Analyzing the Recycling Operations Data of the White Appliances Industry in the Turkish Market

Alperen Bal, Peiman Alipour Sarvari and Sule Itir Satoglu

Abstract There is legislation that makes manufacturers responsible for incorporating recycling of waste electric and electronic equipment (WEEE). The white appliances industry is one of these sectors and in many countries, particularly those that are members of the European Union, there are regulations to guarantee the recycling of white appliances. This paper aims to investigate the data analysis of the white appliances industry in terms of reverse logistics operations. The most important usage and logistics operation data of a white appliances manufacturer are identified and evaluated by using data-mining methods. Important factors for types of white appliances are analyzed with respect to the lifespans of products, regional data, transaction times, campaign period, and choice of new products. A neural network is applied for prediction importance and ANOVA and Pearson correlation tests for region, lifespan, and brand of new product data are performed using SPSS. The results demonstrated that customers are prone to buying the same brand when they are delivering waste white appliances. Besides analysis of the campaign time, important inferences for strategic planning could be drawn from the lifespan and regional data.

Keywords ANOVA · Big data · Data analytics · Neural networks
Recycling · Reverse logistics · WEEE

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Introduction

Product recovery has gained considerable attention within the context of sustainability. Also governmental regulations and customer perspectives on environmental issues have motivated the organization of product recovery systems in companies. The first legislation on environmentally conscious manufacturing (ECM) drew the attention of both researchers and practitioners at the beginning of the 1990s. Recent governmental regulations in Turkey have also set out collection targets for electrical and electronic equipment (EEE) manufacturers as well as defining the formation of product recycling and remanufacturing procedures. Table 1 gives collection targets for EEE manufacturers in proportion to the total product produced in five categories. In this context, manufacturers are working toward establishing reverse logistics networks, while some of them have already done so.

Governmental regulations also oblige manufacturers to report the data of all operations to the Ministry of Environment and Urbanization. Therefore, collection of the data has become a very critical issue for reporting and also a very good resource for gaining remarkable inferences for manufacturing and logistics operations as well as managerial and marketing perspectives. The vast availability of data, on the other hand, has stimulated researchers to find more effective segmentation tools in order to discover more useful information about their markets and customers due to the inefficient performance of traditional statistical techniques (or statistics-oriented segmentation tools) when handling such voluminous data (Sarvari et al. 2016). For this reason, data mining has been seen as a solution to this problem. In fact, big data has attracted a great deal of attention because it provides the ability to derive patterns, increase profit margins, find potential markets, and carry out various predictions for the service and manufacturing sectors (LaValle et al. 2011). In supply chain management and logistics, Wang et al. (2016) reviewed big data analytics by investigating research and applications. Logistics data are generated from different sources in distribution networks such as

Table 1 WEEE collection targets according to 2012 regulations (Ministry of Environment and Urbanization, Turkey 2012, Regulation No. 28300)

Collection category	2013 (%)	2014 (%)	2015 (%)	2016 (%)	2017 (%)	2018 (%)
1. Refrigerators/coolers/ air-conditioners	1.25	2.25	4.25	8.50	8.50	17.00
2. Large house appliances	2.50	3.75	8.00	16.00	16.00	32.50
3. Televisions and monitors	1.50	2.50	5.50	11.00	11.00	21.50
4. IT and telecommunications and consumer equipment	1.25	2.00	4.00	8.00	8.00	16.00
5. Small household appliances, toys, and electrical and electronic tools	0.75	1.50	2.75	5.50	5.50	11.00

forecasting of the supply capacities of suppliers, demand at demand points, or shipping costs (Najafi et al. 2013).

Big data has been used both in research to validate existing theories and in industry to help business organizations make better decisions (Muhtaroglu et al. 2013), especially in logistics and supply chain management (Wamba et al. 2015). However only 20% of companies make use of big data analytics (Jain et al. 2017). This indicates that there is a big potential to be understood and worked upon in big data analytics implementation in reverse logistics.

In this research, collected data for waste white appliances are analyzed. Figure 1 explains the waste collection network. Initially the customer goes to the vendor of the white appliance manufacturer. After purchasing a new product, service comes for installation. In the meantime, the waste white appliance is taken back from the customer. So collected WEEEs are taken by a third-party logistics-provider company from the service to the recycling facility. The data for WEEEs are monitored throughout the reverse logistics system. In the following sections, we introduce the background of the methods that are used, present the application in detail, and examine the research questions. Lastly, we discuss the results of the analysis.

