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Bayesian Model Averaging and Augmented Autoregressive Distributed Lag Approach for modeling hospital waste amount. Evidence from Dokuz Eylul University hospital in Turkiye

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ABSTRACT

Medical waste management is a growing challenge for healthcare facilities worldwide, particularly in developing countries like Türkiye, where systematic econometric modeling for waste prediction is scarce. This study aims to address this gap by examining the factors influencing medical waste generation at Dokuz Eylul University Hospital (DEUH) from January 2019 to December 2023. The Bayesian Model Averaging (BMA) approach was used to select variables for the econometric model, while Augmented-ARDL analyzed co-integration, DOLS explored long-run effects, and the Fourier Todo-Yamamoto test examined causality relationships. The findings show that Bed Occupancy Rate (BOR), Bed Turnover Rate (BTOR), and Number of Days Hospitalized (NDH) have a statistically significant positive effect on medical waste in the long run. Conversely, Cycle Interval (CI) and Number of Inpatients (NI) have a negative but statistically insignificant effect. Causality analysis indicates a unidirectional relationship from BOR, CI, NDH, and NI to waste amount (WA), while there is bidirectional causality between BTOR and WA. These results suggest that increases in medical waste can impact hospital resource utilization and efficiency. The interaction between BTOR and WA indicates that high turnover may increase medical waste, while the increase in waste could affect hospital resource management. This study highlights the importance of BOR and BTOR in the long-term planning of medical waste management and hospital operations.

1. Introduction

In recent years, the global demand for improved healthcare services has surged, driven by increasing population needs. This demand has led to the rapid expansion of hospitals in both the private and public sectors (Srivastav et al., 2010). While this expansion aims to provide better patient care, it has also resulted in a significant increase in the amount of medical waste generated by these healthcare organizations. Hospitals, whose primary mission is to provide medical assistance, inadvertently pose health risks to the community when medical waste is not properly managed.

In modern healthcare settings, nearly all materials, devices, and objects used eventually become waste. Managing this waste effectively has become one of the most complexes and challenging issues humanity faces, especially as the global population grows and the demand for medical services increases. As a result, effective waste management in healthcare is critical, both for ensuring environmental sustainability and for safeguarding public health.

Healthcare waste includes all materials from healthcare organizations, both infectious and non-infectious. Poor management of this waste poses health risks to workers and the public, making systematic waste management essential (WHO, 2005; Mohee, 2005). Factors like technological advances, population growth, evolving consumption, and increased medical services have raised the burden of medical waste (Işık and Çopur, 2023).

Several factors complicate medical waste management, such as

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limited resources, poor waste segregation, insufficient storage, hazardous materials, and lack of adequate personnel training (Bayhan & Görücü, 2020). Improper management can severely impact human health and the environment (Yadav, 2024). Additionally, effective waste management is crucial not only for health and environmental protection but also for economic reasons, as poor practices can lead to costly public health issues (Keskin and Dönmez, 2021).

Healthcare organizations are major contributors to medical waste, with waste volume varying based on the facility type and patient volume (Ikeda, 2019). The COVID-19 pandemic has highlighted the challenges in waste management, emphasizing the need for better handling practices during public health crises (Öztürk, 2021). Proper waste management is crucial for infection prevention and control in healthcare settings, and can also reduce healthcare-associated infections, improve operational efficiency, and boost staff morale (Anicetus et al., 2022).

Medical waste must be properly separated, stored, transported, and treated in order for healthcare organizations to abide by national waste management guidelines. Effective waste management techniques are necessary (Gavrancic et al., 2012). Raising awareness can also enhance waste management procedures, as can continual training and observation. Enhancing waste management in public health facilities is advised through advocacy and refresher training (Sujon et al., 2022).

Effective management of medical and hazardous waste in healthcare organizations is essential for protecting public health and the environment. Key practices—such as waste segregation, transportation, and disposal—are crucial for infection control. National policies, regulatory frameworks, and training programs support improved waste management, enabling healthcare organizations to maintain safer and healthier environments through continuous staff education and adherence to standards.

This study aims to conduct a systematic analysis to determine hospital waste rates in Türkiye and to contribute to the related literature and By using BMA and Augmented Autoregressive Distributed Lag (A-ARDL) methods. This study examines in detail the generation rates of different types of medical waste and the factors affecting them in healthcare organisations. In addition, the research also contributes to the literature as one of the first comprehensive econometric modeling in Türkiye to evaluate the effects of the pandemic on medical waste generation in healthcare organizations.

The amount of medical waste in Türkiye steadily increased between 2013 and 2021. In 2013, approximately 71,173 tons of medical waste were generated, which grew to 83,190 tons in 2014 and 113,857 tons in 2015. By 2016, the amount slightly decreased to 98,376 tons but remained relatively stable into 2017 at 98,729 tons. A notable rise occurred in 2018, with 107,400 tons recorded, followed by 109,478 tons in 2019. The upward trend continued in 2020 and 2021, with medical waste quantities reaching 125,566 tons and 135,869 tons, respectively. These figures underscore the critical need for robust medical waste management strategies to address the increasing volumes effectively (Turkish Ministry of Environment, Urbanization and Climate Change, General Directorate of EIA, Permit and Inspection, 2023)

In Turkiye, inadequate data and lack of standardization pose a significant problem in determining hospital waste generation rates (Cingöz and Tinni, 2020). The econometric analysis of the specific factors affecting the medical waste generation rates of hospitals in Türkiye constitutes an important gap in the literature. In particular, studies on the effects of variables specific to hospital operations such as BOR, BTOR and NDH on medical waste generation are limited (Cingöz and Tinni, 2020; Tunagür et al., 2018; Doğanyiğit, 2020). In this context, an analysis of data from a university hospital in Türkiye aims to fill this gap and better understand the factors affecting medical waste generation.

