INNOVATIVE APPROACHES TO IMPROVING WASTE MANAGEMENT AND REDUCING ECOLOGICAL FOOTPRINT

Mirela Laura Cârpaciu[1], Andreea Ardelean[2*]
[1)] *Automatic Data Processing, Bucharest, Romania*
[2)] *University of Bucharest, Bucharest, Romania*

Abstract
This study analyses historical plastic waste data to identify generation and recycling patterns and to support more effective public policy formulation. It aims to enhance waste management practices and mitigate the ecological footprint through a comprehensive analysis of plastic waste characteristics and trends. With the use of pre-processed dataset, exploratory data analysis (EDA) in Python, linear regression, K-Means clustering, and ARIMA models for temporal forecasting were applied. Results indicate that waste volumes explain approximately 90% of the variation in an aggregated indicator, highlighting a system oriented towards large and concentrated flows. Clustering identified four distinct waste profiles, with a pronounced geographical dimension (including an extremely large volume cluster almost exclusively associated with Uganda), suggesting the need for differentiated strategies across countries. ARIMA models, though limited by short time series, demonstrated the potential for anticipating future trends, occasionally outperforming a seasonal naive benchmark. The study's main contribution lies in integrating a complete analytical chain—from preprocessing and EDA to predictive modelling and segmentation—offering a practical framework for prioritizing interventions in plastic waste management and informing public policies targeting both large and dispersed, underutilized flows.

Keywords
Waste management, ecological footprint, plastic waste, data analysis, sustainability, Python

JEL Classification
Q50, Q51, Q53, Q58, O10, O20, C10, C80

[*] Corresponding author, **Andreea Ardelean** – andreea.ardelean@faa.unibuc.ro

Introduction

The escalating global waste crisis, particularly concerning plastic waste, poses a significant threat to environmental sustainability, human health, and the planet's ecological integrity (Macheca et al., 2024). Rapid urbanization, consumption-driven economies, and finite natural resources exacerbate this challenge, making the adoption of effective waste management strategies and the reduction of ecological footprints imperative. Efficient waste management is not merely an environmental obligation but a strategic investment in a cleaner, healthier, and more prosperous future, contributing to resource conservation, pollution reduction, and the advancement of circular economy principles (Svidronova & Merickova, 2022).

This paper aims to contribute to these efforts by conducting an in-depth analysis of plastic waste management data. It seeks to provide essential insights and strategic recommendations to optimize recycling processes and mitigate environmental impact. Through an exploratory data analysis approach, coupled with advanced machine learning techniques, this study identifies key waste patterns, assesses influencing factors, and develops predictive models to support evidence-based decision-making for sustainable waste management strategies.

The first section of the paper outlines the global and national context of the plastic waste problem. The second section defines the specific objectives and research questions, and the third section reviews existing waste management methods and theoretical frameworks. The following sections detail the research methodology, including data sources, preprocessing steps, and the analytical models employed, and then present and discuss the key results obtained from the analysis. The last section of the paper concludes the study, offering a synthesis of findings, specific recommendations, and identifying limitations and avenues for future research.

1. Review of the scientific literature

The global context includes accelerated growth in production and consumption, sustainability and persistence in the environment, environmental impact, ocean pollution, soil and freshwater pollution, greenhouse gas emissions, recycling challenges, and international initiatives.

Jambeck et al.’s (2015) study highlighted the alarming scale of plastic waste entering the ocean from land, estimating that millions of tons of plastic enter the marine environment annually. This massive contribution of poorly managed waste underscores the urgent and global nature of the plastic pollution problem and the urgent need for effective management strategies. Geyer, Jambeck, and Law’s (2017) research demonstrated that, of all the plastics ever produced, an overwhelming proportion—billions of tons—persist in the environment, accumulating in ecosystems and exerting ongoing and long-term pressure on planetary health, including in the form of microplastics. The plastic waste problem is a global crisis defined by the rapid accumulation of plastics — especially single-use plastics — in terrestrial and aquatic ecosystems. According to reports by the United Nations Environment Programme (UNEP) and directives by the European Commission (such as Directive (EU) 2019/904), this accumulation generates a devastating ecological impact, from visible pollution to the invisible presence of microplastics, affecting biodiversity, human health, and the integrity of natural systems.

The national context involves adherence to EU objectives, the current situation of waste management, low recycling rates, poor infrastructure, lack of civic education, problems with landfills, legislation and implementation, and economic and social impact. Romania still faces significant challenges in managing plastic waste, although progress has been made (Mihai & Ulman, 2024; Gavrilescu et al., 2023). However, there is significant potential for improvement through investments in infrastructure, promoting innovation in recycling, developing the circular economy, and implementing effective education campaigns.

