration in the presence of a sufficient oxygen supply. The amount of SO_2 was higher in June 2021 and NO_2 was higher than that of other gaseous species in October 2021 and 2022 (Figure 4.25). Similarly, the concentration of total PM was the highest in the sampling period in 2021 and 2022 (Figure 4.26). The lowest concentration of metallic contaminants is because of the nature of the waste, where most of the materials are plastic (Al-Omran, Khan, Perna, et al., 2023).

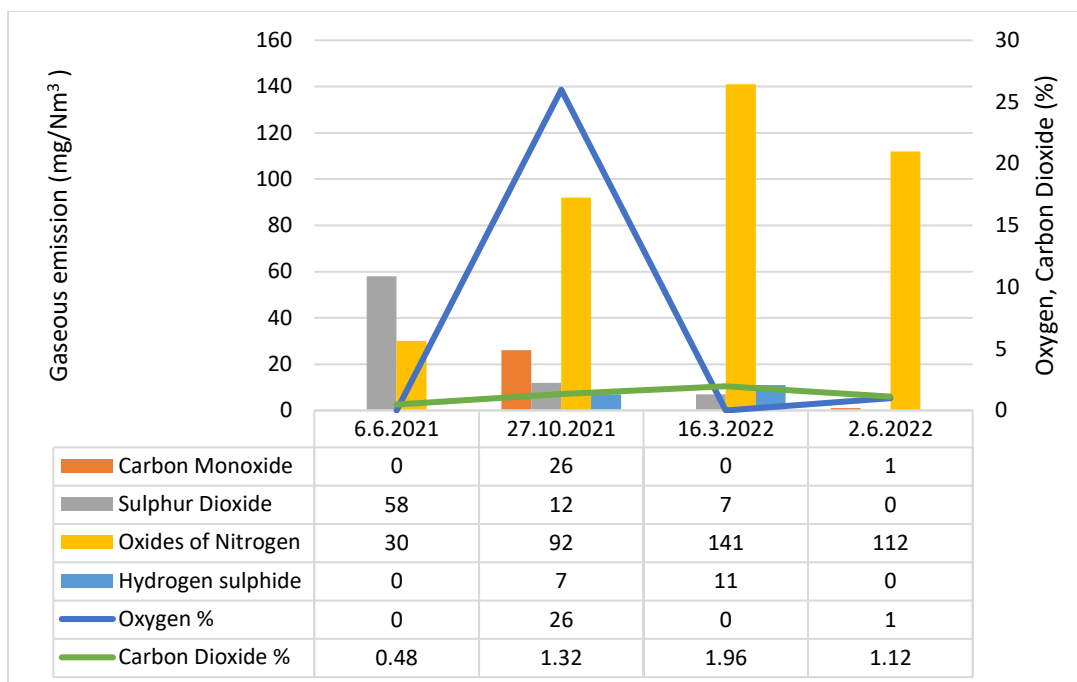


Figure 4.25 Selected gaseous emissions to the environment from incinerators during four sampling periods.

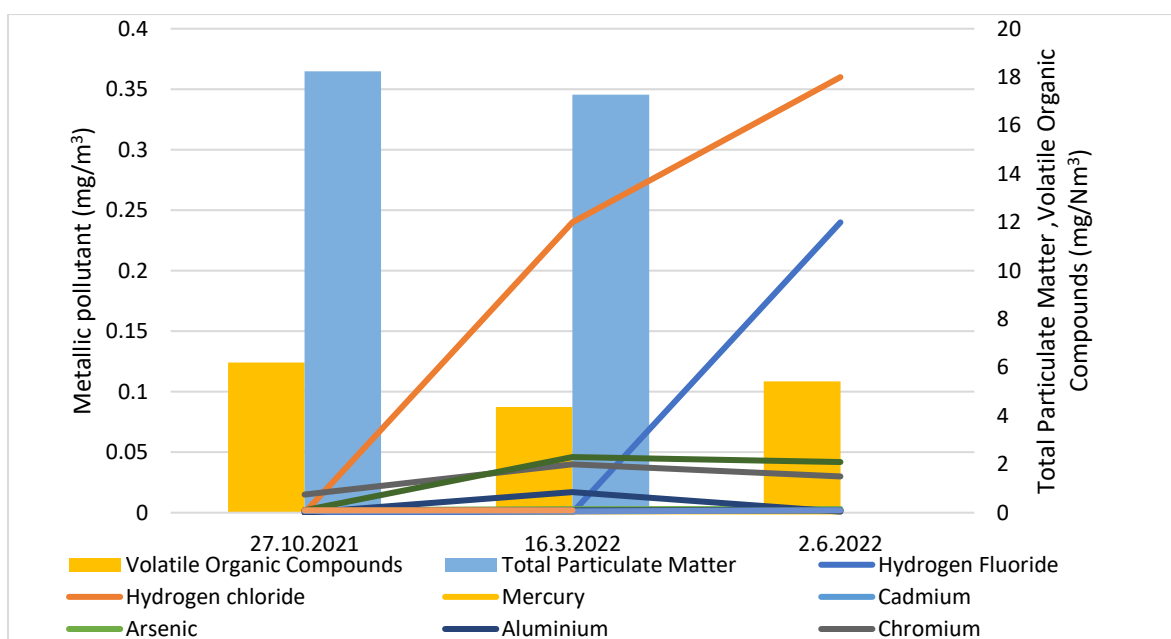


Figure 4.26 PM and metallic pollutants released into the atmosphere.

Bottom ash from MW incineration was studied by Zhao et al. (2010), and they found that bottom ash encompasses high levels of PAHs (polyaromatic

hydrocarbons), highly exceeding the soil limits. Consequently, serious environmental problems might be caused by bottom ash if not adequately managed. Moreover, the chemical analysis of the study revealed that the major components of the bottom ash are silicon dioxide (SiO_2), calcium oxide (CaO) and Aluminum Oxide (Al_2O_3). In addition, high concentrations of metallic elements, such as Al, copper (Cu), iron (Fe), magnesium (Mg), manganese (Mn), Titanium Ti, zinc (Zn) and chromium (Cr), are also found, and most of these metals are associated with the stable residual fraction.

The quantity of generated bottom ash is notably high which becomes a concern (Figure 4.27), particularly with the surge in MW quantities during the pandemic. Several experimental studies showed the efficacy of reusing and recycling bottom ash, specifically in construction materials.

The experimental investigations revealed the promising use of MW bottom ash in concrete as a supplemental cementitious material (Malavan & Manju, 2017). The investigations focused on studying the effect of the chemical, physical, and microstructural characteristics of the bottom ash on the attributes of blended concrete through contemporary advancements. The studies' results exposed the efficiency of mixing the bottom ash with cement or sands in certain precise ratios, confirming its adherence to the standard leaching determined by the US EPA (Genazzini et al., 2003; Manjunath et al., 2023). Matalkah (2023) provided an experimental investigation of the recycling bottom ash to improve its reactivity for cleaner utilization in concrete mixtures using different activation methods. Moreover, Jaber et al. (2022) focused on treating the bottom ash post-grinding and mixing it with an asphalt mixture (base layer) by using different proportions. The study found the proper proportion that the bottom ash should be mixed with asphalt instead of the conventional filler utilized in the mixture.

CO₂ constitutes a vast portion of GHG emissions due to the energy-intensive process of cement production. Blending cement with bottom ash could offer a sustainable solution, reducing the environmental footprint of the cement industry, particularly in countries facing heightened demand for cement. Also, mixing sand with bottom ash could alleviate the substantial demand for sand in construction. Utilizing the bottom ash in cement and sand could curtail both landfill usage and environmental pollution (Manjunath et al., 2023). Hence, there is a critical necessity for further research on bottom ash, given its significant potential for sustainability.



Figure 4.27 Generated bottom ash in BWTC, pictures taken during the site visit.

As attained earlier, during the COVID-19 pandemic, the amount of MW increased with the increasing number of infected cases and the introduction of vaccination programs. The company's treatment capacity is limited, in this case, MW accumulation cannot be treated immediately, thus threatening public and environmental health. It's crucial to improve MW disposal's efficiency and sufficiency and overcome the lack of treatment capacity. Therefore, it's necessary to increase the number of disposal facilities in the country for similar public health emergencies. The establishment of mobile incinerators equipped with similar

treatment equipment would speed up the effective treatment of MW in peak periods of some emergencies, taking into account the appropriate place for the processing as per the policy on infectious waste. It is possible to achieve joint cooperation and mutual assistance with one of the MW treatment companies. It is worth mentioning a successful case in which the mobile incinerator in Wuhan effectively relieved the pressure of MW treatment (Singh et al., 2020). Moreover, associated technology of gas emission control systems must be installed, and it is better to use waste-to-energy incinerators, particularly in the case of plastic (Abedin et al., 2022).

4.6 Estimation of MW in Normal Situations and Associated Factors Using ML

MW generation investigation should encompass private and public sector healthcare facilities. The number of private healthcare facilities represents a large proportion of the total healthcare facilities in Bahrain (Mohamed et al., 2009; NHRA, 2020). At the same time, public sector facilities hold a significant share of the healthcare landscape. The key aspects of healthcare facilities in Bahrain from 2010 to 2019 are demonstrated in Figure 4.28. The figure reveals that government facilities have 82% of the total beds available and 54% of doctors for healthcare services. In addition, the majority of the patients in the country are treated in governmental facilities where the admissions rate is 68% and the outpatient rate is 80%. Investigating the two types of healthcare facilities in this study could provide a comprehensive approach, ensure a holistic understanding of MW generation, and pave the way for sustainable and efficient waste management in Bahrain's healthcare sector.

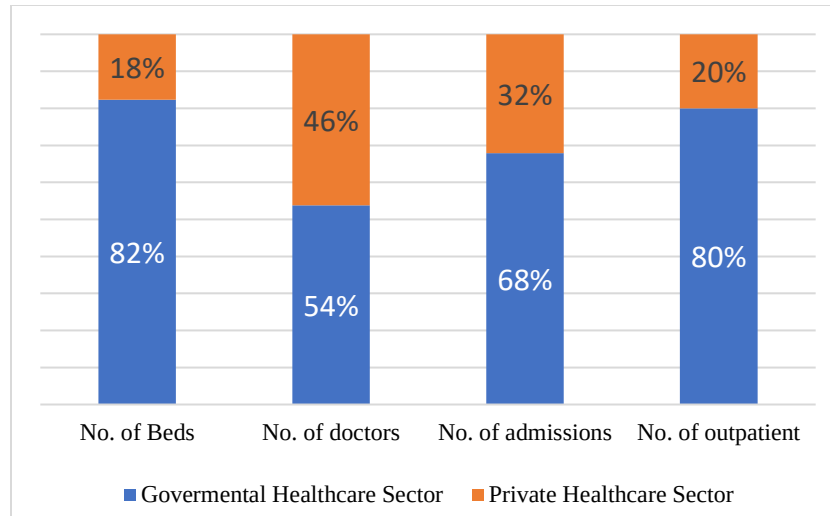


Figure 4.28 Average number of beds, doctors, admissions, and outpatients of healthcare facilities in Bahrain (2010 – 2019), data source: (Information & eGovernment Authority, 2022).

4.6.1 MW Generation Rates in the Selected Hospitals.

The quantity of MW generated in the government hospital, SMC, over 50 months, spanning from January 2019 to February 2023, is graphically represented in Figure 4.29. Notably, the amounts of MW specifically associated with COVID-19 cases were intentionally excluded from the SMC database, as mentioned in section 3.2.5.1. However, despite this exclusion, there was a noticeable overall increase in waste generation after January 2020. In June 2021, when COVID-19 cases escalated in Bahrain (Al-Omran et al., 2021; Al-Omran, Khan, Perna, et al., 2023), there was a significant surge in waste generation. This rise in waste generation during the stated period in the hospital could potentially be attributed to the consequences following the recovery from COVID-19.

In SMC, the generation rate per occupied bed per day was calculated for 2022, where the average MW was 58,948.6 ($\pm 9,873$) kg/month with a hospital bed capacity of 1127 beds. The MW generation rate was determined as 2.61 kg/occupied bed/day, and 1.744 kg/bed/day

The generation rate in the selected government hospital in this study is less than the results found in governmental hospitals by some studies in other countries such as Kuwait which found the MW generation rate between 3.87 and 7.44 kg/bed/day (Jasem M. Alhumoud & Alhumoud, 2007), and in Jordon (3.49 kg/bed/day) (Bdour et al., 2007).