Factors complicating medical waste management in Türkiye include limited resources, inadequate staff training and poor waste segregation related to hazardous substances (Tunç, 2024; Şahin, 2024). This reduces the effectiveness of waste management processes in hospitals and increases environmental risks. For example, Şahin state that the knowledge level of hospital staff on the collection and transportation of medical waste is insufficient (Şahin, 2024). Therefore, training and awareness-raising activities on medical waste management are critical to increase the knowledge of healthcare workers and improve waste management processes (Keskin and Dönmez, 2021; Batur et al., 2021). Implementation experiences from DEUH confirm the impact of these challenges on operational processes and reveal the need to develop more effective methods in this area.

As one of the large-scale hospitals in Türkiye, DEUH carries out various practices in medical waste management towards the goals of environmental sustainability and public health protection. These include segregation of waste by type, sterilization of infected materials and implementation of safe disposal methods. However, challenges such as limited resources, inadequate training and lack of infrastructure are among the major factors affecting medical waste management. Findings from previous studies suggest that these shortcomings limit the effectiveness of waste management. In this context, our study aims to analyze the current waste management processes of DEUH and evaluate their contribution to environmental and operational sustainability.

1.1. Medical waste

Medical wastes such as sharps (needles, scalpels, etc.), biological wastes (blood, infected tissues) and chemical wastes (pharmaceuticals, laboratory chemicals) pose serious risks to healthcare workers and society when not managed properly (Oladapo et al., 2023; Koolivand et al., 2012; Polat, 2022). Radiated waste requires special management procedures as it contains radioactive materials, while general medical waste (gloves, masks), although less hazardous, should be disposed of with care (Atthar et al., 2022; Veličković and Ilić, 2023). All these waste types require an effective waste management strategy to protect public health and the environment.

Medical waste includes materials generated during healthcare activities that pose health or environmental risks. This waste encompasses used needles, syringes, bandages, contaminated dressings, expired medications, and items exposed to bodily fluids or infectious substances (Cai and Du, 2021). It is classified into types like hospital waste, regulated medical waste, and infectious waste (Purnomo et al., 2021). Effective management is essential to prevent disease spread and reduce related health and environmental hazards.

Regulated medical waste includes sharps, blood products, microbiological waste (e.g., cultures of infectious agents), and pathological specimens (e.g., tissues, organs) (Rutala and Weber, 1997). Generated in hospitals, clinics, labs, and research centers, proper management of this waste is crucial to protect healthcare workers, patients, and the community. Sustainable practices are essential to mitigate the harmful effects on public health and the environment (Jang et al., 2006).

Medical waste management involves the collection, segregation, transportation, treatment, and disposal of healthcare waste (Lee and Lee, 2022). Technologies like incineration, thermal plasma, and sanitary landfilling ensure safe disposal (Cai & Du, 2021). Effective management plans are essential to mitigate health and environmental risks, with facilities following regulatory guidelines for temporary storage (Mhady et al., 2019).

Hospital waste generation varies by country: 2.5 kg/daybed in the UK, 4.5 kg in the USA, 2.3 kg in France, and 1.5 kg in India (Blenkharn, 2006; Mühlich et al., 2003; Patil & Shekdar, 2001). In Turkiye, waste generation has increased from 0.43 kg/daybed in 2000–1.68 kg/daybed in 2017 (Korkut, 2018), highlighting the need to accurately estimate waste generation rates for effective management.

The motivation for our research is that there is no econometric modeling in the literature to estimate the medical waste generation rate of hospitals in Turkiye. The second section provides a comprehensive literature review, followed by the third section, which outlines the econometric theory applied in the study. The fourth section presents the data and empirical findings, while the fifth section concludes with policy

recommendations.

2. Literature review

Medical waste management (MWM) is crucial for ensuring the safety of healthcare workers and the general public. The COVID-19 pandemic has significantly increased the volume of medical waste, underscoring the need for effective waste management strategies. This literature review synthesizes findings on medical waste estimation, management processes, and the environmental and public health implications of improper disposal, with a focus on current challenges and proposed solutions.

Accurately estimating medical waste volume is a key challenge in waste management. Tsai (2021) noted a significant increase in waste during the COVID-19 pandemic in Taiwan and emphasized the need for strategies like self-treatment and joint-treatment to manage the surge. Himayati et al. (2021) stressed the importance of proper sorting, storage, transportation, and treatment to prevent disease transmission.

Singh et al. (2021) highlighted the need for comprehensive waste management, especially during health emergencies, and argued that the lack of holistic approaches and technological adaptation hampers sustainable practices. Pramana et al. (2023) supported this, emphasizing the importance of healthcare personnel's knowledge and stakeholder engagement for effective waste management.

The need for robust infection control in medical waste management was highlighted during the pandemic. Peng et al. (2020) reported that SARS-CoV-2 could survive on medical waste, posing risks if protocols are not followed. Wei et al. (2021) advocated for timely processing and local treatment to address the environmental challenges posed by waste accumulation during health emergencies.

Ongoing challenges remain despite increased focus on MWM. Adeoye and Lateef (2018) called for stricter regulations and better adherence to best practices due to the public health and environmental risks of improper disposal. Yazie et al. (2019) emphasized the importance of following guidelines for all stages of waste management.

Technology's role in improving waste management is growing. Khan et al. (2019) discussed the need for proper treatment methods, while Jie et al. (2023) proposed a machine vision-based system to improve waste sorting, especially with the rise in Personal Protective Equipment (PPE) waste during the pandemic (Cai et al., 2023).

Proper segregation of medical waste is crucial to reducing risks. Abdullah and Almukhtar (2013) emphasized accurate waste classification to minimize hazards, while Khan (2020) recommended categorizing waste into infectious, pathological, sharps, and pharmaceutical types to reduce health and environmental risks. Pramana et al. (2023) found that healthcare personnel's knowledge and attitudes significantly affect waste management outcomes.