The importance of efficient waste management derives from multiple benefits and needs: protecting the environment, reducing pollution, conserving natural resources, reducing greenhouse gas emissions, economic benefits, creating new industries and jobs, reducing disposal costs, adding value from recycled materials, improving public health, preventing the spread of diseases, improving quality of life, promoting sustainability and the circular economy, contributing to achieving sustainable development goals at local, national and global levels (Svidronova & Merickova, 2022). Including eco-innovations in smart city waste management, like IoT (internet of things), AI (artificial intelligence), and data analytics have gained a lot of momentum lately, but a huge challenge here is the high initial costs, data privacy, and integrating complex systems (Rorat & Kacprzak, 2017). Many companies are now pushed to adopt eco-innovations to gain a competitive advantage and prevent waste generation, so an important concern is examining the prevention capabilities of different organizational entities towards the environment (Sumrin et al., 2021). There is a lot of interest in finding innovative strategies in sustainable waste management (Mashudi et al., 2023), such as underscoring the impact of integrating AI technologies, or advocating for a more holistic approach towards technology and societal participation (Aswini, 2023). Yet, despite notable efforts in this direction, there are still many challenges, such as inadequate infrastructure or insufficient funding, or not enough public awareness (Mandal, Kundu & Mondal, 2024).

Therefore, investing in modern and integrated waste management systems is not only an environmental obligation, but a strategic investment in a cleaner, healthier, and more prosperous future.

Thus, the general objective of this paper is to conduct an in-depth analysis of plastic waste management data to provide essential insights and strategic recommendations to optimize recycling processes and reduce environmental impact.

Specific Objectives would be:

- Exploratory analysis of plastic waste data:

− To conduct a detailed exploratory analysis of plastic waste data to understand the characteristics, distribution, and trends of scanned plastic waste (e.g. number of bottles, weight, material type, product size in ml).

− To identify the main contributors to the recorded plastic waste, such as brands, manufacturers, and countries of scanning and manufacturing.

- Assessment of correlations and influencing factors:

− To investigate potential correlations between various variables in the datasets (e.g. bottle weight, number of bottles, product size).

- Identifying temporal and seasonal trends:

− To analyse the evolution of plastic waste quantities and types over time (monthly, annually) to detect trends, seasonal cycles, or anomalies.

- Developing data-driven recommendations:

− To formulate practical and strategic recommendations to improve the collection, sorting, and recycling of plastic waste, based on insights obtained from data analysis.

These objectives translate into the following research questions that the article will attempt to answer:

- What are the main characteristics (number, weight, type, size) of plastic waste recorded in the datasets, and how are they distributed?
- Who are the main contributors (brands, manufacturers, countries of scanning/manufacturing) to the volumes of plastic waste identified?
- Are there significant temporal or seasonal trends in the generation or collection of plastic waste during the period analysed?
- What correlations can be identified between plastic waste attributes (e.g. weight vs. product size) and how can they be interpreted?
- What insights can be extracted from data analysis to optimize waste management strategies, especially about recycling and reducing environmental impact?

In order to answer to these questions, it is necessary, as a first step, to study existing waste management methods. So, in the following, a summary of the most important methods will be made and then it will be continued with the quantitative analyses applied to the specified data included in the study.

Waste management is a complex and multidisciplinary process, involving a series of methods and strategies aimed at minimizing the negative impact of waste on the environment and human health, while maximizing resource utilization. Modern approaches are based on the waste management hierarchy, a conceptual pyramid that prioritizes actions according to their environmental impact. This hierarchy establishes a preferential order of management strategies, from the most desirable to the least desirable: waste prevention/reduction, reuse, recycling, other recovery (including energy recovery), and disposal (landfilling). Efficient waste management is essential for sustainability, guided by the principles of the Waste Hierarchy, a fundamental legislative priority at the European level, according to Directive 2008/98/EC. This hierarchy, described in detail by authors such as Tchobanoglous et al. (2015), establishes a preferential order for waste management strategies: prevention, reuse, recycling, other forms of recovery (such as energy recovery) and, ultimately, disposal. The rigorous application of this hierarchy minimizes negative environmental impacts and maximizes resource utilization.

In the context of a circular economy, as promoted by institutions such as the European Environment Agency (EEA) and theorized by pioneers such as Walter R. Stahel (2010) in his concept of the 'Performance Economy', the most important aspect of efficient waste management is the prevention of its generation. By prioritizing sustainable

product design, reuse, and extension of the life cycle of materials, the pressure on natural resources and waste management systems is significantly reduced. Waste management is not only a technical challenge, but a crucial 'environmental challenge' at a global level, with profound implications for economic development and the health of the planet, as Godfrey (2019) points out. Therefore, effective management, based on the waste hierarchy, is essential to turn this challenge into a sustainability opportunity.
Modern Approaches and Complementary Concepts include:

- Circular Economy:

This is an economic model that aims to eliminate waste and pollution, keep products and materials in use, and regenerate natural systems. It opposes the linear "extraction-production-consumption-disposal" model.