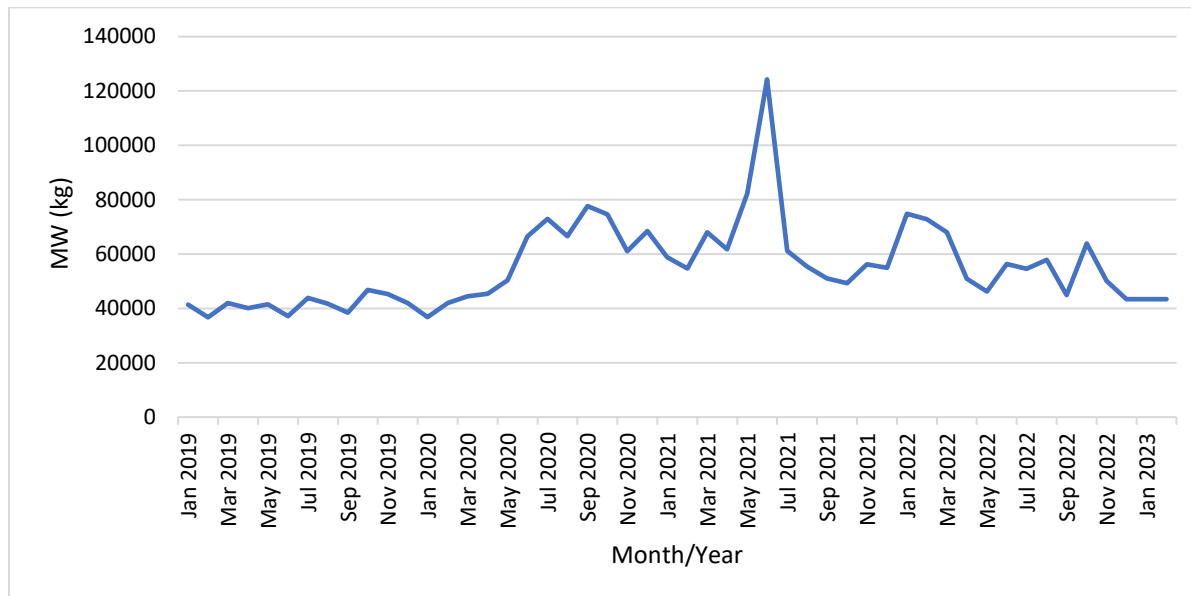


Figure 4.29 Total Medical waste in SMC from January 2019 to February 2023

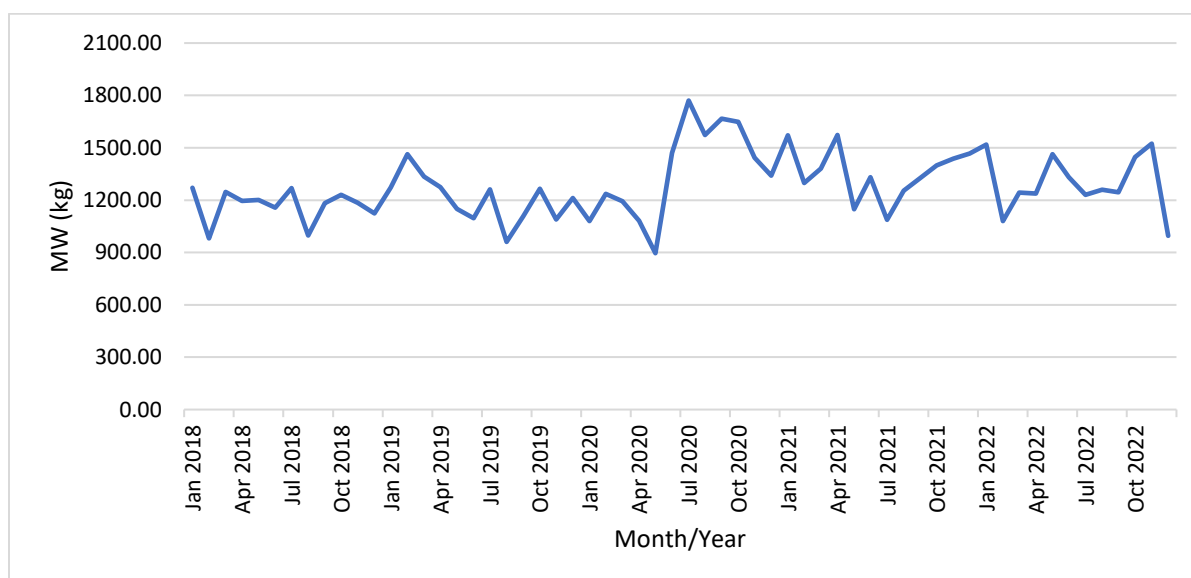


Figure 4.30 Medical waste in PH from January 2018 to December 2022

The monthly amounts of generated MW in the PH over 60 months, from January 2018 to December 2022, are depicted in Figure 4.30. The figure reveals fluctuating patterns in MW over this period. In early 2018, MW was approximately 1200 kg, but it experienced variations in subsequent months. From June 2019 to August 2020, there was a significant decline in MW, with the lowest recorded value of 896 kg in May 2020. The MW levels showed subsequent ups and downs, reaching a peak of 1770.48 kg in July 2020. Following that, the trend showed fluctuations until December 2022.

In PH, the average MW production in 2022 was 1,298 (± 166) kg/month with 77 beds. The calculated average generation rate was 1.040 kg/occupied bed/day and 0.562 kg/bed/day.

The rates in kg/bed/day in the two selected hospitals fall in the range of the estimated MW by WHO in the less developed and developing countries (0.50 to 3.00 kg/bed/day) (Al-Shallash & Shereif, 2007). The present study found considerable variation in the generation rate, the rate of MW production in the public hospital is more than in the private hospital. This finding is consistent with many other studies (Bdour et al., 2007; Komilis et al., 2012).

The generation rate in kg/bed/day determined in this study is relatively small compared to other countries like the United States (8.4 kg/bed/day) and Canada (8.2 kg/bed/day). Kazakhstan (5.4 kg/bed/day) and Iran (and 3.7 kg/bed/day), and the European countries, Spain (4.4 kg/bed/day) and Italy (4.1 kg/bed/day) (N. Singh et al., 2022). However, it is more than other studies in some European and Asian countries like Greece and Pakistan which have about 0.3 kg/bed/day each. Moreover, it is more than the neighbouring Gulf country UAE, where the generation rate varied from 0.28 to 0.33 kg/bed/day with an average of 0.3 kg/bed/day (Awad et al., 2021; N. Singh et al., 2022).

Limited studies used occupied beds in addition to the hospital beds to measure the generation rate, for instance, in North Greece, the rate of infectious waste generation was determined to be 0.85 kg occupied bed/day or 0.58 kg bed/day (Sanida et al., 2010). Also, the MW generation rate was measured in Iraq in kg/occupied bed/day and it varied from 0.85 to 1.11 (Thameel et al., 2022). Komilis et al (Komilis et al., 2012) displayed bed occupancy as an important parameter as it changes from day to day but they did not use it because the information was not available, and the number of official beds was used.

Based on occupied beds, waste generation related to patient care activities is more accurately represented by the number of patients using the facility at a given time.

4.6.2 Hyperparameter Optimization

After computing the performance metrics based on parameter default values from the training and test data, the optimal combinations of hyperparameters were acquired. The tuned hyperparameters for the single ML algorithms were found, as shown in Table 4.14 and Table 4.15.

Table 4.14 shows the parameters corresponding to three RF models and one LightGBM model within an ensemble framework for SMC. The ensemble weights determine the contribution of each algorithm to the final prediction model, with the first RF weighing 0.533, the second 0.067, and the third 0.333. The "Max Features" parameter represents the maximum number of features considered when splitting nodes in the model; it controls the number of features considered at each split in the RF models, with the first and second RF models both using 0.200 as the max features value, while the third RF model uses 0.400. The "Min Samples Leaf" and "Min Samples Split" determine the minimum number of samples required to create a leaf node and split a node, respectively, with each RF model having different values for

these parameters. In the LightGBM model, the ensemble weight is 0.067, indicating its contribution to the overall ensemble prediction. The learning rate parameter controls the step size at each boosting iteration, with a value of 0.1158. The min split gain parameter specifies the minimum gain required to split a leaf node in the LightGBM model, with a value of 0.5789. The subsample parameter determines the fraction of samples used for training each tree, with a value of 0.9000. Finally, the "No. of Estimators" parameter specifies the number of estimators (or trees) used in each model, which varies between 10 and 600.

The parameters for the PH model are summarized in Table 4.15, which indicates that the first, second RF, first ERT and XGB have equal and lowest ensemble weights of 0.067, while the second ERT and third RF have the equivalent and highest ensemble weights of 0.267. The maximum number of features and the minimum number of samples required to create or split a leaf node varies across the RF and ERT models. The EN model employs parameters like "Alpha," which equals 0.001, and it controls the regularization strength, and "L1 Ratio," which determines the balance between L1 (LASSO) and L2 (Ridge) regularization and it equals 1. The tolerance value in this context likely refers to the convergence tolerance, which determines the threshold at which the training process stops iterating based on the convergence of the model's optimization algorithm. So, the EN model would continue iterating until the optimization process reaches a tolerance level of 0.0001, indicating sufficient convergence. The max iteration was 1000. The XGB model utilizes parameters such as "Base Score", "Learning Rate", and "Max Depth" to fine-tune the boosting process; they equal 0.500, 0.300 and 6, respectively. The number of estimators (or trees) used in all models ranges from 25 to 100.

These hyperparameters and ensemble weights collectively influence the performance of the ensemble model. By combining the predictions from each model, the ensemble aims to achieve enhanced accuracy and predictive power.

Understanding and tuning these parameters are critical in optimizing the model's performance for research purposes.

Table 4.14 Hyperparameter and weights of Ensemble VR model of SMC.

	1 st RF	2 nd RF	3 rd RF		LightGBM
Ensemble Weights	0.533	0.067	0.333	Ensemble Weights	0.067
Max Features	0.200	0.200	0.400	Learning Rate	0.1158
Min Samples Leaf	0.0194	0.0132	0.0284	Min Split Gain	0.5789
Min Samples Split	0.0631	0.0107	0.0009	Subsample	0.9000
No of Estimators	50	600	10	No of Estimators	25

RF: Random Forest, LightGBM: Light Gradient Boosting Machine.

Table 4.15 Hyperparameter and weights of Ensemble VR model of PH.

	1 st RF	2 nd RF	1 st ERT	2 nd ERT	3 rd RF	EN	XGB
Ensemble Weights	0.067	0.067	0.067	0.267	0.267	Ensemble Weights 0.200	Ensemble Weights 0.067
Max Features	0.500	0.400	0.600	0.700	0.700	Alpha 0.001	Base Score 0.500
Min Samples Leaf	0.034	0.050	0.016	0.009	0.004	L1 Ratio 1	Learning Rate 0.300
Min Samples Split	0.022	0.002	0.026	0.031	0.009	Max Iteration 1000	Max Depth 6
No of Estimators	25	50	25	10	25	Tolerance 0.0001	No of Estimators 100

RF: Random Forest, ERT: Extra Random Trees, EN: Elastic Net, XGB: Extreme Gradient Boosting Regressor

4.6.3 Performance of ML Algorithms

Various relevant features were considered and tested as inputs in the model to identify the optimal models for the datasets utilized in this study. The study aimed to find the most effective models for the given datasets by exploring different combinations of the selected features and which combination of features would yield the best result in prediction accuracy and performance. For the SMC dataset, the initial experiment involved 5 features, including inpatients, outpatients, surgeries, population, and hospital capacity. This resulted in an R^2 value of 0.79, indicating a moderate level of predictive accuracy. To further improve the model, an additional feature, 'Age65andAbove', was incorporated, leading to a significant enhancement in the R^2 value, being enhanced to 0.904. In the PH dataset, 7 features were initially

considered, including inpatients, outpatients, surgeries, hospital capacity, deliveries, patient admission days, and bed occupancy. The resulting R^2 value was 0.742, indicating a relatively lower level of predictive accuracy. To improve the model, an additional feature, 'personal loan', was added to account for its potential impact on private hospitals, which improved the R^2 value to 0.917. Subsequently, the population feature was introduced, further enhancing the model's predictive capability with an improved R^2 value of 0.943. These findings demonstrate the iterative feature selection and incorporation process to optimize the models for each dataset, resulting in improved prediction performance. The final proposed models' performance measures for governmental and private hospitals are shown in Table 4.16.

Table 4.16 Performance measures of the proposed model for SMC and PH hospitals.

	SMC	PH
Sample size	50	60
RMSE	0.099257	0.13332
MAE	0.032	0.037
MSE	0.003	0.003
R^2	0.904	0.943
Features	Inpatients, outpatients, surgeries, population, Age65andAbove, hospital capacity (number of beds).	Inpatients, outpatients, surgeries, personal-loan, population, hospital capacity (number of beds), deliveries, patient days, bed occupancy.
Baseline Algorithms	'RF', 'RF', 'RF', 'LightGBM'	'RF', 'RF', 'ERT', 'ERT', 'RF', 'EN', 'XGB'

As shown in Table 4.16, the performance measures using RMSE, MAE, MSE and R^2 for SMC and PH are 0.099257, 0.032, 0.003 and 0.904; 0.13528, 0.048, 0.004, and 0.917, respectively.

It is important to highlight that various metrics were used to evaluate the models' performance, unlike other studies that rely solely on a single metric, such as MSE (Arabgol & Ko, 2013).

Considering the performance measures, the voting ensemble method in this study is a successful, superior method and the best model for both SMC and PH, as they had the highest R^2 score and the lowest RMSE, MAE, and MSE scores. It means that a voting ensemble comprising three RF and lightGBM algorithms can be used to predict the future amounts of MW for the government hospital, and a voting ensemble comprising 3 RF, EN, XGB and 2 ERT algorithms for the private hospital, even with a small dataset.