Training and education are vital for effective waste management. Gai et al. (2010) linked better understanding of waste policies with comprehensive training, while Farzadkia et al. (2018) highlighted that factors like patient numbers and facility type influence waste production, emphasizing the need for tailored programs. Udofia et al. (2015) identified inadequate training as a major barrier to effective waste management, especially in African healthcare settings.

Effective medical waste management relies on proper infrastructure and resource allocation. Hendi (2024) emphasized the need for updated infrastructure to reduce health and environmental risks, noting that inadequate systems can lead to improper disposal methods, such as burning or mixing waste. Ali et al. (2017) stressed the importance of regular assessments to improve practices. The regulatory framework is also critical; Jovanović et al. (2016) highlighted the role of legal guidelines from organizations like WHO to ensure compliance, while Alharbi et al. (2021) noted that many developing countries lack comprehensive policies, increasing public health and environmental risks.

Ezirim and Agbo (2018) found that the implementation of medical waste management policies in Nigerian healthcare organizations reduced waste production, emphasizing the need for such policies. Jun et al. also highlighted the dangers of improper medical waste management, particularly in developing countries, where it can exacerbate the spread of infectious diseases.

The environmental impact of medical waste is a growing concern. Tushar et al. (2023) highlighted the risks of poor waste management, especially in emerging economies, and recommended centralized systems to improve efficiency and reduce harm. Kwikiriza et al. (2019) emphasized the need for a comprehensive approach that addresses both hazardous and non-hazardous waste for sustainable healthcare practices.

Wei et al. (2021) highlighted the environmental challenges associated with the increase in medical waste since the SARS outbreak, noting that improper disposal can lead to significant public health risks and environmental degradation. Sustainable practices in medical waste management are therefore crucial for minimizing these risks.

The economic impact of medical waste management is substantial. Tumangke (2019) noted that treating hospital medical waste can cost up to eight times more than non-medical waste, necessitating careful planning to control expenses while meeting health and safety standards. Kumar et al. (2015) highlighted the need for continuous supervision to motivate staff and improve waste management outcomes.

Training and periodic education programs can also lead to cost savings by reducing bio hazardous waste generation. Johnson et al. (2013) found that integrating MWM training into hospital education programs resulted in sustained reductions in waste generation. Tumangke (2019) further emphasized that continuous training and awareness campaigns are essential for healthcare workers to understand the importance of proper waste management practices.

The COVID-19 pandemic has greatly affected medical waste generation and management. Sangkham (2020) observed an increase in waste, especially disposable PPE, which intensified existing challenges. Singh et al. (2021) emphasized the need for proper identification, collection, segregation, storage, and transport of waste to treatment facilities, highlighting the importance of sustainable waste management practices, particularly in crises.

Kalantary et al. (2021) found that the increase in waste generation during the pandemic required hospitals to adjust their waste management practices to reduce the risk of disease transmission. Similarly, Malekahmadi et al. (2014) noted that 73 % of hospitals in Tehran had implemented waste segregation, and 93.3 % had designated temporary storage areas, highlighting the importance of segregation as a key component of effective waste management.

Medical waste management is vital for public health and environmental sustainability. Research emphasizes the need for proper segregation, staff training, and technology use, along with regulatory compliance and infrastructure improvements. The COVID-19 pandemic has highlighted the importance of adaptable, sustainable systems to handle sudden waste surges while maintaining public safety.

3. Econometric methodology

We used the BMA method to identify candidate explanatory variables. The BMA method was employed to determine the significance of the variables affecting medical waste generation while addressing model uncertainty, as it evaluates all possible models and calculates the probability of each variable being included, providing a comprehensive assessment beyond relying on a single model. According to the BMA results, variables with a Posterior Probability of Inclusion greater than 0.5 qualify for inclusion in the model. Thus, using BMA reliably determines the importance of variables while accounting for model uncertainty.

The stationarity of the time series used in this study is investigated using the ADF (Dickey and Fuller, 1981), ADF-SB (Perron and Vogelsang, 1992) and Furuoka (2017) tests. The choice of these tests was

influenced by the characteristics of the series. While the ADF (Dickey and Fuller, 1981) and ADF-SB (Perron and Vogelsang, 1992) tests are widely used, they have limitations in capturing the combined effects of nonlinearity and structural breaks. To overcome these challenges, the Furuoka (2017) test is used as it is specifically designed to address scenarios where both nonlinearities and structural breaks are present. This methodological choice allows for a more accurate and comprehensive assessment of the stationarity properties of the series, aligning the analysis with the actual characteristics of the data and strengthening the reliability of the results.

In order to investigate the existence of a cointegration relationship between the variables, the A-ARDL method proposed by Sam(2019) et al. This method works effectively for time series data with different orders of integration, providing a robust analysis of both short-run and long-run dynamics. Furthermore, Dynamic Ordinary Least Squares (DOLS) method is applied to determine the long-run effects of independent variables on medical waste amount. In fact, DOLS is a method that aims to provide consistent estimates in the presence of potential endogeneity and serial correlation problems, which in turn leads to robust estimation of the long-run coefficients. The causality relationship between the variables is analyzed using the Fourier Toda-Yamamoto test developed by Nazlioglu et al. (2016).

4. Data and empirical results

The data we used in the study were obtained from DEUH, which is one of the 3 largest hospitals in Izmir, Turkiye with 1131 bed capacity. The study period covers January 2019 to December 2023. The selection of the period from January 2019 to December 2023 was driven by the need to observe medical waste generation data continuously for a sufficient period of time to allow for more robust and reliable results. The time period examined captures the effects of various factors considered in the study, including seasonal fluctuations and the impact of global events such as the COVID-19 pandemic. Moreover, this period was chosen to accommodate the time series design of the study and to ensure an adequate data set for statistical analyses. The availability and regular recording of data over this time period further enhanced the comprehensiveness and validity of the study.