- Extended Producer Responsibility (EPR):

This is a principle according to which producers are responsible for the entire life cycle of their products, including post-consumer collection and recycling.

- Advanced Sorting Technologies:

These include the use of optical sensors, artificial intelligence, and robotics to improve the efficiency and accuracy of waste sorting, especially plastic.

- Legislation and Public Policies:

The role of legislative frameworks (e.g. EU directives, national laws) in setting recycling targets, banning certain single-use plastics, and stimulating innovation is crucial.

- Education and Public Awareness:

The importance of involving citizens in separate collection and in adopting responsible waste behaviour must not be neglected.

- Statistical analysis of waste data:

Statistical analysis plays a fundamental role in understanding the complexity of waste generation and management. By applying appropriate statistical methods, researchers and decision-makers can extract valuable information from large volumes of data, identify patterns, assess the effectiveness of policies, and forecast future trends. By combining these methods, statistical analysis provides a solid basis for transforming raw waste data into actionable information, essential for improving management practices in those areas.

- Predictive models in waste management:

In the modern context of waste management, the use of predictive models has become indispensable. These models use historical data and, advanced statistical analysis, and artificial intelligence techniques to forecast future trends, estimate waste quantities, identify influential factors, and support operational and strategic decisions. The main goal is to transform raw data into actionable information, anticipating future needs and challenges.
In an effort to modernize and streamline waste management, the application of statistical methods and predictive models has become indispensable. As classic resources such as 'A Handbook of Statistical Analyses using R' (Everitt & Hothorn, 2011) and 'Discovering Statistics Using IBM SPSS Statistics' (Field, 2018) highlight, statistical analysis provides the tools needed to understand the complexity of waste data.

Furthermore, predictive models, including regression, clustering, and time series analysis (Hyndman & Athanasopoulos, 2018; James et al.2013), allow for the anticipation of waste generation trends, the optimization of collection routes, and infrastructure planning. A recent systematic review, conducted by Bustamante and Pires (2020), confirms that 'machine learning applications in solid waste management' are essential to transform raw data into informed operational and strategic decisions, thus improving the sustainability of the entire system.

Plastic waste represents one of the most pressing environmental challenges globally in the 21st century. Due to its durability, resistance to degradation, and massive production volume, plastic accumulated in the environment has devastating consequences on ecosystems, biodiversity, and, indirectly, on human health. We observe aquatic pollution (oceans, seas, rivers, lakes), terrestrial and soil pollution, air pollution, climate change but also the problem of microplastics, nano plastics, and single-use plastic waste. Thus, the impact of plastic waste on the environment is complex and multidimensional, threatening planetary health in the long term (Li et al., 2021; Evode et al., 2021). Recognizing and understanding these effects underlines the urgency of adopting effective waste management strategies, based on prevention, reuse and recycling.

Modernizing waste management is fundamentally dependent on an effective synergy between legislative frameworks, ambitious public policies, and the adoption of advanced sorting technologies. Key European Union documents, such as the Directives and Regulations on waste, transposed into national legislation (e.g. Law 211/2011 in Romania), impose strict standards and ambitious targets for recycling and recovery. These legislative requirements become catalysts for the implementation of 'advanced sorting technologies', including those based on artificial intelligence, which allow for a much more precise and efficient separation of waste fractions. This strategic integration not only facilitates the achievement of recycling targets but also contributes to the transition to a circular economy, transforming waste from a problem into a resource.

2. Research methodology

This paper uses data from .csv files available on Kaggle (a data science competition platform) focused exclusively on information about plastic waste collected between March 2021 and December 2024 in the following countries: Canada (CA), Great Britain (GB), Kenya (KE), Malawi (MW), Mozambique (MZ), Rwanda (RW), Tanzania (TZ), Uganda (UG), South Africa (ZA), Zambia (ZM), United Arab Emirates (AE), Angola (AO). These files, named "Plastic Bottle Waste", constitute the main dataset for exploratory analysis, identification of main contributors, assessment of correlations between plastic attributes, and temporal trend analysis. By using these datasets, the article conducts an in-depth analysis of the intrinsic characteristics of plastic waste and its trends. Data processing was done in Python 3.13.7 with the following libraries: Pandas (for data manipulation), Matplotlib, Seaborn (for visualizations), Scikit-learn (for regression and clustering), Statsmodels (for autoregressive integrated moving average - ARIMA) and Yellowbrick (for Elbow Method visualization). The variables used are described in Table 1, by name and type.