In comparison to other studies that used the MLR method, the proposed model in this study demonstrates greater success in this particular aspect than certain other studies (Bdour et al., 2007; Ceylan et al., 2020; Golbaz et al., 2019; Jahandideh et al., 2009; Karpušenkaitė et al., 2016; Thakur & Ramesh, 2018). Based on used metrics, the proposed model performed closer to that of the ML algorithms for predicting MW amounts that give superior results, for instance, the ANN models developed by Jahandideh and others (2009) and Thakur & Ramesh (2018), generalized additive and smoothing splines models developed by Karpušenkaitė and others (2016), GRNN, which is a form of ANN proposed by Adamović and others (2018) and ARIMA model developed by Ceylan and others (2020). Moreover, by comparing the R^2 value, the suggested model is closer to the voting ensemble model using Random Forest - Adaptive Boosting - Gradient Boosting Machine algorithms developed in Turkey (Erdebilli & Devrim-İçtenbaş, 2022).

The performance of the proposed models in this study is better than that of many other ML algorithms for predicting MW amount. For example, ANN (MSE = 1.930) and ANN augmented with genetic algorithm ANN-GA (MSE = 2.9563) developed by Arabgol & Ko (2013) in Iran. Also, it outperformed the multilayer feedforward MLF-ANN model ($R^2 = 0.61103$) that predicted Lithuania's short annual data case (Karpušenkaitė et al., 2016). The proposed model also surpasses the Kernel-based models (average $R^2 = 0.82$ – 0.86) and Neuron-based models (average $R^2 = 0.68$ –

0.74) proposed by Golbaz and others (2019). The model herein exhibits superiority over the deep learning method ($R^2 = 0.466$, and $MAE = 0.079$) and Kernel-based SVM ($R^2 = 0.221$, and $MAE = 0.202$) developed by Altin and others (2023).

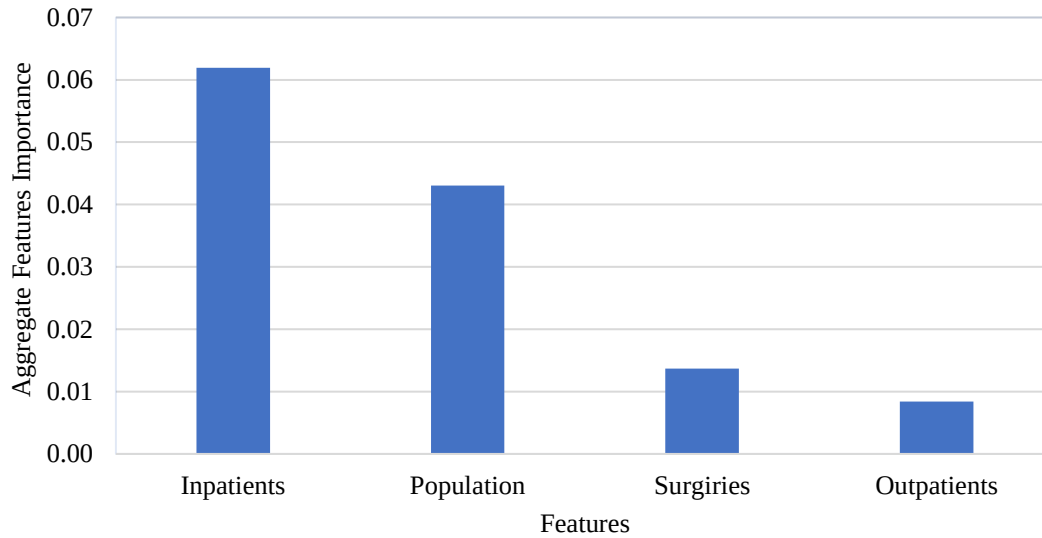


Figure 4.31 Aggregate features importance for SMC dataset.

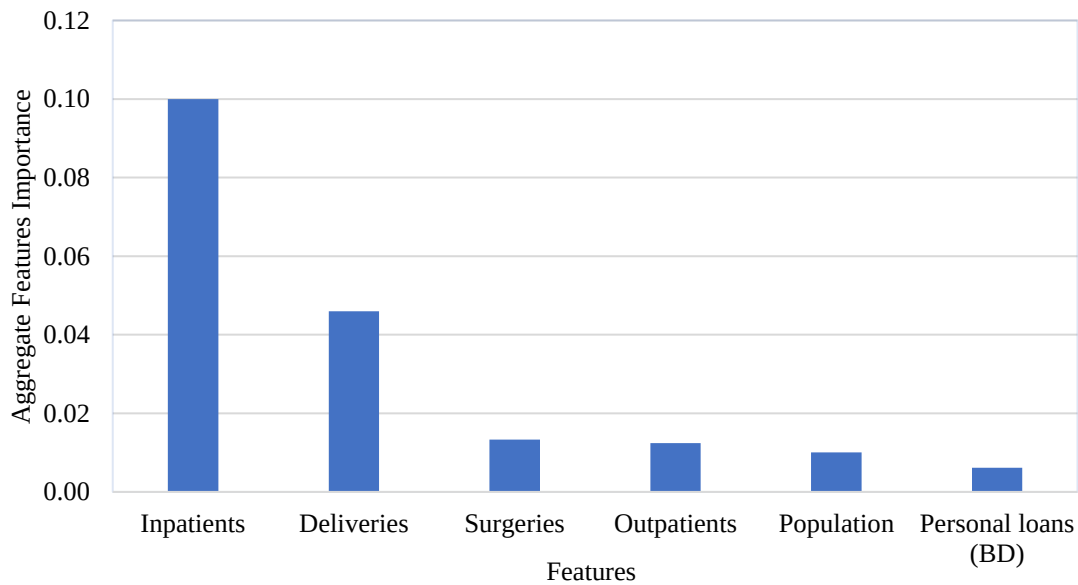


Figure 4.32 Aggregate the importance of features for the PH dataset.

The ML algorithms used in this study yielded insights into the relative importance of parameters influencing the MW quantities. The degree of significance features for the governmental hospital is shown in Figure 4.31. The findings reveal

that only four features are significant for MW amounts in SMC, and the relevance follows the order: number of inpatients, populations, surgeries and outpatients. On the other hand, six features are found to be significant for MW amounts in PH, and the order of relevance is the number of inpatients, deliveries, surgeries, outpatients, population and personal loans as presented in Figure 4.32.

An overview of the results obtained in this study shows that the number of inpatients is the most critical feature for both SMC and PH, while the least significant was found to be the number of outpatients. These results partially align with previous studies reported by Tesfahun, Kumie, & Beyene (2016), wherein they found that both the number of inpatients and outpatients are significant factors; they found a strong correlation between inpatients and MW generation but less correlation with outpatients. Another study found that the inpatients and population are significant factors (Wei et al., 2021). In contrast, a similar study by Golbaz et al. (2019) included the inpatients using the MLR method, but it did not emerge as a significant factor. Altin et al. (2023) studied the inpatients in their study using Kernel-based SVM and Deep learning, but they did not point out the importance of significant features. The most intriguing finding is that the population is a significant feature in both hospitals, but its importance on MW generation is more pronounced in governmental hospitals than in private ones.

The population was the second most important feature for the government hospital, while it was fifth place in the private hospital. The population plays an essential role in government hospitals' MW generation for several reasons. Firstly, government hospitals are often more accessible to a wide range of people, including underserved communities, as they provide services free of charge to the citizens (WHO-Bahrain, 2022). Also, government hospitals often serve a larger and more diverse patient base, leading to increased healthcare activities and procedures. Additionally, the scope of services offered by government hospitals is generally

broader, including specialized treatments and referral cases, leading to a more significant impact on waste generation and resulting in more MW generation. Therefore, the finding that the population's influence on MW generation is higher in government hospitals is aligned with the hospital's broader role in catering to diverse healthcare needs within the community.

Furthermore, another remarkable finding is that the inclusion of personal loan data in the private hospital dataset significantly improved the model's performance, where R^2 improved from 0.742 to 0.917. The personal loans feature was added to the model as a control variable, it has an indirect effect on the quantities of MW, it is significant, and it improved the performance of the model and made it more realistic.

Numerous studies have proved a relationship between patients' financial standing and seeking medical care in private hospitals (Moe & Naing, 2011; Woolhandler et al., 1983). In this study, although other more crucial features exist, the personal loan feature remains undeniably significant in predicting MW in private hospitals. This highlights the relevance of personal loan information as a noteworthy factor influencing MW generation in private healthcare facilities.

This study found the best model for estimating the MW generation with a good performance and identifying the most critical features. Ceylan and others (2020) obtained a superior model for estimating the amounts of MW using a time-series method ($R^2=0.9888$); however, no significant factors were proposed by their study. In addition, other studies that used ML methods did not identify the most important factors associated with MW prediction (Arabgol & Ko, 2013; Karpušenkaitė et al., 2016). Korkut (2018) achieved a significant score by utilizing only a single input factor: population. However, knowing the other most important features associated with the MW amounts is imperative for substantial implications

for strategic decision-making. The findings can provide valuable insights and guidance for developing effective strategic plans.

It was stated that MW estimation is often a complex and challenging task due to the lack of data and the fact that many different factors can influence the amount of MW (Erdebilli & Devrim-İçtenbaş, 2022). The proposed model for MW estimation in this study had an excellent performance as it was based on utilizing real data and providing the most relevant input variables.

4.7 Health Workers' Behavior in MW Segregation

4.7.1 Descriptive analysis

The number of respondents that were collected to investigate the factors of MW segregating behavior in healthcare facilities was 144 respondents. As analysed, Table 4.17 provides valuable insights into the respondent's distribution characteristics. The majority of the respondents were female (70.8%), and most of the respondents were Bahraini (75%). Also, it highlights their highest educational qualifications, with 59% holding bachelor's degrees. The table categorizes respondents based on their roles in the healthcare sector, such as medical doctors and nurses leading the other categories, with 54.9 and 36.1%, respectively. Most respondents work in clinical departments (56%) like oncology & dialysis, pediatrics, obstetrics and others, followed by allied health and specialized services departments (15%) such as physiotherapy, laboratory and pharmacy. It also provides insights into the place of workers and whether they attended a training program or otherwise. Approximately 71% of respondents are from public healthcare facilities, and only 40% attended training in MW.

Table 4.17 Demographic characteristics of respondents.

Variables	Categories	Frequency	Percentage (%)
Gender	Male	42	29.2
	Female	102	70.8
Nationality	Bahraini	116	80.6
	Non-Bahraini	28	19.4
Age	Less than 30	39	27.1
	30-39	66	45.8
	40-49	25	17.4
	50 and above	14	9.7
Highest Qualification	Under Secondary	2	1.4
	Secondary	1	.7
	Diploma degree	14	9.7
	Bachelor degree	85	59.0
	Master degree	17	11.8
	Professional degree	20	13.9
	Doctorate	5	3.5
Position type	Medical doctor	79	54.9
	Nurse	52	36.1
	Health Assistant	1	.7
	Others	12	8.3
Department	Clinical Departments	81	56
	Allied Health and Specialized Services	21	15
	Outpatient Departments (OPDs)	20	14
	Others	22	15
Place of work	Public	102	70.8
	Private	42	29.2
Training attending in MW	Yes	58	40.3
	No	68	47.2
	Don't remember	18	12.5

4.7.2 Reliability and Validity Measurement Model Analysis

The Measurement model reliability was tested via Cronbach's alpha (α) and composite reliability (CR) (Arkorf et al., 2020). Measurement model validity was assessed through convergent validity using average variance extracted -AVE and factor loading (L. Zhang et al., 2020) and discriminant validity using Fornell-Larcker criterion and Heterotrait monotrait ratio (HTMT) ratio (Arkorf et al., 2020; Fornell & Larcker, 1981).

Table 4.18 Reliability and validity

	Cronbach's alpha (α)	Composite reliability (CR)	Average variance extracted (AVE)
AC	0.947	0.957	0.904
AR	0.863	0.869	0.784
ATT	0.906	0.917	0.782
BEH	0.948	0.95	0.951
INT	0.943	0.947	0.855
PBC	0.877	0.904	0.576
PN	0.862	0.877	0.645
SN	0.947	0.954	0.904

The values of Cronbach's α and CR are above the threshold of 0.7, as revealed in Table 4.18, which confirms the questionnaire's reliability. The values of AVE are higher than 0.5, indicating that the corresponding construct has good convergent validity. A factor loading greater than 0.7 indicates that the factor is significantly loaded on the related construct, reflecting the factor's convergent validity. The factor loading is presented in Appendix 6, it shows that the factor loadings of PBC3 and PN5 are 0.694 and 0.686, respectively. Although these values are below the threshold of 0.7, they are considered acceptable in this study; according to some authors, it was suggested that factor loadings slightly below 0.7 can be accepted, particularly when the items are crucial for the model, and the reliability and validity are achieved, although the stricter criterion is 0.7 (Sarstedt et al., 2022; S. Yang et al., 2018).