Seasonal effects are observed in the variables used in this study since they have monthly frequency data. Although there are many methods for decomposing seasonal effects, the TRAMO/SEATS method performs better in the presence of structural breaks. For this reason, seasonal effects on the series used are decomposed by TRAMO/SEATS method. More detailed information on the variables is presented in Table 1. The amount of medical waste generated in the hospital and the potential explanatory variables influencing it are detailed in Table 1.

To understand and analyze the factors affecting medical waste generation rates, the variables used in this study were carefully selected. Bed occupancy rate (BOR) was used to examine the impact of patient density on the amount of medical waste, reflecting hospital capacity utilization. BTOR was included to determine the impact of patient turnover on waste generation and is directly related to hospital operational dynamics. The number of patients (NI) was chosen to assess the amount of waste associated with the frequency of medical procedures, as a key variable indicating the intensity of healthcare services. Cycle time (CI), an indicator measuring efficiency in hospital operations, was used to analyze the potential impact of shorter processes on waste management. Finally, Number of days hospitalized (NDH) was chosen to test the hypothesis that long lengths of stay can lead to an increase in infectious and biological waste, by expressing the average time a patient spends in the hospital. These variables are critical for optimizing medical waste management and uncovering the key factors that influence the amount of waste.

Table 1
Variables definition.

Symbol	*Variables*	*Unit*	*Period*	*Source*
WA	Medical Waste Amount	Kg	2019M1–2023M12	DEUH Statistics Unit
BOR	Bed Occupancy Rate	Rate		
BTOR	Bed Turnover Rate	Rate		
CI	Cycle Interval	Hours		
NDH	Number of days hospitalized	Day		
NI	Number of Inpatients	Patients/ month		

Descriptive statistics of the variables are presented in Table 2 for the purpose of getting to better characterize the variables.

Examining the descriptive statistics, it is seen that the mean and median values of the variables other than CI are closer to each other. Considering the units of measurement of these variables, the fact that the difference between the maximum and minimum values is not very large, as well as the small standard deviations, indicates that the changes in these variables are not too much. The CV value of 0.9498 for CI and 0.20 for other variables indicates that CI is not homogeneously distributed, while other variables are homogeneously distributed. Regarding the Jarque-Bera test statistic and the related probability values, it is understood that all variables do not have a normal distribution at the 5 % significance level. However, according to the 1 % significance level, it is possible to say that WA, BTOR and BOR are normally distributed.

In order to reduce or completely eliminate the possible heteroskedasticity problem in the analysis, the natural logarithmic form of the variables is preferred. For the selection of the variables to include in the model among the candidate explanatory variables, the BMA method was used and the results are given Table 3.

As shown in Table 3, we used 60 observations and $p = 5$ explanatory factors for the study. All feasible $2^5 = 32$ models were visited using model iteration. Seven of these models have a cumulative posterior model probability (CPMP) contribution of at least 0.9. Considering an average model size of 4.700, the models typically include roughly five explanatory variables. We used a Zellner g-prior for the regression coefficients and the same non-informative priors proportional to $1/\sigma 2$ for the constant and error variance. Nonetheless, there are a number of model and parameter g-priority alternatives. However, the Beta-binomial (1, 1) model prior, which gives each model dimension an equal probability, is what we apply in our work. The Benchmark prior after (Fernandez et al., 2001) with a fixed value for $g = \max(n, 2^p) = \max(60, 32) = 60$ is the default g-prior. In this case, the shrinkage parameter is $\delta = g/(1 + g) = 0.9836$, where $\delta = 0$ indicates complete shrinkage and $\delta = 1$ indicates no shrinkage.

In our investigation, we made the presumption that shrinkage would be minimal. The error variance's posterior mean estimations have a mean$\underline{\sigma}^2 = 0.005$. LCI, LBOR, and LNDH have negative posterior mean coefficients, while LNI and average and LBTOR have positive posterior mean coefficients. The variables' effects on the dependent variable are indicated by the signs of the posterior mean coefficients. In addition, Table 3 shows the estimated posterior inclusion probabilities (PIPs), estimates of the standard deviations, and posterior means of the coefficients for each potential explanatory variable. In the event that the PIP value exceeds 0.50, the candidate variable will be incorporated into the model. Therefore, it was determined to incorporate all potential explanatory variables into the model. In addition to Table 4, the variable inclusion map is used to construct the BMA model's comprehensive information in Fig. 1. The top 8 models out of the 32 visited are displayed on the variable inclusion map. The models' CPMPs are displayed on the x-axis, and their PMPs are rated from highest to lowest. The y-axis displays each of the five explanatory variables. A bar whose width is proportionate to the model's PMP is used to indicate each pair of models and variables. If a predictor with a positive coefficient is included in the

Table 2
Descriptive statistics.

	WA	BTOR	BOR	CI	NDH	NI
Mean	65.968	3.8653	72.897	63.241	21253.4	3742.5
Median	64.901	3.9759	80.064	35.186	23357.3	3942.4
Maximum	84.713	5.2928	92.305	322.59	26012.5	4854.2
Minimum	51.604	1.4921	31.806	11.636	9736.7	1518.5
Std. Dev.	7.7044	0.7629	15.374	60.069	4467.9	723.20
CV	0.1168	0.1974	0.2109	0.9498	0.2102	0.1932
Jarque-Bera	6.4943	8.7911	7.9484	128.72	9.9100	15.822
Probability	0.0388	0.0123	0.0188	0.0000	0.0070	0.0003
Observations	60	60	60	60	60	60

CV: Coefficient of variation

Table 3
BMA results.

Varibales	Mean	Std.dev	PIP
LCI	−0.2714	0.0626	0.9998
LBOR	−1.0628	0.5804	0.8746
LNI	0.6031	0.4204	0.8022
LBTOR	0.1747	0.3495	0.5303
LNDH	−0.2560	0.4923	0.5032

N of *obs* = 60 Number of predictors= 5, N of models= 32, For CAMP≥ 0.9 = 7, Mean model size= 4.7, Models: Beta-binomial (1, 1); Cons.: Noninformative; Coef.: Zellner's g. g: Benchmark; g = 60; Shrinkage, g/(1 + g) = 0.9836, $\underline{\sigma}^2$ = 0.005.