Table no. 1. Type of variables used in the analysis

Variable name	Data type
product_barcode	Numeric/String
product_label	String
product_size	String
brand_name	String
manufacturer_country	String
manufacturer_name	String
scan_country	String
data_url	String
bottle_weight	Float
bottle_count	Float
scan_date	Date (YYYY-MM-DD)
year	Int
month	Int
day_of_week	Int
product_size_ml	Float
recycled_rate	Float

Source: Kaggle, Plastic Bottle Waste.

Data cleaning and preprocessing included:

- Missing value handling: rows with missing values in the target variable `recycled_rate` were removed.
- Data type conversion: the `scan_date` column was converted to a datetime format to facilitate temporal analysis.
- Creation of the target variable `recycled_rate`: given the time series nature of the data, the target variable `recycled_rate` was defined as the total sum of `bottle_count` from the previous quarter, aggregated by `scan_country`. This approach allows for the prediction of the recycling rate based on recent historical data.

Subsequently, an exploratory analysis was performed to understand the distribution and relationships between the variables. Key visualizations included the heat map of correlations that revealed linear relationships between the numerical features and the target variable (Fig. 1). Most of the coefficients recorded positive values, as it can be seen in the correlation heatmap of numerical features, which is a powerful visual tool that shows how the variables included in the study relate to each other.

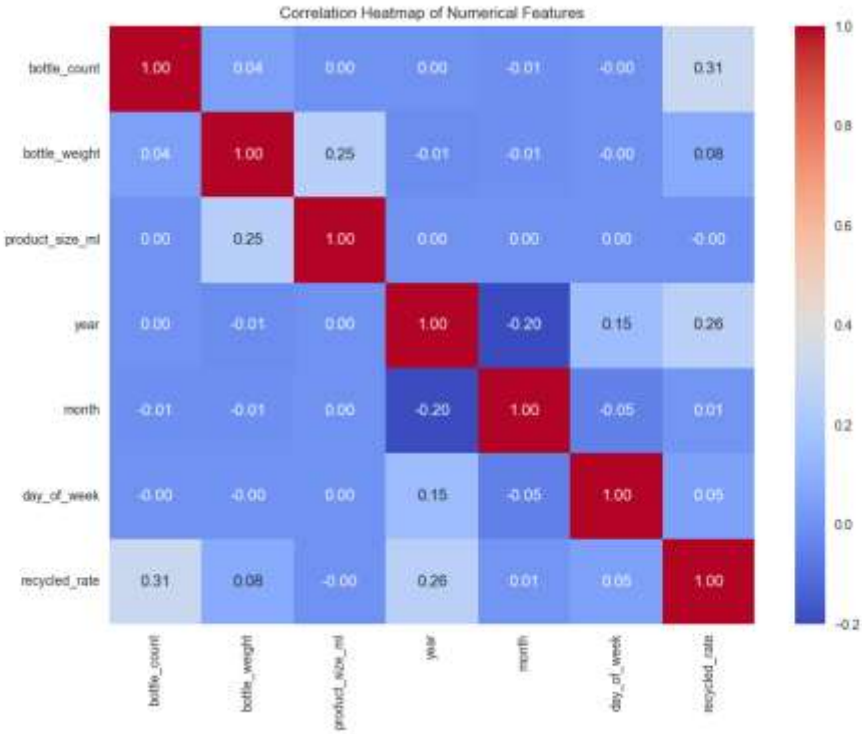

Figure no. 1: Correlation Heatmap of Numerical Features
Source: authors based on data taken from https://www.kaggle.com/

For the distribution of the recycling rate by country, a box-plot diagram was added to illustrate the variation of `recycled_rate` depending on 'scan_country' for Canada (CA), Great Britain (GB), Kenya (KE), Malawi (MW), Mozambique (MZ), Rwanda (RW), Tanzania (TZ), Uganda (UG), South Africa (ZA), Zambia (ZM) (Fig. 2). Wide variations of the variable can be identified in countries like Kenya, Mozambique, and Tanzania. However, with low recycling rates, Mozambique and Tanzania face significant challenges in managing plastic waste, while Kenya implemented some initiatives to limit the plastic pollution crisis. Additionally, a few countries have outliers: Rwanda, Uganda and Zambia. Those countries have made significant strides in waste management and recycling.