The discriminant validity of the model was examined by HTMT and Fornell-Larcker criterion values. As proposed by Henseler, HTMT analysis is an innovative method for testing the discriminant validity. The HTMT values are less than 0.9 as shown in Table 4.19, indicating good discriminant validity (Henseler et al., 2015). Additionally, using the criteria provided by Fornell and Larcker, as shown in Table 4.20, the square root of the AVE (in bold) on the diagonal exceeds the absolute value of the correlation coefficient between potential variables, the non-diagonal. This implies that the internal correlation is stronger than the external one, which illustrates the differences between potential variables and indicates a high

discriminant validity (Fornell & Larcker, 1981). Therefore, the scale passes the reliability and validity test.

Table 4.19 Discriminant validity- Heterotrait monotrait ratio (HTMT)

	AC	AR	ATT	BEH	INT	PBC	PN	SN
AC								
AR	0.729							
ATT	0.766	0.623						
BEH	0.474	0.509	0.52					
INT	0.568	0.596	0.661	0.757				
PBC	0.47	0.462	0.546	0.724	0.766			
PN	0.534	0.603	0.695	0.835	0.879	0.847		
SN	0.602	0.599	0.627	0.445	0.549	0.506	0.64	

Table 4.20 Discriminant validity- Fornell Larker

	AC	AR	ATT	BEH	INT	PBC	PN	SN
AC	0.951							
AR	0.671	0.886						
ATT	0.717	0.555	0.884					
BEH	0.454	0.461	0.487	0.975				
INT	0.543	0.537	0.622	0.715	0.925			
PBC	0.467	0.433	0.518	0.679	0.724	0.759		
PN	0.496	0.519	0.625	0.769	0.801	0.755	0.803	
SN	0.572	0.547	0.584	0.424	0.52	0.474	0.581	0.951

4.7.3 Structural Model Evaluation

To check the significance of the various hypothesis paths, the goodness of fit of the measurement and structural model was assessed. To evaluate the structural model, the R^2 , Q^2 , and path significance were considered. The R^2 is a common indicator for measuring the overall predictive strength of the model and has been broadly used in the empirical studies of SEM; a higher value of R^2 means a higher predictive accuracy (Joe F Hair et al., 2011). Table 4.21 shows that all R^2 values of endogenous latent variables are more than 0.19, which indicates an acceptable goodness of fit for the proposed model (L. Zhang et al., 2020). Q^2 is the predictive

relevance of the endogenous constructs, which measures whether a model is predictive or not; values of Q^2 with 0.02, 0.15, and 0.35 indicate weak, moderate, and strong predictive relevance (Joseph F Hair et al., 2013). As shown in Table 4.21, the model has an acceptable goodness of fit, and predictive relevance is established. Furthermore, the model fit was further evaluated using Standardized Root Mean Squared Residual (SRMR). The obtained value of SRMR was 0.089, less than 0.10, indicating a good model fit (Savari et al., 2023).

Table 4.21 Model Fit R^2 and Q^2 of PLS-SEM estimation

	R^2	Q^2 predict
AR	0.450	0.442
ATT	0.514	0.500
BEH	0.617	0.277
INT	0.700	0.486
PN	0.403	0.345

The remarkable finding of this investigation is that the model explanation in MW segregation intention is superior, explaining 70% of the total variance. Model performance can be considered high among models in the literature that used the same SEM technique. It's almost in the same range as the model found by Savari et al. (2023) (77%) in investigating pro-environmental behavioral intention. In contrast, it surpasses many other studies, such as the model developed by Liu et al. (2017) that explained 27% of pro-environmental behavior intention, and the model obtained by Zhang et al. (2020) explained 60% of total variance for intention and 22% for the behavior of residents' waste segregation.

4.7.4 Hypotheses Testing

The statistical significance of each path coefficient was tested using the Bootstrapping method provided by PLS up to 5000 samples with 95% confidence. The resulting path coefficients are shown in

Table 4.22 and Figure 4.33.

Table 4.22 Results of hypothesis testing.

Hypothesis	Path coefficient β	T statistics	P values	Decision
H1: AC $\rightarrow$ AR	0.671	10.426	0.000	Supported
H2: AR $\rightarrow$ PN	0.224	2.215	0.027	Supported
H3: AC $\rightarrow$ PN	0.123	1.011	0.312	Not Supported
H4: PN $\rightarrow$ INT	0.507	5.722	0.000	Supported
H5: PN $\rightarrow$ BEH	0.549	5.804	0.000	Supported
H6: ATT $\rightarrow$ INT	0.172	1.931	0.054	Not Supported
H7: SN $\rightarrow$ INT	0.007	0.089	0.929	Not Supported
H8: PBC $\rightarrow$ INT	0.249	3.559	0.000	Supported
H9: INT $\rightarrow$ BEH	0.272	2.518	0.012	Supported
H10: SN $\rightarrow$ PN	0.388	4.44	0.000	Supported
H11: AC $\rightarrow$ ATT	0.717	8.649	0.000	Supported

The proposed hypotheses in Chapter 2 were tested. The hypothesis is rejected if the p-value is less than 0.05 (Han, 2014). The results of the data analysis revealed that the AC has a significant positive impact on the AR ($\beta = 0.671$, $t = 10.426$, $p = 0.000$), which supported H₁. Also, The results show that the AR significantly impacts PN positively; thus, it supported H₂ ($\beta = 0.224$, $t = 2.215$, $p = 0.027$) and was consistent with the results of (Onwezen et al., 2013; Joohyung Park & Ha, 2014). However, the impact of AC on PN was not significant ($\beta = 0.123$, $t = 1.011$, $p = 0.312$). Thus, H₃ is not supported.

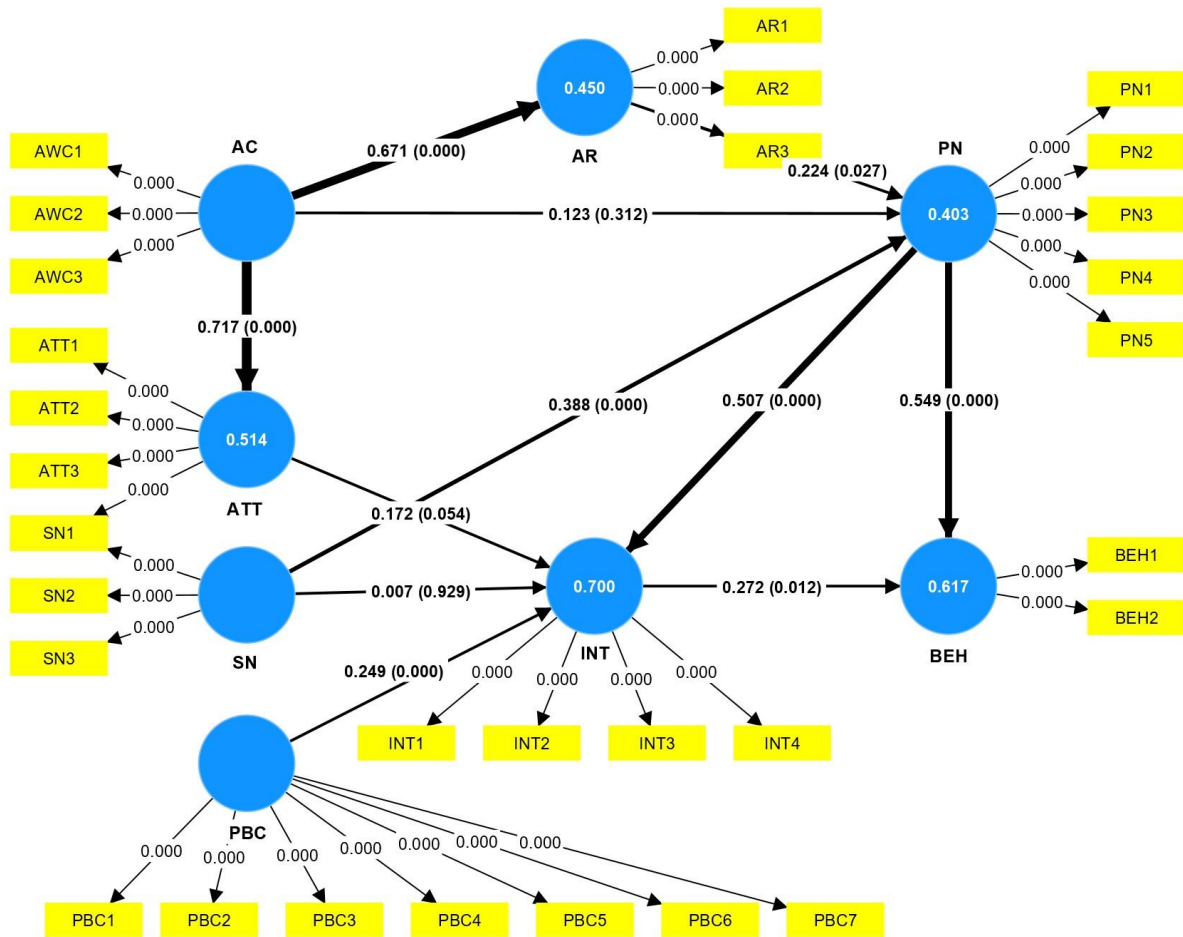


Figure 4.33 The model with path coefficient, p-value and R^2 . Note: The thickness of the arrow corresponds to the path coefficient value.

The results reveal that PN significantly influences the health workers' behavioral intention and their behavior ($\beta = 0.507$, $t = 5.722$, $p = 0.000$) and ($\beta = 0.549$, $t = 5.804$, $p = 0.000$), respectively, thus supporting H_4 and H_5 . Personal norm was the most substantial determinant of the intention of health workers to segregate MW, as shown in Figure 4.33, which is consistent with the results of investigating domestic waste sorting (Bortoleto et al., 2012; J. Shen et al., 2020). Also, the finding aligns with (De Groot & Steg, 2009; Han et al., 2015; J. J. Kim & Hwang, 2020; Shin et al., 2018). These studies revealed that the most potent and vital predictor of behavioral intention in pro-environmental behaviors is the personal norm, which refers to the individual's perception of the morality or ethics of behavior (Hamid et

al., 2021; Harland et al., 2007; Savari, Mombeni, et al., 2022). Hence, if health workers recognize MW segregation behaviors as correct, they would be more inclined to segregate MW.

The results of data analysis also show that the attitude toward MW segregation does not statistically significantly impact intention ($\beta = 0.172$, $t = 1.933$, $p = 0.054$) and thus does not support H_6 . This contradicts other pro-environmental behavior investigations (J. Li et al., 2018; Savari & Khaleghi, 2023). Hence, the health workers' positive or negative attitudes toward MW segregation do not substantially shape their intention. However, the p-value is very close to 0.05, suggesting that while the influence of attitude on their intention is not statistically significant, it may still be worth considering, according to the American Statistical Association (2016). There is potential for enhancing the positive attitudes of health workers to lead to the intention to segregate MW effectively. It was confirmed that attitude is generally recognized as a precursor for human behavior, and it is considered a critical element in uncovering hidden human behaviors (J. Li et al., 2018). Hence, a positive environmental attitude probably plays a significant role in shaping the behavior of health workers, and further exploration in this direction could be valuable.

The study found that the SN does not influence intention ($\beta = 0.007$, $t = 0.089$, $p = 0.929$); thus, H_7 is not supported. This finding corroborated with (Joohyung Park & Ha, 2014; J. Shen et al., 2020) but is contrary to other studies (L. Zhang et al., 2020) that investigated pro-environmental behaviors. This finding suggests that the impact of SN or social norms, such as the perception of what others expect or endorse regarding segregating MW, is not a significant driver of health workers' intentions to engage in the behavior. This result may indeed be induced by the busy and demanding nature of the respondents' work in the medical field. Health workers often have highly demanding and time-sensitive responsibilities, which can limit their ability to conform to perceived social norms or expectations related to waste

segregation. Accordingly, social pressures do not significantly affect the forming behavioral tendencies to segregate MW.

Moreover, the results show that the effect of PBC on the health workers' behavioral intention was statistically significant and positive ($\beta = 0.249$, $t = 3.559$, $p = 0.000$); thus, it supported H_8 . This is consistent with (Arkorful et al., 2021; De Groot & Steg, 2009). Individuals with high self-esteem and the belief that they can take pro-environmental action are more expected to engage because PBC demonstrates the difficulty or ease of understanding the behavior (Savari, Naghibeiranvand, et al., 2022).

In this investigation, the health workers' intention impacts their MW segregation behavior ($\beta = 0.272$, $t = 2.518$, $p = 0.012$), which supported H_9 ; this finding is aligned with (Heidari et al., 2018) in waste segregation behavior. It was found that intention is a good predictor of actions in pro-environmental behavior studies, including preventative medicine (McCaffery et al., 2003), public health (Godin & Kok, 1996) and psychology (Armitage & Christian, 2003; Armitage & Conner, 2001; Sheeran, 2002).