Table 4
Model ranking results.

Variables	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5
LCI	✔	✔	✔	✔	✔
LBOR	✔	✔	✔	✔	✔
LNI	✔	✔	✔	✔	
LNDH	✔		✔		
LBTOR	✔			✔	✔

model, the bar is blue; if a predictor with a negative coefficient is included in the model, the bar is red; and if a predictor is not included in the model, it is gray. The CPMP x-axis in our example is shown between 0 and 1, as all models are included in the map (Guliyev, 2024).

The results in Table 4 present the top 5 models among the 32 models visited by the BMA approach.

The ranking shows that among the 5 candidate explanatory variables, the model including all of the candidate explanatory variables CI, BOR, NI, NDH and BTOR would be the best model. Note that CI and BOR are included in the model for the first 5 alternatives (Rank 1 - Rank 5). This result indicates that CI and BOR are very important determinants of WA. In the light of all this evidence, Eq. (1) can be written for the determinants of WA.

$$WA_t = f(BOR_t, BTOR_t, CI_t, NDH_t, NI_t) \quad (1)$$

Following the evaluation of the descriptive statistics of the variables and the results of the BMA, before estimating model (1), we will focus on graphical analysis to have a better understanding of the trends and fluctuations of these variables and unit root analysis to examine the stationarity of the variables. Despite the fact that descriptive statistics provide general information about the variables, they are not sufficient to comprehend their dynamics over time. In order to fill this gap, time series graphs of the variables plotted in natural logarithms are presented in Fig. 2.

The graphs show the amount of medical waste and the changes in variables considered to have an impact on medical waste at DEUH between January 2019 and December 2023. The effects of the COVID-19 pandemic on healthcare services are clearly observed in the graphs. The amount of medical waste shows a general decreasing trend, with a sharp decline observed since the onset of the pandemic, particularly in early 2020. This can be attributed to the decrease in the number of patients admitted to hospitals. In the post-pandemic period, although fluctuations in the amount of medical waste have been observed, the overall trend appears to be downward. During the pandemic period, there was a significant decrease in the BTOR, followed by a gradual recovery. Following fluctuations in 2021 and 2022, the bed occupancy rate reached a relatively more stable level in 2023. The decrease in bed occupancy rate is a major factor in explaining the decline in the amount of medical waste. BTOR showed a significant decrease in 2020 due to the impact of the pandemic.

This refers to the decline in the occupancy level of hospital beds.

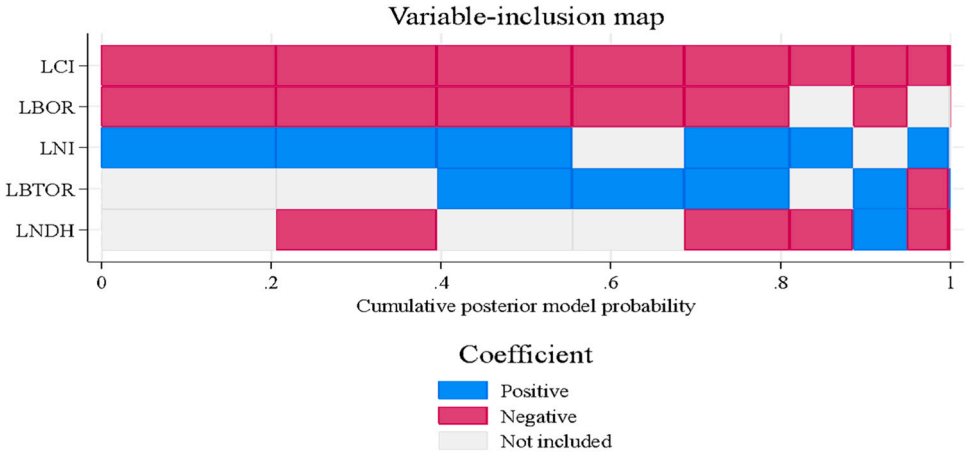


Fig. 1. Variable-inclusion map.

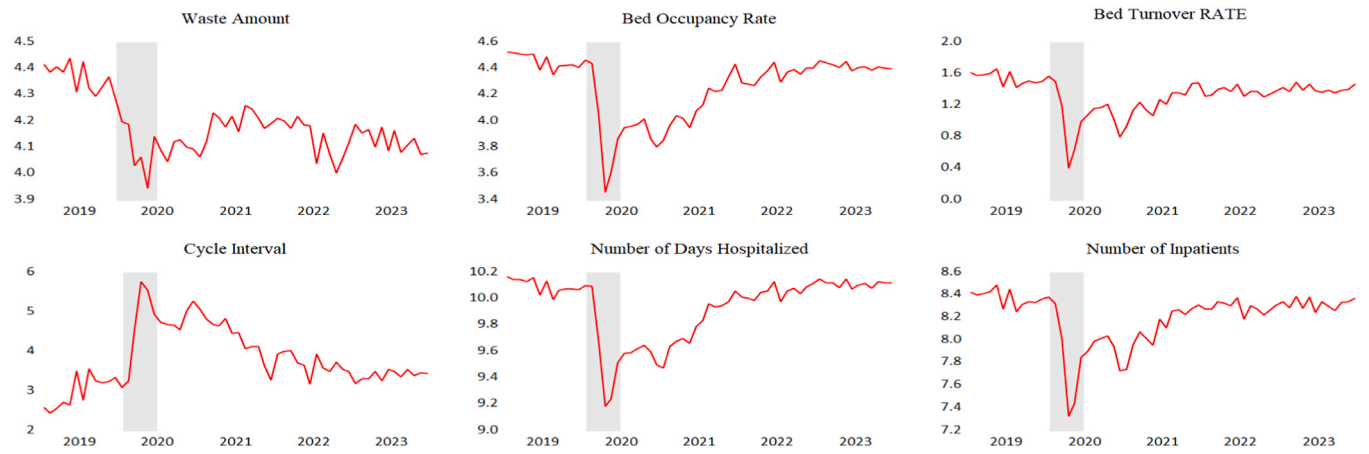


Fig. 2. Time series graphics of variables.