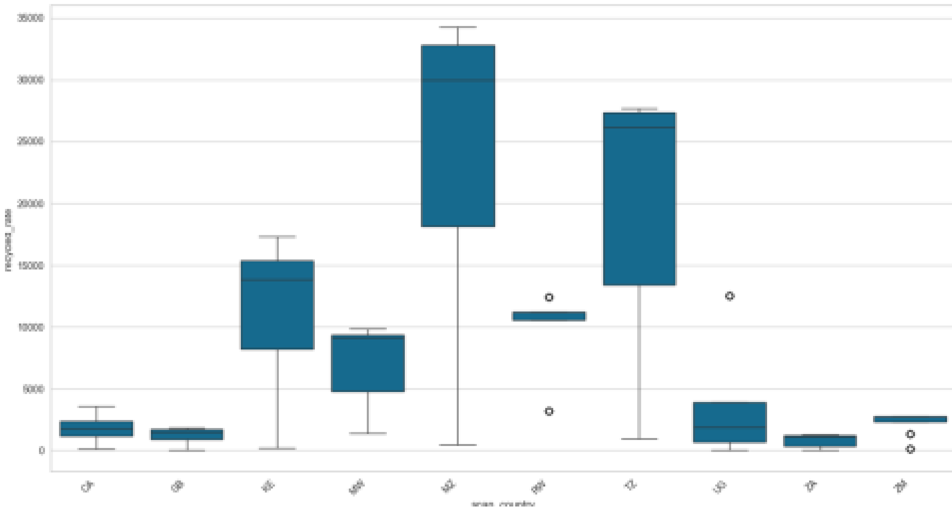

Figure no. 2: Recycled rate distribution by top scan country
Source: authors based on data taken from https://www.kaggle.com/

Linear regression was used to model the relationship between the explanatory variables and the target variable, *recycled_rate*. This model was selected for several key reasons:

- Interpretability: Linear regression yields easily interpretable coefficients, enabling a clear assessment of both the direction and magnitude of the association between each predictor (e.g., *bottle_count*, *bottle_weight*, *product_size_ml*) and *recycled_rate*.
- Parsimony and Robustness: Given the large number of observations and the presence of heterogeneous feature distributions, a linear model offers a favorable balance between simplicity and robustness. Compared to highly flexible non-linear models, it is less susceptible to overfitting and does not require extensive hyperparameter tuning.
- Consistency with the Data Structure: Exploratory data analysis indicated approximately monotonic and near-linear relationships between the main predictors and the response variable, supporting the suitability of a linear approximation as an initial modeling approach.
- Favorable Simplicity–Performance Trade-off: Empirical evaluation demonstrated a high coefficient of determination (R^2), indicating that the linear model explains a substantial proportion of the variance in *recycled_rate*, thereby reducing the need for more complex and less interpretable alternatives.

The linear regression model was implemented within a machine learning pipeline comprising:

(1) standardization of numerical features using StandardScaler;
(2) one-hot encoding of categorical variables using OneHotEncoder;
(3) estimation of the model using LinearRegression.

Model performance was assessed using an 80/20 train–test split, with Mean Squared Error (MSE) and R^2 employed as evaluation metrics.
The K-Means clustering algorithm was used to identify patterns in waste characteristics, using the numerical variables *bottle_count*, *bottle_weight*, and *product_size_ml*. Before clustering, all features were standardized to ensure equal contribution to distance-based calculations.
The optimal number of clusters was determined using the Elbow Method, evaluated across a range of candidate values for *K*. For visualization purposes, the resulting clusters were projected onto a two-dimensional space using Principal Component Analysis (PCA) (Fig. 3).

The choice of K-Means was motivated by the following considerations:

- Computational Efficiency when applied to large datasets.
- Interpretability of Results, as cluster centroids directly reflect average feature values.
- Effectiveness for Exploratory Segmentation, particularly when combined with feature scaling and PCA, even in the presence of imbalanced initial distributions.

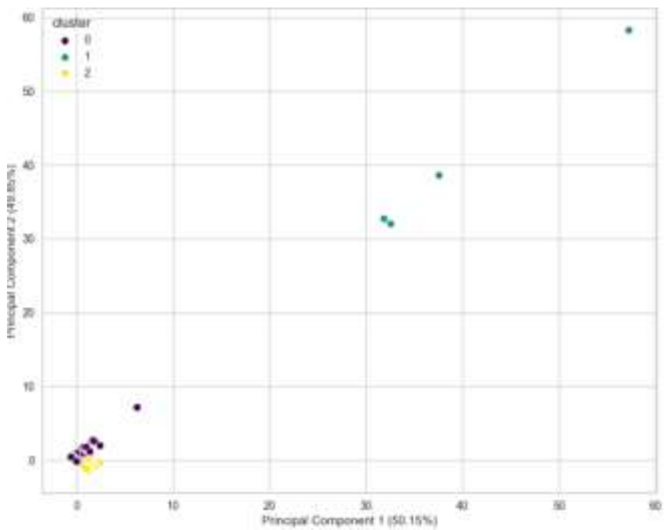

Figure no. 3: Clusters Visualization using PCA
Source: authors based on data taken from https://www.kaggle.com/

ARIMA models were applied to forecast the temporal evolution of *recycled_rate* at the country level. The analysis was conducted on quarterly aggregated time series for selected countries (e.g., *MZ*, *GB*).
Model parameters were fixed at ARIMA(1,1,0) for the following reasons:

- Limited Time Series Length: The number of available quarterly observations per country was relatively small, restricting the reliable estimation and comparison of more complex model specifications.
- Use of a Standard Baseline Model: ARIMA(1,1,0) represents a commonly adopted baseline, where:
    - $d = 1$ (first-order differencing) addresses trend components and promotes stationarity;
    - $p = 1$ captures short-term temporal dependence;
    - $q = 0$ preserves model simplicity and mitigates the risk of overfitting.
- Exploratory Objective: The primary goal was to demonstrate forecasting feasibility and to compare ARIMA performance with that of a seasonal Naive benchmark, rather than to develop a fully optimized production-ready model.

More advanced parameter optimization procedures (e.g., AIC/BIC-based selection), seasonal extensions (SARIMA), and the inclusion of exogenous variables are identified as future research directions and are discussed further in the limitations section.

3. Results and discussion

The linear regression model developed for predicting recycled_rate produced the following performance metrics on the test dataset:

- ared Error (MSE): approximately 13.9 million
- Coefficient of Determination (R^2): ≈ 0.8973

The high R^2 value indicates that nearly 90% of the variability in the recycling rate is explained by the predictors included in the model, suggesting that the available operational data contain sufficient informational content to support meaningful predictive modeling. Although the MSE appears large in absolute terms, this result is largely attributable to the scale of the target variable, which reflects aggregated quantities of waste rather than normalized or per-unit measures.

Analysis of model coefficients and pairwise correlations indicates that waste volume-related variables—namely bottle_count, bottle_weight, and product_size_ml—are among the strongest determinants of recycled_rate. This finding suggests that existing collection and recycling systems tend to perform more efficiently in contexts where waste streams are large and highly centralized, whereas smaller and more dispersed waste streams are comparatively less well captured by current infrastructure.

The application of K-Means clustering to the variables bottle_count, bottle_weight, and product_size_ml resulted in the identification of four distinct waste pattern clusters. These clusters differ substantially not only in terms of volume and weight characteristics but also with respect to their geographical composition:

- An extremely large-volume cluster, predominantly associated with Uganda, indicating highly concentrated waste streams, likely linked to specific products, industrial processes, or distribution channels.

- Small- and medium-volume clusters, encompassing countries such as South Africa, Zambia, and Mozambique, which reflect more dispersed patterns of consumption and collection.

From a geographical and policy perspective, these findings highlight that countries and regions cannot be treated as homogeneous units. Some contexts are characterized by large, concentratable waste flows, for which investments in centralized, large-scale recycling infrastructure may be most effective. In contrast, other contexts require decentralized, proximity-based collection systems to efficiently capture dispersed waste streams. The clustering results, therefore, provide a valuable framework for segmenting waste management strategies and tailoring interventions to local conditions.

The correlation analysis (Figure no. 1) confirms strong positive relationships among bottle_count, bottle_weight, product_size_ml, and recycled_rate. From a practical standpoint, this implies that policy and operational interventions targeting large waste streams are likely to yield the most immediate and substantial gains in recycled quantities.

At the same time, the distributional analysis reveals that most observations for bottle_count and bottle_weight are concentrated at relatively low values, with a pronounced right-skewed tail toward higher values. This structure indicates that a small number of collection points or events generate disproportionately large volumes of waste, while a large number of small generators contribute modest amounts individually. Such a “long-tail” distribution suggests that current recycling systems may implicitly favor large-scale contributors, and that achieving more ambitious sustainability targets will require improved integration of smaller waste streams into the collection and recycling network.

ARIMA(1,1,0) models applied to quarterly aggregated time series for selected countries yielded relatively high MSE and RMSE values in absolute terms (Fig.4). Nevertheless, the models demonstrated several important qualitative outcomes:

- they were capable of capturing the general temporal trends in *recycled_rate* evolution;
- in certain cases, they outperformed seasonal naive benchmarks, indicating that even simple ARIMA specifications can provide added predictive value.
- However, these results must be interpreted with caution due to several limitations:
- the short length of the available time series restricts the statistical reliability of parameter estimates;
- ARIMA parameters were not systematically optimized using information criteria such as AIC or BIC;
- potentially influential exogenous factors—including regulatory changes, economic conditions, and public awareness campaigns—were not incorporated into the models.