Furthermore, SN positively impacts the PN of the health workers ($\beta = 0.388$, $t = 4.440$, $p = 0.000$), thus supporting H_{10} . This finding is consistent with the results of (J. Shen et al., 2020). This insight suggests that social interactions substantially influence the health worker's internalized beliefs or values toward the behaviors within healthcare facilities. When pervasive social pressures emphasize the significance of specific behaviors, it becomes challenging for individuals to deviate from these prevalent social norms. Subsequently, pro-environmental behaviors, such as MW segregation among health workers, tend to be reinforced and adopted as a collective standard.

Health workers' AC significantly and positively impacts their attitude toward MW segregation ($\beta = 0.717$, $t = 8.649$, $p = 0.000$), thus confirming H_{11} . The finding

aligns with the results of Lin & Dong (2023) in TPB, which investigated the effect of environmental AC on pro-environmental actions.

4.8 Chapter Summary

The findings of the research can be summarized in the following.

1. IEA was implemented to assess the two environmental issues of MW: increasing the quantities of MW and its mismanagement using the DPSIR framework, policy analysis and policy options methods. Different social, economic, and technological drivers and pressures could increase the quantities and mismanagement of MW. These issues could cause adverse environmental, human health, and economic impacts. As a result of policy analysis, it was revealed that most existing policies tackle the impacts of the issues. Sustainability scenarios were suggested by segregating MW to reduce the MW quantities and use alternative treatment technologies for more effective MW management.
2. MW quantities during COVID-19 generated from the main sources were estimated in Bahrain and other selected GCC countries.
 - a) In Bahrain, the quantities were 35,480 kg/day from facemasks, 1894 kg/day from PPE used by the selected health facilities, 16,633.505 kg from vaccines and 53,551.240 kg from PCR tests until May 11, 2021. The cubic equation to predict the amount of CMW was found, and it was expected to increase to 13,000 kg/day by the middle of July 2021.
 - b) In the selected GCC countries, the quantities were 1107.980 kg/day from the facemask used by the public, 2,554,812 kg from vaccination, and 2,595,772 kg from PCR tests until March 26, 2022. Moreover, using ARIMA, the daily amount of CMW produced by infected cases in GCC was predicted to be 3667.25 kg/day by December 31, 2022.

- c) The people's interest in MW through RSV was investigated and compared with the quantities of COVID-19 waste. “Google Trends” was used to collect data on the public interest. It was found that there was a high interest in MW issues in Saudi Arabia, Bahrain, and UAE when the pandemic had just started. However, after that, the public interest decreased significantly and stayed low until the last week of the study period. While in Kuwait, the MW issue's popularity appeared at the end of the study period. However, the public interest in Oman was slightly higher than in other countries, but it has continuously fluctuated over the pandemic.
3. The factors associated with COVID-19 that impact the quantities of MW in Bahrain were explored using SEM through AMOS. The predicted variable was the generation of CW that the treatment company collected and treated; the predictors were the number of infected cases, deaths, vaccines, and PCR tests. The data was monthly from February 2020 to May 2022.
- a) The vaccination and newly infected cases were statistically significant predictors, with standardized coefficients of 0.77 and 0.20, respectively. But, the factors, number of tests and deaths were not statistically significant.
 - b) The stringency index factor proved to be a moderator for the relationship between the CW and the two predictors, vaccination and new cases.
 - c) In dealing with this sudden increase in MW, the incineration facility has been outstripped and faced immense pressure over handling MW generated during COVID-19. Therefore, increasing the number of medical waste facilities was the best solution to overcome the issue.
4. MW generations and associated factors were predicted using ML techniques in a representative private and a governmental hospital in Bahrain. Monthly

data spanning from 2018 to 2022 for the private hospital and from 2019 to February 2023 for the governmental hospital was utilized.

- a) The ensemble voting regressor was determined as the best model for both datasets. The governmental hospital's model explains 90.4 % of the total variance. And for the private hospital, the model explains 91.7% of the total variance.
 - b) The model's performance is successful in achieving a low error rate in terms of performance metrics RMSE, MAE, and MSE, indicating its effectiveness in ensuring high precision.
 - c) For the governmental hospital, the significant features in predicting MW generation were found to be the number of inpatients, population, surgeries, and outpatients, in descending order of importance. In the case of the private hospital, the order of feature importance was the number of inpatients, deliveries, personal income, surgeries, and outpatients.
5. The behaviors of health workers toward the MW segregation were assessed through an integrated NAM-TPB model using PLS-SEM.
- a) The model's explanatory power accounts for 70% of the total variance in MW segregation behavioral intention and around 62% in MW segregation action.
 - b) MW segregation behavioral intention of health workers is significantly influenced by their personal norms and perceived behavioral control. And MW segregation action is significantly influenced by the intention to segregate MW and the personal norms of the health workers.

Chapter 5

Conclusion and Recommendations

5.1 Introduction

In pursuit of sustainable development and environmental responsibility, the SDGs emphasize the need to harmonize human progress without destroying nature. The 2030 Agenda has provided a global vision for peace and prosperity, driving nations towards achieving these ambitious goals. However, the unforeseen outbreak of the COVID-19 pandemic posed unprecedented challenges to societies and disrupted progress towards the SDGs. Amidst these challenges, estimating MW accurately emerged as a critical concern for proper and effective MW management. Medical waste generation surged with the increase in healthcare activities and the implementation of pandemic response measures. Ensuring the safe disposal and environmentally responsible management of MW became imperative to protect public health and the ecosystem during the pandemic and in normal situations.

In this chapter, a summary of the achieved objectives is provided in section 5.2, and the insightful findings derived from the rigorous analysis are presented in the preceding section 5.3. The limitations and challenges encountered during the research process are acknowledged in section 5.4, recognizing their importance in shaping future investigations. Lastly, a set of informed recommendations is presented in section 5.5, ultimately contributing to the improvement of MW quantification and management in Bahrain.

5.2 Objectives

This study aimed to estimate the amount of MW and explore the associated factors. The objectives and research questions that were answered and achieved through this research are:

- Investigation of the main issues related to MW in Bahrain through the IEA method. Therefore, figuring out the driving forces and pressures and determining their impacts on the environment and humanity, then comprehensively studying the existing MW policies. Accordingly, setting future scenarios to develop policies, options and suggestions. This is achieved in section 4.2.
- Estimation of the amount of MW generated in the Kingdom of Bahrain and other GCC countries, during the COVID-19 pandemic, is accomplished in sections 4.3 and 4.4.
- Exploration of the factors associated with MW quantities during the COVID-19 pandemic is performed in section 4.5.
- Prediction of the amount of MW generated in Bahrain through identifying the significant features using ML during the normal situation is achieved in section 4.6.
- Investigating the factors affecting health workers' compliance with MW segregation behavior is accomplished in section 4.7

5.3 Findings

The study seeks to enhance the understanding of MW generation, its influencing factors, and its implications for healthcare facilities in the Kingdom of Bahrain. A thorough exploration of various aspects related to MW, including

predictive models, essential features, and the significant factors affecting MW generation, was undertaken in this dissertation.

IEA was implemented in this study to assess the environmental issues of MW in Bahrain. Different social, economic, and technological drivers and pressures could lead to an increase in the quantities and mismanagement of MW. These issues could cause adverse environmental, human health, and economic impacts. It was revealed as a result of policy analysis that most of the existing policies tackle the impacts of the issues, but lack in tackling the drivers and pressures.

Moreover, the solid MW generated in Bahrain has been calculated from various COVID-19-related activities. The waste calculated in a smaller country with less than 2 million population is considerably high to invite the attention of scientists towards sustainable treatment. The country is facing an issue of solid MW generation in the form of facemasks 3,547.974 kg/day, PPEs 1,849 kg/day, vaccination 23,337.625 kg and PCR-tests 53,551 kg from the first case that appeared on February 24, 2020, until April 4, 2021.

The amounts of solid MW generated in the five selected GCC countries (Saudi Arabia, Emirates, Oman, Kuwait, and Bahrain) from different sources were also calculated. The total waste generated from the facemask used by the public in the selected GCC countries was 110,797,952 kg/day, the vaccination was 2,554,812 kg, and the PCR test was 2,595,772 kg from the start of the pandemic until March 26, 2022. Besides, the daily CMW till December 31, 2022, was predicted to be 3,667.25 kg/day.

Furthermore, the public interest in MW during COVID-19 was investigated using the tool Google Trend. The purpose of this tool was to measure how frequently the medical waste term and relative terms are searched by Google, compared to the

total number of searches conducted on Google. It was found that there was a high interest in MW issues in Saudi Arabia, Bahrain, and UAE when the pandemic had just started. However, after that, the public interest decreased significantly and stayed low until the last week of the study period. While in Kuwait, the MW issue's popularity appeared at the end of the study period. However, in Oman, the public interest was slightly higher than in other countries, but it continuously fluctuated throughout the pandemic period.

Then, the factors associated with the increased amount of MW during the pandemic were explored. The number of cases, diagnostic tests, deaths and vaccination were examined as predictors, and only two factors were found to be significant predictors: the number of cases and vaccination. Moreover, the effect of health policies (stringency index) in combating coronavirus was measured as a moderator for the relationship between each significant predictor and the amount of COVID-19 waste. The stringing index was found a significant moderator in the relationship between the predictors (new cases and vaccination) and the amount of COVID-19 waste. It was concluded that vaccination and new cases at high levels of stringency have a stronger and more substantial effect on the amount of MW during the pandemic than at low levels of stringency.

The MW generation rate was determined as 2.610 kg/occupied-bed/day in the governmental hospital with 1,127 beds. The generation rate in the selected private hospital with 77 beds was found as 1.040 kg/occupied-bed/day.

Additionally, this study successfully estimated the generation of MW and identified important influencing features in a governmental and private hospital in Bahrain using ML. The ensemble voting regressor models demonstrated superiority in capturing the complex relationships between the predictor variables and MW generation. The number of inpatients, population, surgeries, and outpatients for the

governmental hospital emerged as significant features influencing MW generation. The number of inpatients, deliveries, surgeries, outpatients, population and personal income were found to be important features in the private hospital. The model performance evaluation indicated predictive solid capabilities with high coefficients of determination; $R^2 = 0.9040$ for the government hospital model and $R^2 = 0.917$ for the private hospital model. The developed models can accurately estimate MW quantities based on the identified features. These findings contribute to understanding MW generation and provide valuable insights for waste management planning and decision-making in healthcare settings.

For the last objective, two theories were integrated, the TPB and NAM, to assess the behavior of health workers toward MW segregation. The proposed model explains 70% of the variance in intention to segregate the MW and around 62% of the variance in the action of MW segregation. PN and PBC can significantly predict the MW segregation intention of health workers. While the behavior of segregating the MW is predicted by their intention and PN.

5.4 Limitation

The estimation of COVID-19 MW in the GCC region posed challenges as it was difficult to calculate waste originating from PPE sources due to the unavailability of data regarding the quantities of used PPE in those countries. Consequently, the findings of this part of the study are confined to specific geographic regions and cannot be extrapolated to GCC countries or other nations.

It was not possible to determine the precise MW generation rate per department because permission was not granted to access the waste rooms in the departments of the hospital. As different departments or specializations within a hospital have different waste generation rates, determining the accurate rates

requires a department-specific approach. Hence, the lack of access to the waste room restricted the study from weighing the generated MW across distinct hospital departments.

Another limitation in the study pertains to the accessibility of substantial and pertinent datasets for predicting MW and identifying associated factors within the chosen governmental hospital. A substantial volume of data is required to establish a robust and reliable system for MW prediction using machine learning. However, SMC just recently initiated its health data recording in 2019. Therefore, this research was constrained by a limited dataset consisting of only 50 monthly observations.

Several challenges were encountered when working with the Google Trends tool. The study analyzed Google searches only in the English language; therefore, the study's results have limited generalizability. Moreover, the study was unable to include any specific search volume data about gender, age or occupation in the analysis because Google Trends does not offer information on user demographics. The study could not focus on investigating the interest in managerial positions in environmental agencies like policymakers. The study is focused on only four terms related to MW during COVID-19, which are being calculated herein. Still, in other related terms, the search volumes and amounts of MW could be affected by confounding factors (e.g., precautionary measures taken in the selected countries and public attention to the MW due to media coverage). However, these factors were not considered in this study because the tool used does not cover these factors.

5.5 Recommendations

Based on the integrated assessment, it is recommended to reform policies and focus more on the main drivers and pressures that are the root causes of the problem, to overcome these deadly environmental issues. New guidelines and policy reforms

are required for MW management, and to seek sustainable solutions for unexpected crises in future. In any community, solid waste aspects, including MW, are related to human needs; therefore, waste production, dealing, and disposal reflect people's awareness. So, it is crucial to involve the community in this issue and dedicate efforts to change behavior to raise awareness among the people, i.e. on the safe disposal of PPEs like facemasks. This aligns with the emphasis of COP26 in terms of raising awareness and focusing on the youth about environmental issues.

Increasing the amount of waste is a formidable challenge, especially with the increasing number of cases and the attempt to contain the virus by introducing vaccination programs. The system needs to be strengthened manage MW safely and sustainably, it's vital to ensure the capacity of the existing facilities for MW treatment; therefore, preparing a proper temporary treatment unit for any similar pandemic in future is highly recommended.