Recovering started in 2021, but pre-pandemic levels have not been fully reached. Cycle Interval showed an increasing trend from 2019 to early 2020, indicating that the duration of use of beds was increasing. However, this trend reversed during the pandemic period and fluctuations were observed in the cycle time. It can be said that the turnover time has an inversely proportional relationship with the amount of medical waste; since the increase in the cycle period contributes to the decrease in the amount of medical waste; such an effect has been realized on the series. There was a significant decrease in the length of hospital stay with the pandemic period. As of 2021, although the length of stay has shown an upward trend again, it has not reached pre-pandemic levels. Examining the relationship between hospital length of stay and the amount of medical waste, it can be concluded that the decrease in the number of patients admitted to the hospital and the shortening of the time spent in the hospital may have supported the decrease in the amount of medical waste. Number of Inpatients, there was a considerable decrease in the number of inpatients at the beginning of the pandemic and then a recovery trend was observed. In 2022 and 2023,

Table 5
Unit root results.

Unit Root Tests	Variables	Constant				Constant and Trend			
		Test stat				Test stat			
ADF(Dickey and Fuller,1981)	levels								
		TV				TV			
	LBOR	−1.9503				−2.7078			
	LBTOR	−3.0926**				−3.0944			
	LCI	−2.3008				−2.3072			
	LNDH	−1.8249				−2.5621			
	LNI	−2.5340				−2.8603			
	LWA	−2.9130**				−3.2618*			
	1st difference								
	ΔLBOR	−6.2927***				−6.3325***			
	ΔLBTOR	−6.3322***				−6.3404***			
	ΔLCI	−8.1221***				−8.2204***			
	ΔLNDH	−5.8387***				−5.8919***			
	ΔLNI	−7.2812***				−7.2581***			
ADF-SB(Perron and Vogelsang, ,1992)	levels								
		TV	BT			TV	BT		
	LBOR	−3.4120	2020M03			−7.1016***	2020M02		
	LBTOR	−4.5725**	2020M04			−5.1099**	2020M03		
	LCI	−2.6834	2021M05			−4.8699	2020M04		
	LNDH	−3.0659	2021M04			−4.6319	2021M04		
	LNI	−3.9058	2020M04			−4.7416	2020M04		
	LWA	−5.0589***	2019M11			−5.3622**	2021M01		
	1st difference								
	ΔLBOR	−11.725***	2020M03			−10.545***	2020M03		
	ΔLCI	−10.973***	2020M04			−10.972***	2020M04		
	ΔLNDH	−10.779***	2020M02			−9.856***	2020M04		
	ΔLNI	−9.9658***	2020M03			−9.5521***	2020M06		
Fourier ADF-SB(Furuoka, 2017)		TV	BT	F stat	k	TV	BT	F stat	k
	LBOR	−4.9335**	2020M04	7.5024**	1	−5.0745**	2020M04	5.7262	1
	LBTOR	−5.3896**	2020M04	4.9385	1	−5.6186***	2020M04	4.2016	1
	LCI	−5.9681***	2020M03	14.972***	1	−7.6482***	2020M03	13.544***	1
	LNDH	−4.1085	2020M04	5.3861	1	−4.3882	2020M04	4.2229	1
	LNI	−4.8955**	2020M04	2.8867	1	−5.0926**	2020M04	3.6723	1
	LWA	−6.2235**	2020M01	6.1538*	2	−6.2007***	2020M01	6.2014*	2

***, ** and * indicate that the null hypothesis of non-stationarity is rejected at 1 %, 5 % and 10 % significance levels, respectively. TV and BT are used for Test Value and Break Time, respectively.

the number of inpatients remained relatively stable but did not reach pre-pandemic levels. This decline could be a main factor explaining the decrease in the amount of medical waste.

Although the graphs contain valuable information for assessing the series' degree of stationarity prior to analysis, they are not enough to demonstrate the series' degree of stationarity. The structural break in all series at the start of the pandemic and the subsequent trend structure suggest that linear unit root tests, like ADF (Dickey and Fuller, 1981), might not be enough to assess the series' level of stationarity. Perron and Vogelsang (1992) tests that consider breaks and Furuoka (2017) tests that consider both sharp breaks and smooth structural breaks simultaneously in the unit root analysis are helpful because of the series' break and fluctuation.

The results presented in Table 5 are a basic reference point for us to decide on the degree of stationarity of the series. The ADF (Dickey and Fuller, 1981) test results indicate that only the level values of the LWA series allow us to reject the null hypothesis for both the equations with constant and the equations with constant and trend. This implies that the ADF (Dickey and Fuller, 1981) test results indicate that only the LWA series is stationary at level, while the other variables are stationary at first difference. ADF-SB (Perron and Vogelsang, 1992) test results indicate the break dates in the series as well as the test values. Analyzing the break dates, it is observed that all series experienced a break at the beginning of the COVID-19 period. This finding is consistent with the break dates shown in Fig. 2 and shows that the ADF-SB (Perron and Vogelsang, 1992) test correctly identifies the break dates. Regarding the test equations with constant and constant + trend, it is concluded that BTOR and WA series are stationary under the break, while the other variables become stationary when first differences are taken.

The results of the FADF-SB (Furuoka, 2017) test show that both the test values and F statistics for BOR, CI and WA variables are statistically significant. This indicates that a decision should be made for these variables according to the results of the FADF-SB (Furuoka, 2017) test. Thus, it is decided that these variables are stationary at level. On the other hand, although the test values for BTOR, NDH and NI variables require the rejection of the null hypothesis, since the F statistics indicating the significance of the Fourier terms are insignificant, it would be appropriate to make decisions about these variables according to the results of the ADF-SB (Perron and Vogelsang, 1992) test.