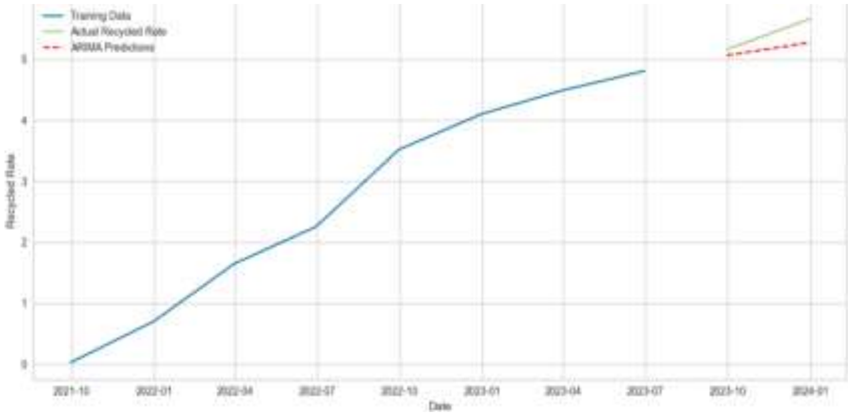

Figure no. 4: ARIMA Forecast for the recycled rate in Mozambique
Source: authors based on data taken from https://www.kaggle.com/

As a result, the time series analysis should be viewed primarily as exploratory, serving to demonstrate forecasting feasibility rather than to support operational decision-making. Future work would require longer time series, richer contextual data, and more advanced modelling approaches to produce robust and actionable forecasts.
These results provide a solid basis for understanding plastic waste management, identifying areas of good performance and those requiring intervention.

Conclusions
This paper demonstrated the effectiveness of data analysis and machine learning techniques in understanding and predicting issues related to plastic waste management. A strong correlation between waste volume and recycling rate was identified, waste patterns were grouped into 3 distinct clusters, and predictive models were developed for recycling rates at the country level.

Paper Contributions include:

- building a complete analysis and modelling pipeline, from preprocessing to visualization.
- developing a methodology for creating a relevant target variable for time series in the context of recycling.
- generating insights into waste patterns and factors influencing recycling rates.

Based on the empirical findings, the following recommendations are proposed, ordered by urgency, feasibility, and expected impact:

Priority 1: High Urgency and Short-Term Feasibility

- Optimize Large-Volume Waste Streams:
  - Given the strong association between waste volume and recycling performance, immediate efforts should focus on improving collection efficiency and processing capacity for large, concentrated waste streams. This strategy offers the highest potential for rapid increases in recycled quantities with relatively predictable resource requirements.

Priority 2: Urgent, with Moderate Resource Requirements

- Develop Targeted Approaches for Small and Dispersed Generators:
    - To address the identified structural asymmetry, tailored mechanisms should be implemented for small-scale waste sources, such as proximity-based collection points, incentive schemes, and targeted awareness campaigns. While requiring institutional coordination, these interventions can be deployed incrementally.

Priority 3: Medium-Term Impact, Infrastructure-Dependent

- Expand and Standardize Data Collection Frameworks:
    - Transitioning from exploratory analyses to robust decision-support systems requires more granular and consistent data collection, including longer temporal coverage, plastic type differentiation, and source-level information. Such investments are foundational for improving long-term planning accuracy.

Priority 4: Strategic Importance, Policy- and Resource-Dependent

- Invest in Context-Specific Recycling Infrastructure:
    - Observed geographical disparities in recycling performance call for targeted investments in collection and processing infrastructure, particularly in regions with persistently low recycling rates. The implementation of this recommendation depends on local economic, institutional, and political conditions.

Priority 5: Methodological Development and Future Research

- Advance Statistical and Machine Learning Models:
    - Future work should prioritize systematic ARIMA parameter optimization, the evaluation of advanced non-linear models (e.g., Random Forests, Gradient Boosting methods), and the incorporation of exogenous variables. These efforts are essential for improving predictive accuracy and deepening causal understanding over the long term.

Study Limitations and Directions for Future Research relate to limited data, external characteristics and plastic types. The performance of the ARIMA models was limited by the relatively small number of quarterly observations. The study did not integrate complex external factors (e.g., government policies, economic changes, social events) that can significantly influence recycling rates. A more detailed analysis of different types of plastic could provide more specific insights.

Future research should focus on integrating richer datasets and exploring more advanced time series prediction models and causal factors.

References

[1] Aswini M.S. (2023) Waste management and circular economy: reducing environmental footprints and promoting recycling, Redshine Archive, 8(4). https://doi.org/10.25215/9392917848.32

[2] Bustamante, S. S., & Pires, A., (2020) ‘Machine learning applications in solid waste management: a systematic review’, *Environmental Science and Pollution Research*, 27(19), 23269-23290.

[3] Everitt, B. S., & Hothorn, T., (2011) *A Handbook of Statistical Analyses using R*, CRC Press.