It is recommended to systematically measure and balance both the non-hazardous (general waste) and hazardous MW within hospitals, to align with the WHO standard in the proportions of 80-85% for general waste and 15-20% for hazardous MW. Implementing an accurate measurement system could promote efficient waste management, ensuring rigorous segregation.

The study suggests providing training about the risks associated with MW and strategies for safe handling and disposing of it for all levels of medical staff frequently and extensively and educating them about the protocols and practices to ensure a healthier and safer working environment. Moreover, it was proved that “perceived behavior control” influence the health workers' behavioral intentions to segregate the MW. Health workers who have confidence in their skills and knowledge are more likely to be engaged in MW segregation. In this respect, offering training programs like locally organized workshops could improve skills

and encourage a shift toward MW segregation behavior. Also, the training programs should focus on fostering and reinforcing health workers' personal norms. Additionally, to explore more factors that could lead the health worker to segregate medical waste, it is suggested to explore external factors, such as workload, time constraints, and healthcare facility priorities, that can significantly affect the behavior and intentions of health workers.

The principles of sustainability the 3Rs, reducing, recycling, and reusing can be applied to medical waste. It is recommended to implement strict enforcement of MW segregation at its source within healthcare facilities, ensuring effective reduction of hazardous MW. Given the potential to reuse and recycle the MW, particularly the treatment residues like bottom ash in the construction sector, its utilization can produce durable and high-strength concrete and cement, addressing environmental pollution and promoting cleaner production of construction material as well. Therefore, experiments investigating the feasibility of utilising the bottom ash in construction sector in the Kingdom of Bahrain are suggested, for greener applications and sustainable development.

Furthermore, further scientific research is highly recommended to study the increasing MW generation rate and its proper management. For example, empirical research is desirable to determine the exact amount of generated MW in the case with segregation of all types of MW from the source and compare it to the case without segregation. Identifying the precise rate could assist in transferring recycling and a circular economy. Moreover, it is imperative to determine and apply the appropriate treatment technology considering the safe environment and public health, given the effectiveness of the thermochemical treatment method (such as pyrolysis). Such research needs to be supported by the government and followed up by specialized authorities like the Supreme Council for Environment SCE, NHRA and other relevant bodies. Further research and implementation of the findings can

aid in developing sustainable waste management strategies and promote efficient resource allocation in the healthcare sector.

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Appendix (1)

Machine learning models in the literature estimate MW generation and associated factors.

Region	Methodology	Studied factors	Significant factors	Performance measures	Reference
Fars, Iran	MLR, ANN	Type of hospital (private, governmental, educational and non-educational), hospital capacity (number of beds), bed occupancy.	Hospital capacity and bed occupancy (by MLR)	ANN ($R^2 = 0.99$, MAE = 0.046, and RMSE = 1.19). MLR ($R^2 = 0.24$, MAE = 9.55, and RMSE = 285.63).	(Jahandideh et al., 2009)
Iran	MLR, ANN, ANN-augmented with GA (genetic algorithm)	Type of hospital, Hospital capacity, Bed occupancy	-	MLR (MSE = 28.8659), ANN (MSE = 1.930), ANN-GA (MSE = 2.9563).	(Arabgol & Ko, 2013)
Lithuania	ANN, MLR, PLS, SVM, Four NPR.	Number of visits at hospitals, number of new-borns, retired residents, circulation of beds and number of beds, number of children, average life expectancy, doctors' visited, patient numbers, average time spent in hospital, bed days, number of day cases in hospitals, cases of AIDS, HIV and cancer.	-	*NPR-generalised additive ($R^2 = 0.90455$). NPR -smoothing splines models ($R^2 = 0.98584$). ANN-multilayer feedforward ($R^2 = 0.61103$).	(Karpušenka itė et al., 2016)
28 countries in European Union	GRNN	GDP, domestic material consumption, number of beds, immunization measles, health expenditure, incidence of tuberculosis, people having a longstanding illness, number of doctors, bed days in hospitals, urban population, population of the ages 65 and above, life expectancy at birth, victims in road accidents, death rate crude, human development index, inability to face unexpected financial expenses.	Number of beds, incidence of tuberculosis, immunization measles, people having a longstanding illness, bed-days in hospitals, number of doctors, urban population, population of the ages 65 and above, human development index, inability to face unexpected financial expenses	$R^2=0.975$, RMSE=0.27, MAE=0.18, MAPE=11.80	(Adamović et al., 2018)
Uttarakhand, India	MLR, ANN, polynomial regression.	Type of hospital (general hospitals, nursing home, clinics and centers, child and maternity hospitals), Bed occupancy	Type of hospital, Bed occupancy.	MLR ($R^2 = 0.822$, RMSE = 0.227, and MAE= 0.177). ANN ($R^2= 0.954$, RMSE= 0.134, and MAE= 0.018).	(Thakur & Ramesh, 2018)

Karaj, Iran	MLR, ANN, ANFIS, SVM, LSSVM, FSVM.	Active beds, hospital's staff, number of wards, hospital type (government, private, social hospital), occupied beds, inpatients, hospital's activity years.	Hospital type, hospital's staff.	Kernel-based models (average $R^2 = 0.82-0.86$ and average MSE = 0.003–0.008). Neuron-based models (average $R^2 = 0.68-0.74$, average MSE = 0.009–0.023).	(Golbaz et al., 2019)
Istanbul	ARIMA, SVR, GM (1,1), Linear Regression	-	-	*ARIMA ($R^2=0.9888$, RMSE=763.6852, MAPE=11.7595, MAD=588.4712)	(Ceylan et al., 2020)
Turkey	Ensemble VR (RF, AdaBoost, GBM)	Total hospital per year, crude birth rate, total beds per year, GDP	All	MAE =843.702, RMSE =922.042, $R^2=0.970$, MAPE =0.057	(Erdebilli & Devrim-İçtenbaş, 2022)
Perak, Malaysia	NAR-NN	-	-	R^2 = average (0.686739-1)	(Rashid et al., 2022)
Turkey	Kernel-based SVM, Deep learning	Number of surgeries, outpatients, inpatients, intensive care days, and intensive care patients.	-	Deep Learning ($R^2 = 0.466$, MAE = 0.079, RMSE = 0.094). Kernel-based SVM ($R^2 = 0.221$, MAE = 0.202, RMSE = 0.264).	(Altin et al., 2023)

Note:

GDP: Gross domestic product.

ANN: Artificial Neural Networks, MLR: Multiple Linear Regression, PLS: Partial Least Squares, SVR: Support Vector Regression, SVM: Support Vector Machines, FSVM: Fuzzy Logic Support Vector Regression, NPR: non-parametric regression, GRNN: General Regression Neural Network, ANFIS: Adaptive neuro-fuzzy inference system, LSSVM: Least Squares Support Vector Regression, ARIMA: Autoregressive integrated moving average, GM: Grey Modeling, RF: Random Forest, AdaBoost: Adaptive Boosting, GBM: Gradient Boosting Machine, NAR-NN: Non-linear Autoregressive Neural Network

* The mentioned metrics are for the best model in the study.

Appendix (2)

A survey to assess the medical waste segregation among health workers in the Kingdom of Bahrain

Dear healthcare worker in the Kingdom of Bahrain,

As a PhD student in the Environment and Sustainable Development (ESD) program at the College of Science, University of Bahrain, I am conducting a survey about "Medical waste segregation in the Kingdom of Bahrain".

I would be grateful if you could spare a few minutes of your time to provide your input by answering the questions in this questionnaire.

Your participation and assistance by filling out the following questionnaire will help us achieve the study's goal: to assess the segregation behavior toward medical waste among health workers in healthcare facilities in Bahrain.

Please be assured that all responses will be confidential and private and that your identity will not be revealed in any way. Your answers will be used for scientific research purposes. The data will also be dealt with in a combined or bulk form rather than individually.

Your highly appreciated participation in this scientific research is important for the success of this study. The time required to respond to the questionnaire is expected to be approximately 5-10 minutes. Please answer all the items/questions of the questionnaire based on your personal experience.

In case of any further enquiries, contact us at omrani9@hotmail.com

Thanking you in anticipation for your cooperation.

***In your workplace, do you deal with medical waste?**

- Yes (Please continue answering the remaining questions/ items of the questionnaire)
- No (Thank you very much for your time, and please stop here as this survey is not relate to you).

SECTION 1: GENERAL INFORMATION

This section relates to the respondent's demographic description.

Gender:

- Male
- Female

Nationality:

- Bahraini
- Non-Bahraini

Your age

- year

Work experience (in years)

-

Highest qualification

- Under Secondary
- Secondary
- Diploma degree
- Bachelor's degree
- Master's degree
- Professional degree
- Doctorate degree
- Other (specify).....

Position type

- Medical doctor
- Nurse
- Health Assistant
- Technicians
- Technology
- Other (specify).....

Training attending in medical waste.

- Yes
- No
- Don't remember

Place of work:

- Public hospital
- Private hospital
- Others (Specify).....

Department:

- Medical and Surgical (Oncology & Dialysis)
- Emergency Department
- Critical Care Units
- Pediatrics
- Community Health Department
- Physiotherapy Department
- Obstetrics/Gynecology
- Laboratory Department
- Pharmacy Department
- Orthopedic
- ENT
- OPDs
- Other (Specify).....

SECTION 2: About Medical Waste Segregation Behavior

This section deals with the main aspects of assessing medical waste behavior: Awareness of consequences, Ascription of responsibility, Attitude, Subjective norm, Personal norm, Perceived behavior control, and Medical waste separation intention. *** Please answer the following questions.**

<i>Component</i>	<i>To what extent do you agree with the following</i>	<i>Strongly Disagree (never)</i>	<i>Disagree (rarely)</i>	<i>Neutral</i>	<i>Agree (sometimes)</i>	<i>Strongly Agree (Always)</i>
Awareness of consequences	1. Medical waste segregation helps minimize the negative environmental impacts on the wider environment for contemporary and future generations.					
	2. Medical waste segregation behavior helps reduce the harm caused by any communicable disease to people's health.					
	3. Medical waste segregation helps					

<i>Component</i>	<i>To what extent do you agree with the following</i>	<i>Strongly Disagree (never)</i>	<i>Disagree (rarely)</i>	<i>Neutral</i>	<i>Agree (sometimes)</i>	<i>Strongly Agree (Always)</i>
	minimize any communicable disease infections and environmental degradation.					
Ascription of responsibility	1. I feel jointly responsible for segregating medical waste in my workplace.					
	2. I feel jointly responsible for the negative consequences of not segregating medical waste.					
	3. I feel jointly responsible for the health and environmental consequences of not segregating medical waste.					
Attitude	1. I think medical waste segregation behavior is useful for protecting the environment.					
	2. I think medical waste segregation is significant to further reduce communicable disease and infection.					
	3. I think segregating medical waste will be valuable in alleviating the burden of infection.					
	4. I think medical waste segregation is a wise behavior.					

<i>Component</i>	<i>To what extent do you agree with the following</i>	<i>Strongly Disagree (never)</i>	<i>Disagree (rarely)</i>	<i>Neutral</i>	<i>Agree (sometimes)</i>	<i>Strongly Agree (Always)</i>
Subjective norm	1. Most people who are important to me think I should segregate medical waste.					
	2. People with who I value their opinions would like me to segregate medical waste.					
	3. Segregating medical waste would likely encourage important people to me to act accordingly.					
Personal norm	1. I think I am responsible to segregate medical waste.					
	2. Segregating medical waste is dependent on my own moral obligation.					
	3. I would be happy if I segregate medical waste.					
	4. Segregating medical waste would satisfy my moral principles.					
	5. I will feel betrayed if I do not perform medical waste segregation behavior.					
Perceived behavior control	1. I think that I am capable of segregating medical waste.					
	2. I think I have the knowledge and skills to segregate medical waste.					

<i>Component</i>	<i>To what extent do you agree with the following</i>	<i>Strongly Disagree (never)</i>	<i>Disagree (rarely)</i>	<i>Neutral</i>	<i>Agree (sometimes)</i>	<i>Strongly Agree (Always)</i>
	3. Segregating medical waste or not is completely up to me.					
	4. I think performing medical waste segregation is under my control.					
	5. For me, segregating waste at the workplace is simple and easy process.					
	6. There is no lack of satisfactory facilities for waste separation and collection.					
	7. Waste segregation does not take too much of my time					
Medical waste segregation intention	1. I am willing to segregate medical waste.					
	2. I intend to engage in medical waste segregation activities.					
	3. I will make an effort to segregate medical waste.					
	4. I am ready to segregate medical waste segregation.					
Segregation behavior	1. I segregated healthcare waste for the last patient I attended to.					
	2. I always segregate healthcare waste.					

SECTION 3: Open questions

This section contains open questions about medical waste segregation.

In your opinion, what are the most important reasons for not segregating medical waste in your workplace?

.....

.....

.....

Appendix (3)

Bahrain's Policies (legislative decree and ministerial edict) related to MW:

1) LEGISLATIVE DECREE NO. (10) of 2019 with respect to general hygiene

Article (1), item 12:

Special waste: Any waste resulting from various health care activities in all its forms, nursing, curative and diagnostic, in hospitals and health centers, including laboratories, research centers, radiology, pharmacies, dental treatment and physiotherapy.