As a result, considering the ADF-SB (Perron and Vogelsang, 1992) and FADF-SB (Furuoka, 2017) tests, BTOR, BOR, CI and WA variables are stationary at level (I(0)), while NDH and NI variables are stationary at first difference (I(1)). Since the different stationarity levels of the variables in the model expressed in Eq. (1) require us to follow the ARDL approach (Pesaran et al., 2001), breaks in the series necessitate the application of the Augmented-ARDL method following McNown et al. (2018) and Sam et al. (2019). Building on the previous analyses, the A-ARDL method was utilized to explore the long-run relationships between the variables in greater depth. In the model estimation, January 2020 was chosen as the break date in the dependent variable based on the ADF-SB (Perron and Vogelsang, 1992) and FADF-SB (Furuoka, 2017) test result. The results obtained from the A-ARDL cointegration test, long-run effects and Causality test are presented in detail in Table 6.

Panel A of Table 6 shows that Case 1, which represents the A-ARDL equation without constant and trend, is the best fit model. The degree of cointegration equation is determined as A-ARDL (1, 1, 1, 1, 1, 1); this result indicates that the one-period lagged value of each variable in the model is included in the model as an independent variable. The fact that the F and t values exceed the Peseran et al. (2001) and Narayan (2005) critical values and the $F_{independent}$ value exceed the Sam et al. (2019) critical value, respectively, reveals the existence of a co-integration relationship between the variables. The model demonstrates a high explanatory power (87.8 %), and additional diagnostic tests further strengthen confidence in the estimated results. Specifically, the normal distribution of error terms (JB test), absence of autocorrelation (BG-LM test), and lack of heteroskedasticity (White test) suggest robustness in the model's estimations. The Error Correction Model (ECM) coefficient is negative and statistically significant, indicating that the disequilibrium between the variables tends to return to the long-run equilibrium value. This disequilibrium is corrected in approximately two periods ($1/0.4842 \approx 2$ months). Furthermore, the Ramsey RESET (R-R) test confirms that the model is functionally well-specified. The CUSUM and CUSUMSQ test results indicate that there are no breaks in the model parameters in the analyzed period. Therefore, we can state that the model has a stable structure throughout the sample period.

Following the interpretation of the A-ARDL results, the findings on

Table 6
Cointegration, long-run effects and causality results.

Panel A: A-ARDL Results							
Model	Lag order	Dummy	F	t	$F_{independent}$	Co-integration	
Case 1	1,1,1,1,1,1	2020m01	4.9037**	−4.6714**	4.7914**	✔	
Diagnostic Check							
R^2	F-stat	JB	BG-LM	White	R-R	ECM	Stability
0.8780	38.942***	1.2777	0.3539	1.1088	0.7903	−0.4842***	✔
Panel B: Long-run effect results							
Variables	DOLS coefficients						
Constant	−0.1298						
DT2020m01	−0.1669***						
LBOR	−3.3495**						
LBTOR	1.8143**						
LCI	−0.0873						
LNDH	2.5338*						
LNI	−1.0398						
Panel C: Fourier Todo-Yamamoto Causality Results							
Direction of causality	Test stat	Result					
LWA→LBOR	6.5327**	Causation					
LBOR → LWA	0.0000	No Causation					
LWA→LBTOR	7.9268**	Causation					
LBTOR → LWA	19.915***	Causation					
LWA→LCI	6.8720***	Causation					
LCI → LWA	0.0899	No Causation					
LWA→LNDH	10.976***	Causation					
LNDH → LWA	2.8166	No Causation					
LWA→LNI	19.600***	Causation					
LNI → LWA	1.1759	No Causation					

, * indicate that the null hypothesis is rejected at 5 % and 1 % significance level respectively.

the long-run effects of the independent variables on WA and the causality analysis between the variables are presented in Panel B and Panel C of Table 6, respectively.

The dummy variable DT2020M01, which indicates the beginning of the pandemic, has a negative and statistically significant effect on WA. This is because the restrictions imposed on health services during the COVID-19 pandemic led to a decrease in the amount of WA. During the pandemic, non-COVID-19 routine procedures and elective surgeries were reduced or postponed in hospitals, leading to a decrease in the number of patients admitted to hospitals and therefore a reduction in medical waste. On average, a 1 % increase in the bed occupancy rate leads to a 3.3 % reduction in the amount of medical waste.

The main reason behind this is that higher bed occupancy rates are associated with more efficient use of hospital resources and patients staying in hospital for shorter periods of time. Higher occupancy rates allow for more organized monitoring and management of patients, which also leads to a reduction in medical waste generation. Furthermore, the efficiency of medical waste management and sterilization processes is optimized with increasing occupancy rates, increasing the potential to reduce the amount of waste. Thus, the increase in bed occupancy rate has a positive impact on the management and generation of medical waste.

WA increases by an average of 1.8 % and 2.5 % for every 1 % rise in BTOR and NDH, respectively. This is because an increase in NDH and BTOR leads to the use of more medical supplies and equipment in hospital operations. The longer hospitalization of patients leads to the accumulation of medical waste and hence an increase in the total amount of waste. Also, higher BTOR results in more frequent admissions of patients and more treatment processes, which increases the generation of medical waste. The increase in both variables leads to more intensive utilization of hospital resources, thus increasing the total amount of medical waste. As a result, the increase in BTOR and NDH are considered as important factors that trigger more waste generation in terms of hospital management and resource utilization.

WA is negatively impacted by increases in the variables of CI and NI; however, these effects are not statistically significant. This is due to the limited and indirect impacts of CI and NI variables on the production of medical waste. CI and NI are factors that affect hospital processes but do not directly determine the amount of medical waste. Moreover, medical waste generation is more tightly related to other variables such as hospital resource utilization, treatment processes and material consumption, which makes the impact of CI and NI less pronounced. Therefore, the effects of these two variables on WA are not statistically significant, a situation that should be carefully evaluated from the point of view of hospital management.