[4] Evode N., Qamar SA., Bilal M., Barceló D., Iqbal M.N.H., (2021) Plastic waste and its management strategies for environmental sustainability, Case Studies in Chemical and Environmental Engineering, Volume 4, https://doi.org/10.1016/j.cscee.2021.100142
[5] Field, A., (2018) *Discovering Statistics Using IBM SPSS Statistics*, Sage Publications.
[6] Gavrilescu, D., Seto BC., Teodosiu C., (2023) Sustainability analysis of packaging waste management systems: A case study in the Romanian context, *Journal of Cleaner Production*, Volume 422, https://doi.org/10.1016/j.jclepro.2023.138578, https://www.sciencedirect.com/science/article/pii/S0959652623027361?casa_token=RBSk10rMsMYAAAAA:gW9ZTrgU7VzlFNQQahh9rToX8xCgPZI659ejeGzU5Els0iFjlkNkgbKivlZeBOEIH4Jr4Zw
[7]Geyer, R., Jambeck, J. R., & Law, K. L., (2017) Production, use, and fate of all plastics ever mad, Science Advances, 3 (7), DOI: 10.1126/sciadv.1700782
[8] Godfrey, L., (2019) Waste management: An environmental challenge in a developing economy, Environmental Technology & Innovation, 14, 100361.
[9]Hyndman, R.J., & Athanasopoulos, G. (2018) Forecasting: principles and practice, 2nd edition, OTexts: Melbourne, Australia. OTexts.com/fpp2. Accessed on 1.10.2025
[10]Jambeck, J. R., Geyer, R., Wilcox, C., Siegler, T.R., Perryman, M., Andrady, A., Narayan, R., Law, K. L. (2015) Marine Pollution. Plastic Waste Inputs from Land into the Ocean. Science (New York, N.Y.), 347 (6223), 768-771, https://doi.org/10.1126/science.1260352
[11] Li L., Zuo J., Duan X., Wang S., Hu K., Chang R.., (2021) Impacts and mitigation measures of plastic waste: A critical review, Environmental Impact Assessment Review, Volume 90, ISSN 0195-9255, https://doi.org/10.1016/j.eiar.2021.106642
[12] Mandal P, Kundu AK, Mondal A (2024) Innovations in Waste Management: A Review, Sustaninble Chemical Insight in Biological Exploration, doi: 10.31674/book.2024scibe.007
[13] Mashudi, Sulistiowati R, Handayo S, Mulyandari E, Hamzah N (2023), Innovative Strategies and Technologies in Waste Management in the Modern Era Integration of Sustainable Principles, Resource Efficiency, and Environmental Impact, International Journal of Science and Society, Volume 5, Issue 4
[14] Macheca, A. D., Mutuma, B., Adalima, J. L., Midheme, E., Lúcas, L. H. M., Ochanda, V. K., & Mhlanga, S. D., (2024) Perspectives on Plastic Waste Management: Challenges and Possible Solutions to Ensure Its Sustainable Use, Recycling, 9 (5), 77. https://doi.org/10.3390/recycling9050077
[15] Mihai, FC., Ulman, S.R, (2024) Plastic Waste Trade Issues and Environmental Contamination in Romania. In: Gündoğdu, S. (eds) Plastic Waste Trade. Springer, Cham. https://doi.org/10.1007/978-3-031-51358-9_10
[16] Murray Svidroňová, M., Mikušová Meričková, B., (2022) Efficiency of waste management in municipalities and the importance of waste separation. J Mater Cycles Waste Manag 24, 2644–2655. https://doi.org/10.1007/s10163-022-01511-9
[17] Rorat A., Kacprzak M. (2017) Eco-Innovations in Sustainable Waste Management Strategies for Smart Cities, Happy City - How to Plan and Create the Best Livable Area for the People, EcoProduction, Springer Nature

[18] Sumrin S., Gupta S., Assad Y., Wang Y., Bhattacharya S., Foroudi P. (2021), Eco-innovation for environment and waste prevention, Journal of Business Research, Volume 122, Pages 627-639, https://doi.org/10.1016/j.jbusres.2020.08.001
[19] Stahel, W. R., (2010) The Performance Economy. Palgrave Macmillan.
[20] [Tchobanoglous, G., et al., (2015) Integrated Solid Waste Management: Enineering Principles and Management Issues. McGraw-Hill Education.
[21] European Environment Agency (2025) Waste prevention and the circular economy, https://www.eea.europa.eu/en/europe-environment-2025/thematic-briefings/circular-economy-and-other-enablers-of-transformative-change/overview
[22] European Parliament and Council (2008) Directive 2008/98/EC on waste (Waste Framework Directive)
[23] Plastic Bottle Waste (2021 – 2024) Counts of single-use plastic bottle waste detected by Wastebase,
Available at: https://www.kaggle.com/datasets/wastebase/plastic-bottle-waste
[24] United Nations Environment Programme (2018). Single-use Plastics: A Roadmap for Sustainability, https://www.unep.org/resources/report/single-use-plastics-roadmap-sustainability