Article (2):

Taking into account the provisions of the Environmental Law and the Public Health Law and the regulations and decisions issued in implementation of them:

1. It is prohibited to throw or leave any of the waste stipulated in this law and its executive regulations, except in the places designated for that by the competent authority.
2. It is prohibited to sort and treat waste except in sites prepared or licensed for this and in accordance with the conditions and procedures determined by the executive regulations of this law and the decisions issued in implementation of it.

Article (5):

The party that caused or resulted in special disposals shall take all necessary measures to separate these disposals from other wastes, in accordance with the prescribed requirements and specifications to preserve, collect and transport those wastes determined by the executive regulations of this law, taking into account the provisions of laws, regulations and decisions issued in this regard and in coordination with the concerned authorities.

Article (8):

It is prohibited to transfer waste, whatever its source, from the site of its lifting to the site of treatment, except through companies and institutions licensed and classified for this purpose in accordance with the controls determined by the executive regulations of this law, with the presence of a valid certificate from the municipality with the truck driver proving that.

Article (12):

Without prejudice to any more severe penalty stipulated in any other law, anyone who violates the provisions of this law's Articles (2, 3, 6, 4, and 7) shall be punished with a fine of no less than BD 50 and not more than BD 300.

Violation of the provisions of Articles (5, 8, 9) of this law is punishable by a financial sanction of not less than BD 500 and not more than BD 1000. In the case of a guilty verdict, the court may order the confiscation, removal or return of the thing to its original origin. Withdrawal of the license permanently, and final or temporary closure for a period not exceeding 30 days, depending on the circumstance.

2) MINISTERIAL EDICT NO. (3) of 2020 concerning the management of hazardous waste for health care

This law aims to regulate the process of managing hazardous waste for health care in a safe and sustainable manner, aiming to control these wastes and prevent their spread in a way that guarantees the preservation of health and the environment. It includes 36 articles about healthcare waste management. It contains the main definitions, aims, duties of the producer, duties of the transporter, treatment unit inside the facility, treatment unit outside the facility, import and export of hazardous waste for health care and Other provisions.

Appendix (4)

Policies and regulations related to medical waste

	Policies	Purpose
1	LEGISLATIVE DECREE NO. (10) of 2019	Consider the general hygiene
2	MINISTERIAL EDICT NO. (3) of 2020	It aims to regulate the process of managing hazardous waste for healthcare in a sound manner.
3	Royal Decree 75 of 2016 on ratifying the Paris Agreement within the United Nations Framework Convention on Climate Change (UNFCCC)	The agreement aims to enhance the global response to the threat of climate change by holding the rise in average global temperature below 2 °C above pre-industrial levels and increasing resilience to the adverse impact of climate change, enhancing climate resilience and low greenhouse gas emissions development.
4	Law No. 39 of 2005 ratifying the Stockholm Convention on Persistent Organic Pollutants	This convention aims to develop a precautionary approach from the Rio Declaration on Environment and Development to protect the environment and human health from persistent organic pollutants.
5	Decree No. (26) of 2001 ratifying the Regional Protocol on the Control of Marine Transboundary Movements and Disposal of Hazardous Wastes and Other Wastes.	It aims at the importance of effective cooperation and coordination at the regional level to control the maritime transport of hazardous wastes and other wastes and restrict the import of wastes from non-contracting countries for the purpose of disposal.
6	World Health Organization (WHO) Guiding Principles on Health care medical waste - HCWM	1. Prevent health risks to the public and health workers 2. Support efforts to decrease disease from noxious emissions 3. Support the Basel and Stockholm Conventions 4. Promote practices to decrease exposure to toxic pollutants from incineration.

Source: (SCE, 2022a, 2022b)(Legislation & Legal Opinion Commission, 2021)(Legislation & Legal Opinion Commission, 2019).

Appendix (5)

Emission data from one incinerator during the years 2021 and 2022.

Parameter,	Jun. 2021	Oct. 2021	Mar. 2022	Jun. 2022	Unit of measurement	SCE Standards
Oxygen %	20.4	19.2	17.5	18.8	%	-
CO	0.0	26.0	0.0	1.0	mg/Nm ³	100
SO ₂	58.0	12.0	7.0	0.0	mg/Nm ³	150
NO _x	30.0	92.0	141.0	112.0	mg/Nm ³	200
H ₂ S	0.0	7.0	11.0	0.0	mg/Nm ³	-
CO ₂	0.48	1.32	1.96	1.12	%	-
HF	BDL	0.00	0.00	0.24	mg/Nm ³	4
HCl	BDL	BDL	0.24	0.36	mg/Nm ³	60
VOCs	--	6.201	4.369	5.42	mg/Nm ³	20
Mercury	--	<0.002	<0.001	<0.001	mg/m ³	0.05
Cadmium	--	0.0014	<0.002	<0.002	mg/m ³	0.05
Arsenic	--	<0.002	0.003	0.003	mg/m ³	0.05
Aluminium	--	--	0.017	0.001	mg/m ³	0.05
Cadmium	--	0.0014	<0.002	<0.002	mg/m ³	0.05
Chromium	--	0.015	0.04	0.03	mg/m ³	0.05
Copper	--	0.002	<0.002	<0.002	mg/m ³	0.05
Lead	--	<0.002	<0.002	<0.002	mg/m ³	0.05
Nickel	--	<0.002	0.046	0.042	mg/m ³	0.05
Iron	--	0.0014	0.001	0.002	mg/m ³	0.05
Manganese	--	<0.002	<0.002	<0.002	mg/m ³	0.05
Antimony	--	<0.002	-	--	mg/m ³	--
Cobalt	--	0.001	-	--	mg/m ³	--
Total PM	--	18.245	17.269	--	mg/m ³	30
Dioxin & Furans	--	--	0.02	0.019	ngTEQ/ng	--

SCE Supreme Council for Environment, Kingdom of Bahrain; BDL stands for below detection limit; VOCs Volatile Organic Compounds; PM particulate matter.

Appendix (6)

The results of confirmatory factor analysis.

	AC	AR	ATT	BEH	INT	PBC	PN	SN
AR1		0.869						
AR2		0.909						
AR3		0.879						
ATT1			0.926					
ATT2			0.925					
ATT3			0.787					
ATT4			0.892					
AWC1	0.953							
AWC2	0.947							
AWC3	0.952							
BEH1				0.976				
BEH2				0.974				
INT1					0.919			
INT2					0.861			
INT3					0.962			
INT4					0.953			
PBC1						0.839		
PBC2						0.81		
PBC3						0.694		
PBC4						0.73		
PBC5						0.809		
PBC6						0.748		
PBC7						0.758		
PN1							0.821	
PN2							0.806	
PN3							0.882	
PN4							0.808	
PN5							0.686	
SN1								0.951
SN2								0.961
SN3								0.941



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Estimation of COVID-19 generated medical waste in the Kingdom of Bahrain

Khadija Al-Omran ^{a,b}, Ezzat Khan ^{c,d,*}, Nisar Ali ^e, Muhammad Bilal ^{f,**}

^a Environment and sustainable development program, College of Science, University of Bahrain, Sakhr 32038, Bahrain

^b Mathematics and Science Division, Bahrain Training Institute, Isa Town 33090, Bahrain

^c Department of Chemistry, College of Science, University of Bahrain, Sakhr 32038, Bahrain

^d Department of Chemistry, University of Malakand, Chakdara 18800, Khyber Pakhtunkhwa, Pakistan

^e Key Laboratory for Palygorskite Science and Applied Technology of Jiangsu Province, National & Local Joint Engineering Research Centre for Deep Utilization Technology of Rock-salt Resource, Faculty of Chemical Engineering, Huaiyin Institute of Technology, Huaian 223003, China

^f School of Life Science and Food Engineering, Huaiyin Institute of Technology, Huaian 223003, China

HIGHLIGHTS

- COVID-19 medical waste is a serious threat to the environment.
- Bahrain faces solid waste in the form of Face masks, PPEs, vaccination, and tests.
- Plastic is among the major portion of the waste requiring urgent attention.
- Basic and environmental research for efficient waste conversion can addressing these challenges.

GRAPHICAL ABSTRACT



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ABSTRACT

Coronavirus disease 2019 (COVID-19) is not only a great matter of concern from a medical and health perspective, but it is a serious threat to the environment in terms of waste generated during the prevention and cure of COVID-19. The world has so far compromised more than 3 million human lives, and millions are being infected. Environmental threat is most serious because it can cause secondary complications. As per our knowledge, the amount of waste generated during the pandemic and its estimated quantity has not been assessed, thereby keeping the scientific community, Government authorities and public ignorant of its adverse effects. In this context, we have evaluated the waste generated by the Kingdom of Bahrain, estimated to be 35,480 kg/day (face masks), 1894 kg/day (PPEs) by the selected health facilities, 16,633.505 kg (vaccination-related) and 53,551.240 kg (related to tests conducted so far) in the Kingdom of Bahrain.

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1. Introduction

During the pandemic period, the demand for medical equipment, more specifically personal protective equipment's (PPEs), drastically increased. This increase could be an inevitable consequence of disease

* Correspondence to E. Khan, Department of Chemistry, College of Science, University of Bahrain, Sakhr 32038, Kingdom of Bahrain.

** Corresponding author.

E-mail addresses: ezkhan@uob.edu.bh (E. Khan), bilalua@hyit.edu.cn (M. Bilal).

Article

Integrated Environmental Assessment of Medical Waste Management in the Kingdom of Bahrain

Khadija Al-Omran ^{1,2}, Asma Abahussain ¹ and Ezzat Khan ^{3,*} 

¹ Environment and Sustainable Development, College of Science, University of Bahrain, Sakhir 32038, Bahrain

² School of Logistics and Maritime Studies, Faculty of Business and Logistics, Bahrain Polytechnic, Isa Town 33349, Bahrain

³ Department of Chemistry, College of Science, University of Bahrain, Main Campus, Sakhir 32038, Bahrain

* Correspondence: ezkhan@uob.edu.bh

Abstract: As a global concern, medical waste (MW) links public health, environmental pollution, and resource sustainability. This study aims to assess the two issues related to medical waste in Bahrain: the increasing generation rate of MW and its management. The integrated Environmental Assessment (IEA) methodology was adopted, including the DPSIR (Drivers, Pressures, State, Impact, Responses) framework, analysis of existing policies, and the outlook. Consequently, data were collected from official health statistics in Bahrain, and related policies for the last two decades (2001 to 2021) were also collected, in addition to interviews with Bahrain medical waste (BMW) treatment company. The results show a vast increase in medical waste during COVID-19. Moreover, most of the existing policies address the impact of the BMW issues, but the policies are lacking in tackling the drivers and pressures; there is also a policy gap related to the generation rate. Accordingly, a set of policies was proposed to overcome the two medical waste issues. Moreover, to overcome issues associated with MW, the study recommended reforming regulations aiming to reduce and manage medical waste efficiently in order to focus more on drivers and pressure causing an elevation in MW issues in Bahrain.

Keywords: medical waste management; COVID-19; DPSIR; integrated environmental assessment; policy analysis



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1. Introduction

Medical waste (MW) is defined as solid waste resulting from diagnosis, treatment, and vaccination, including testing, research activities, and manufacture of biological products [1]. This waste contains hazardous and non-hazardous wastes. The non-hazardous waste is primarily composed of general domestic waste, and it does not pose any particular chemical, biological, physical, or radioactive hazard. In contrast, hazardous waste is generally contaminated with pathogens. Thus, misusing this waste or poor handling and discarding can cause many infections and diseases. Adding to that, it can also cause environmental contamination in the case of mismanagement, which can result in pollution of land, plants, water, air, and animals, which can lead to the spread of diseases. Consequently, it needs restrictions and special requirements in the collection, disposal, and treatment methods [2]. Hazardous waste may include various types, such as infectious, genotoxic, pathogenic, chemical, sharps, pharmaceutical, and waste with heavy metals content, pressurized containers, and radioactive [3–5]. In the current pandemic, COVID-19-related medical waste (CMW) has increased with the new daily cases, diagnostic pandemic tests, and vaccination. Therefore, much medical waste was produced and is still being generated due to the epidemiological situation. The MW related to COVID-19 represents a challenge, as it must be disinfected before processing any secondary products. So, this hazardous waste must be disposed of and treated appropriately to protect the environment and human health [6,7], and all countries and communities must be well-equipped for any unwanted situation in future [8].