In literature, the number of studies similar to our study is limited. However, our findings on the relationship between WA and NI contradict Tesfahun et al. (2016), whereas our results on the relationship between WA and BOR are in conformity.

Following a detailed analysis of the long-run effects of the independent variables on the dependent variable, we turn to the causality analysis presented in Panel C of Table 6 to examine the causal relationships of these interactions.

Concerning the results in Panel C of Table 6 there is a unidirectional causality relationship from WA to BOR, CI, NDH and NI variables, while there is a bidirectional causality relationship between BTOR and WA.

These findings reveal that medical waste generation is one of the main factors affecting the utilization of hospital resources, especially in the long run. Considering the long-run effects, the unidirectional causal relationship from WA to BOR, CI, NDH and NI variables suggests that an increase in medical waste generation may affect the bed capacity, utilization rates and length of stay of hospitals. This implies that long-run increases in medical waste generation may increasingly strain hospital resources. For example, the effect on BOR indicates that when more medical waste is generated in a hospital, bed occupancy rates may remain high due to the need to allocate resources accordingly. The relationship between BTOR and WA, where bidirectional causality is observed, reveals that the amount of medical waste both affects and is affected by BTOR in the long run. This bidirectional relationship suggests that, in the long run, more frequent bed utilization in hospital operations may increase the amount of medical waste, and the increased amount of waste may require faster BTOR. These results suggest that in the long run, hospitals should plan their medical waste management processes by taking BTOR into account.

5. Discussions

Our findings in this study reveal how medical waste generation rates are associated with various factors and are in line with previous studies in the literature. The findings of this study support the existing knowledge in the literature on the relationship between medical waste generation and hospital operational processes and differ in some aspects. The increasing effects of variables such as BOR and BTOR on medical waste generation are among the important findings frequently emphasized in the literature (Doğanyiğit, 2020). In particular, by revealing the bidirectional causality relationship between BTOR and the amount of medical waste, it offers a new perspective for this field. This helps us better understand the impact of patient circulation and the intensity of medical interventions on waste generation in hospitals (Doğanyiğit, 2020). Moreover, the effects of variables such as number of patients (NI) and number of days hospitalised (NDH) on medical waste generation have been discussed in previous studies. However, in this study, these effects are elaborated through a more comprehensive econometric analysis. While previous studies generally address individual factors, this study reveals how operational processes interact in a holistic framework (Doğanyiğit, 2020; Tunagür et al., 2018).

In this context, previous studies on medical waste management emphasize the importance of proper segregation and management of medical waste at the source (Tunagür et al., 2018; Yücedağ and Baksi, 2019). The BMA and A-ARDL methods used in our study provide new contributions to areas where previous studies have been limited. These methods offer new opportunities for the development of medical waste management strategies and emphasize the importance of optimizing operational processes (Doğanyiğit, 2020; Tunagür et al., 2018). For example, Doğan and Aktaş state that increasing the level of knowledge of healthcare workers on medical waste management will increase the effectiveness of waste management processes (Doğan and Aktaş, 2017). These findings provide an important basis for improving medical waste management practices. As a result, this study makes an important contribution to better understand the relationships between medical waste generation and hospital operational processes and to fill the gaps in the literature in this field. The findings provide new opportunities for the development of medical waste management strategies and have the potential to contribute to the sustainability of healthcare services (Doğanyiğit, 2020; Tunagür et al., 2018). In contrast, the findings of this study suggest that the impact of cycle time and the number of inpatients on waste generation may be more complex. This indicates that factors influencing waste management could stem from differences in hospital types, infrastructure, and regional characteristics.

6. Conclusions and policy recommendations

This study sheds light on waste management processes in healthcare institutions by analyzing the factors affecting the amount of medical waste in line with the data obtained from DEUH between 2019 and 2023. The findings show that especially BOR, BTOR and NDH variables have an increasing effect on the amount of medical waste and these effects are statistically significant. On the other hand, while the CI and the NI have a decreasing effect on the amount of medical waste, these effects are not statistically significant. According to the causality analysis, the presence of a bidirectional causality relationship between the amount of medical waste and BTOR reveals that waste management and

hospital operations should be organized in an interdependent manner.

Based on these results, we recommend some policy recommendations to improve medical waste management in hospitals. First, waste management strategies that take into account BOR and BTOR are important because these factors directly affect the amount of medical waste. Since high BTOR can increase the amount of waste through increased short stays in the hospital, balancing these processes can both reduce the amount of waste and make hospital resources more efficient. The dissemination of recycling practices and waste reduction methods in hospitals will contribute to the sustainable use of resources. In addition, waste management and sustainability training for healthcare workers can provide a more conscious waste management in daily work processes. Considering the bidirectional causal relationship between BTOR and the amount of medical waste, aligning bed management policies with waste management strategies will optimize resource use. These policies will contribute to long-term environmental sustainability in hospital waste management, while at the same time providing a strategic approach to reduce economic costs.

Although the findings of this study provide important conclusions on the factors affecting medical waste generation, they have some limitations. First, as the analyses are limited to data from DEUH, the results may not be generalizable to other types of hospitals or different geographical regions. Second, since the study data covers the period 2019–2023, a wider time period may be needed to assess long-term trends. Third, although robust econometric methods were applied to analyze the effects of the independent variables used on medical waste generation, environmental, institutional and socioeconomic factors other than these variables may also affect waste management processes. These limitations call for future studies to use larger data sets, different methods and to compare findings from various health care organizations.

CRediT authorship contribution statement

Babashova Sakina: Writing – review & editing, Validation, Methodology. **Durmus Alkan:** Writing – original draft, Resources. **Gasim Nijat:** Writing – original draft, Visualization, Validation, Software, Methodology, Data curation. **DEVEBAKAN NEVZAT:** Writing – review & editing, Supervision, Project administration.

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Data availability

Data will be made available on request.

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