Medical waste generation during COVID-19 pandemic in selected member countries of Arabian Gulf region; Google trend analysis

Khadija Al-Omran^{a,b}, Ezzat Khan^c  and Simone Perna^d

^aEnvironment and Sustainable Development, College of Science, University of Bahrain, Sakhir, Kingdom of Bahrain; ^bSchool of Logistics and Maritime Studies, Faculty of Business and Logistics, Bahrain Polytechnic, Isa Town, Kingdom of Bahrain; ^cDepartment of Chemistry, College of Science, University of Bahrain, Sakhir, Kingdom of Bahrain; ^dDepartment of Biology, College of Science, University of Bahrain, Sakhir, Kingdom of Bahrain

ABSTRACT

The variant SARS-CoV-2 (COVID-19) has affected the entire globe; it has caused acute respiratory illnesses and has led to massive environmental problems associated with extra medical waste and single-use plastics. Herein the total quantity of waste generated in the selected GCC countries from different sources has been calculated. The popularity of the medical waste issue through using relative search volume was investigated to associate it with the quantities of Waste. Data was collected from the first COVID-19 case in the respective country until March 26, 2022, from the public domains, "Worldmeter", "Our World in Data" and "Google Trends". Autoregressive Integrated Moving Average (ARIMA) was used to predict the amount of CMW. The calculated values are 1107.980 kg/day from the facemask used by the public, 2,554,812 kg from vaccination, 2,595,772 kg from PCR tests, also the predicted daily total amount of COVID-19 related Medical Waste (CMW) by the end of 2022 (December 31, 2022) to be 3667.25 kg/day. The trend in the generation of CMW has been identified in selected countries. Generally, the waste is expected to get minimized, but it is a lesson for future planning. Especially With extensive vaccination, the cases are drastically decreased, and life is resuming in the regions.

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KEYWORDS

Forecasting analysis; Google trend analysis; medical waste; plastic personal protective equipment; sustainable management; waste generation in Gulf countries

1. Introduction

In early 2020, the infection rate of Coronavirus (COVID-19) had risen to the level of a global pandemic, with more than 675 million confirmed cases worldwide and more than 6 million deaths reported by the World Health Organization (WHO) till December 18, 2022 (Worldmeter, 2022). The COVID-19 pandemic has affected many aspects of life, such as social activities, consumption, production and travel patterns and also has a significant effect on pollution expulsion and environmental quality (Klemeš, Fan, Tan, & Jiang, 2020). The pandemic has led to a substantial increase in medical waste. For instance, the pandemic has caused a surge in personal protective equipment (PPE) waste and decreased recycling activities and waste diversion due to the unknown nature of the virus (Ikiz, Maclaren, Alfred, & Sivanesan, 2021). In Wuhan, China, where the first case of COVID-19 was observed, the average of medical waste produced before the COVID-19 pandemic was 45 t/d (Yu, Sun, Solvang, & Zhao, 2020), which has been taken to an immense amount of 110–150 t/d with an increase in

COVID-19 cases in mid-February. During the peak period of the pandemic, by March 2020, the amount raised nearly six-fold, reaching an average of 247 t/d (Singh, Tang, Zhang, & Zheng, 2020). In addition, with the number of COVID-19 cases increasing, related to protective items have also increased dramatically, such as gloves, masks, linens, disposable plates, and glasses used by COVID-19 medical staff and patients. Thus, today a surprising and unusual increase in the amount of medical waste being created is observed. In China, until January 20, 2020, the national medical waste disposal level was 1164.0 t/d, and it reached 6066.8 t/d on March 21, 2020 (Ma et al., 2020). With the COVID-19 pandemic, the unexpected increase in medical waste production has created a serious environmental threat. It can significantly affect health in China and the entire world (Sangkham, 2020). The unsafe and insufficient medical waste management pollutes the environment and poses a serious threat to the spread of infectious diseases. It's still uncertain, but it has been observed that the virus could stay up to 9 days on different inanimate surfaces, and the surface

CONTACT Ezzat Khan  ezkhan@uob.edu.bh  Department of Chemistry, College of Science, University of Bahrain, Sakhir 32038, Kingdom of Bahrain.

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Factors associated with medical waste under pandemic situation: a case study of the Kingdom of Bahrain

Khadija Al-Omran^{1,2} · Ezzat Khan^{3,4}  · Simone Perna⁵ · Nisar Ali⁶

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Abstract

Exploring the factors influencing medical waste generation is vital for proper management due to its hazardous nature. Improper treatment would cause secondary environmental pollution, especially related to public health emergencies. However, there is not enough research on exploring COVID-19-associated factors with medical waste generation, and there is a lack of basic understanding of implementing governmental policies related to the pandemic. The medical waste generated due to COVID-19 is directly or indirectly influenced by government policies. The aim of this study is to explore the factors associated with COVID-19 that impact the amount of medical waste in Bahrain. Data about the quantities of COVID-19 waste (CW) from February 2020 to May 2022 were obtained from Bahrain Waste Treatment Company BWTC. Data about predictors related to COVID-19 were obtained from the public domain. The structural equation modeling SEM technique was applied using AMOS software to identify the driving forces. The model results revealed that the vaccination and newly infected cases are statistically significant predictors for waste generation during the pandemic, with standardized coefficients of 0.77 and 0.20, respectively. But the factors, number of tests, and deaths are not statistically significant. Moreover, the stringency index factor moderates the relationship between the CW and the two predictors, vaccination and new cases. In dealing with this sudden increase in medical waste, the incineration facility has been outstripped and faced immense pressure over handling medical waste generated during COVID-19. Therefore, this study recommends increasing the number of medical waste facilities.



Predicting medical waste generation and associated factors using machine learning in the Kingdom of Bahrain

Khadija Al-Omran^{1,2} · Ezzat Khan^{1,3}

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Abstract

Effective planning and managing medical waste necessitate a crucial focus on both the public and private healthcare sectors. This study uses machine learning techniques to estimate medical waste generation and identify associated factors in a representative private and a governmental hospital in Bahrain. Monthly data spanning from 2018 to 2022 for the private hospital and from 2019 to February 2023 for the governmental hospital was utilized. The ensemble voting regressor was determined as the best model for both datasets. The model of the governmental hospital is robust and successful in explaining 90.4% of the total variance.

Similarly, for the private hospital, the model variables are able to explain 91.7% of the total variance. For the governmental hospital, the significant features in predicting medical waste generation were found to be the number of inpatients, population, surgeries, and outpatients, in descending order of importance. In the case of the private hospital, the order of feature importance was the number of inpatients, deliveries, personal income, surgeries, and outpatients. These findings provide insights into the factors influencing medical waste generation in the studied hospitals and highlight the effectiveness of the ensemble voting regressor model in predicting medical waste quantities.

Keywords Medical waste prediction · Machine learning · Ensemble voting regression · Kingdom of Bahrain · Sustainability · Associated factors

Introduction

Medical waste (MW) poses a critical public health concern in all societies due to pathogens, bacteria, chemical anticancer agents, and hazardous and radioactive wastes, all of which can be classified as hazardous wastes, which give rise to an array of diseases (WHO 2014). Moreover, the presence of sharps can cause infections and a great deal

of harm to people who are in contact with them, which is extremely dangerous (Lindahl & Grace 2015). Health hazards and environmental pollution could result in the absence of a proper management system for such medical materials (Neves et al. 2022; Sabour et al. 2007). Hence, it is imperative to have a well-established management system in place. The complexity and heterogeneity of hospital waste production make it very difficult to establish such a management system. Starting such a complex system requires accurately estimating short- or long-term waste generation. Storage, collection, and transfer systems need to be designed and managed based on short-term estimation of MW generation (Matsuto & Tanaka 1993; Sengupta & Agrahari 2017), while long-term estimations are crucial for selecting landfill sites and waste treatment technologies or understanding the impact of new policies and initiatives (Sengupta & Agrahari 2017).

In Bahrain, healthcare waste management (HCW) is a critical aspect of public health infrastructure. Bahrain has introduced distinct national regulatory standards for managing healthcare waste; Legislative Decree No. (10) of 2019

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✉ Khadija Al-Omran
khadija.alomran@polytechnic.bh

¹ Environment and Sustainable Development, College of Science, University of Bahrain, Sakhir 32038, Kingdom of Bahrain

² School of Logistics and Maritime Studies, Faculty of Business and Logistics, Bahrain Polytechnic, Isa Town 33349, Kingdom of Bahrain

³ Department of Chemistry, University of Malakand, Lower Dir, Chakdara 18800, Khyber Pakhtunkhwa, Pakistan

ملخص الدراسة

ترتبط النفائات الطبية بالصحة العامة والبيئة ارتباطاً وثيقاً. الهدف الرئيسي من هذه الأطروحة هو تقدير كميات النفاية الطبية الناتجة وتحديد العوامل المرتبطة بها في مملكة البحرين.

بداية تم تقييم قضيتين أساسيتين تتعلقان بالنفائات الطبية في البحرين، وهما الكميات المتزايدة وإدارتها، وذلك باستخدام منهجية التقييم البيئي المتكامل، بما في ذلك تطبيق إطار DPSIR، وتحليل السياسات الحالية، والتوقعات المستقبلية. وعليه تم جمع وتحليل السياسات ذات الصلة للعقدين الماضيين ما بين (2001 إلى 2021). وقد تبين أن معظم الاجراءات والخطوات المتبعة حالياً تعالج آثار هذه المشاكل ولكنها تفتقر إلى معالجة الدوافع والضغط. وبالتالي للتغلب على هذه المشاكل، يوصى بإصلاح اللوائح لتقليل كمية النفائات وإدارتها بكفاءة والتركيز بشكل أكبر على الدوافع والضغط المسببين لتلك المشاكل.

كذلك، تم تقدير كميات النفائات الطبية الناتجة خلال جائحة كوفيد-19 من مصادر مختلفة في البحرين ودول مجلس التعاون المختارة. حيث تم تقدير كمية النفائات الطبية في البحرين كالتالي: 3,547.974 كجم/يوم (أقنعة الوجه)، و1,894 كجم/يوم (معدات الوقاية الشخصية في المراكز الصحية المختارة)، و16,633.505 كجم (التطعيم)، و53,551.240 كجم (اختبارات PCR) حتى 11 مايو 2021. أما في دول مجلس التعاون تم تقديرها كالتالي: 110,797,952 كجم/يوم (أقنعة الوجه)، و2,554,812 كجم (التطعيم)، و2,595,772 كجم (اختبارات PCR) حتى مارس 2022. كذلك تم استكشاف العوامل المرتبطة بتوليد نفائات كوفيد-19 الطبية خلال الفترة (فبراير 2020 - مايو 2022) باستخدام نمذجة المعادلات الهيكلية. وذلك باستخدام بيانات نفائات كوفيد-19 من شركة البحرين لمعالجة النفائات بالإضافة إلى بيانات متعلقة بالمتغيرات المستقلة. حيث كشفت النتائج أن التطعيم والحالات المصابة الجديدة تعد من العوامل الرئيسية ذات دلالة إحصائية لتزايد النفائات أثناء الوباء. علاوة على ذلك، وجد أن عامل مؤشر الصرامة (Stringency Index) هو عامل معيّل/ضبط (Moderator) مهم بين كمية نفائات الكوفيد و بين المسببين الرئيسيين (التطعيم والحالات الجديدة).

تم إيجاد معدل توليد النفائات الطبية في المستشفيات الحكومي والخاص بـ 2.610 و1.040 كجم/سرير-مشغول/يوم، بالترتيب. إضافة إلى ذلك، تم تطبيق التعلم الآلي للتنبؤ بكميات النفائات الطبية الناتجة والعوامل المرتبطة بها. حيث تم استخدام مجموعتين من البيانات واحدة تابعة لمستشفى حكومي و الأخرى تابعة لمستشفى خاص. النتائج كانت أن ensemble voting regressor هو أفضل نموذج لكلا المجموعتين. حيث يتمتع النموذجان المقترحان بدقة فائقة حيث كان عامل التحديد عالي جداً. بالنسبة للمستشفى الحكومي، كانت العوامل

المهمة بترتيب تنازلي من حيث الأهمية هي، عدد المرضى المقيمين في المستشفى، وعدد السكان، والعمليات الجراحية، والمرضى الخارجيين. بينما في المستشفى الخاص العوامل المهمة هي، عدد المرضى المقيمين في المستشفى، وعدد الولادات، والعمليات الجراحية، والمرضى الخارجيين، وعدد السكان، والقروض الشخصية. أخيراً، تم فحص العوامل النفسية التي تدفع العاملين في المجال الطبي إلى الالتزام بفرز النفايات الطبية وذلك باستخدام بيانات الاستطلاع. تم استخدام وتحليل نموذج متكامل يجمع بين نموذج التنشيط المعياري ونظرية السلوك المخطط بطريقة PLS-SEM ، وتم صياغة واختبار إحدى عشرة فرضية إحصائية. يلقي هذا النموذج المتكامل الضوء على الدوافع وراء دافعية العامل في فرز النفايات الطبية، موضحاً 70% من إجمالي التباين. تشير النتائج إلى أن المعايير الشخصية والسيطرة السلوكية المتصورة تؤثر بشكل كبير على الدافعية لفرز النفايات الطبية.

جامعة البحرين



برنامج البيئة والتنمية المستدامة

كلية العلوم

حساب كميات النفايات الطبية المتولدة والعوامل المرتبطة بها في مملكة البحرين

أطروحة مقدمة كجزء من متطلبات الحصول على درجة دكتوراه الفلسفة في
البيئة والتنمية المستدامة

إعداد

خديجة آل عمران

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إشراف

د. عزت خان

أستاذ مشارك

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