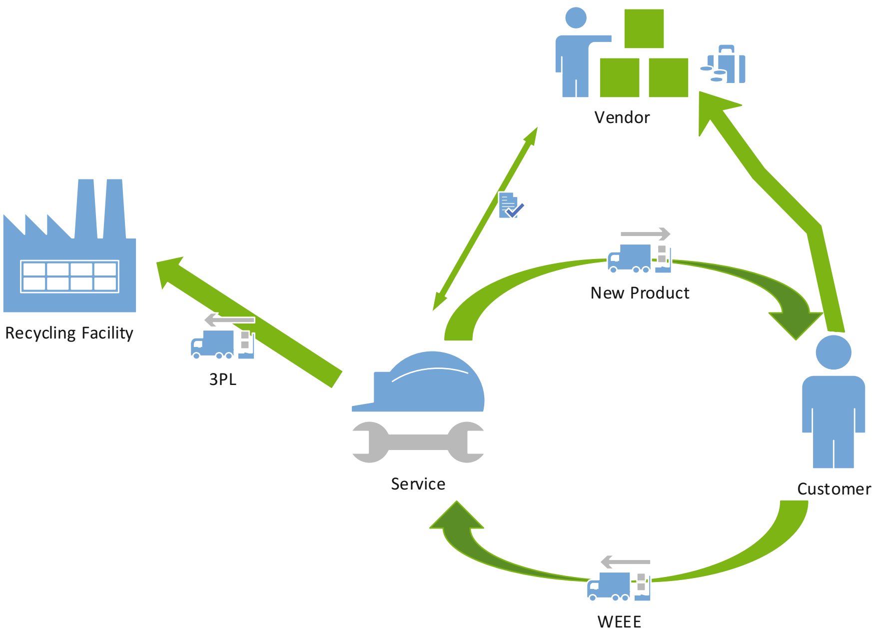

Fig. 1 Reverse logistics process for collecting waste white appliances

Research Framework

Big Data

The term "big data" has become popular recently; it refers to massive datasets with a large structure that are hard to handle using conventional database management systems and traditional data-processing tools (Akoka et al. 2017). "Big Data represents the Information assets characterized by such a High Volume, Velocity and Variety to require specific Technology and Analytical Methods for its transformation into Value" (De Mauro et al. 2015). In the context of waste white appliances, this involves a number of applications that can be expected to benefit from large-scale capture and analysis of data from these WEEEs.

The CRISP-DM (Cross-Industry Process for Data Mining) methodology is an industry-proven way to guide data-mining efforts that provides a structured approach to planning a data-mining project. This methodology consists of six phases that cover the full data-mining process.

Business understanding. In this phase, business objectives are determined, the situation is assessed, data-mining goals are determined, and a project plan is produced.
Data understanding. The second stage addresses the acquisition of data resources and understanding the characteristics of those resources. It comprises the initial data collection, data description, data exploration, and data quality verification.
Data preparation. This includes selecting, cleaning, constructing, integrating, and formatting data.
Modeling. In this part, sophisticated analysis methods are used to obtain information from data. Modeling includes selecting modeling techniques, generating test designs, and building and assessing models.
Evaluation. After the model has been chosen, data-mining results can be evaluated to achieve the business objectives. This phase includes evaluating the results, reviewing the data-mining process, and determining the next steps.
Deployment. In this stage, the evaluation results are taken and new knowledge is integrated into the everyday business process to solve the original business problem. Elements of this phase include plan deployment, monitoring and maintenance, producing a final report, and reviewing the project.

Neural Networks

Neural networks take biological systems as a model and aim to simulate their behavior. Neural networks have been used for prediction purposes for both classification and regression of continuous target attributes (Tobergte and Curtis 2013).

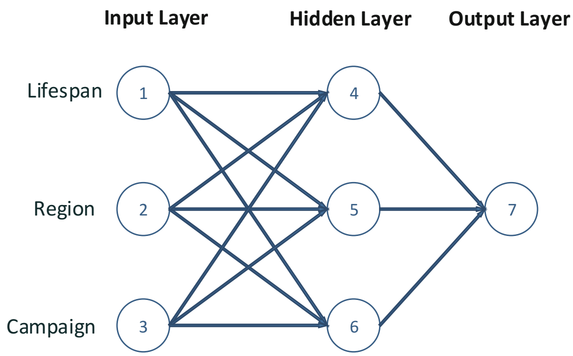

Fig. 2 A neural network with an input layer, one hidden layer, and an output layer

A neural network consists of nodes and arcs. Nodes represent neurons in the biological analogy and arcs correspond to dendrites and synapses. Each arc is related to a weight, whilst each node is defined by an activation function. The weights of the arcs adjust the values received as inputs by the nodes along the incoming arcs. The neural network learns through being trained. It makes an adjustment whenever it makes an incorrect prediction. The learning process occurs by examining individual records, generating a prediction for each record, and making adjustments to the weights (Fig. 2).

Application

The initial dataset used in this study is obtained from a database of the recycling system of a white appliance manufacturer and consists of approximately half a million cases of collected WEEEs. The data include 1. and 2. group of WEEE (see Table 1). To be more precise, five groups of white appliances, namely refrigerators, washing machines, drying machines, dishwashers, and ovens, are included in the data. Data analysis was performed using the statistics software IBM SPSS Modeler and IBM SPSS 23 (Table 2).

In the model, we wanted to focus on the predictor fields that matter most and least. The dependent variable was the product group and the independent variables were the same product, campaign, lifespan, region, and transaction hour. A maximum training time criterion was considered as the stopping rule. In addition, the dataset was divided into training and test groups. The training data comprised 80% of the whole dataset and the remaining 20% were used as the test data. According to the results, being the same product was the most important predictor for our model (0.41). After that, campaign (0.25), lifespan (0.21), region (0.08), and transaction hour (0.04) were the other predictors, respectively (Fig. 3).

Table 2 The field variables of the dataset

Field variable	Remarks
Campaign	The type of campaign giving special offers or discounts to customers who return their waste white appliances. Campaign times generally start from the close of the third quarter and end at the close of the year
Lifespan	A record of the production year of the collected waste white appliances is always taken. Therefore, the lifespan of these products is obtained considering the collection time
Product group	Five groups of white appliances, namely refrigerators, washing machines, drying machines, dishwashers, and ovens
Region	Ten different regions exist countryside in a logistics manner
Same product	The question of whether or not the newly sold white appliance or small household appliance is the same type of product. In other words, if a certain type of washing machine is sold and exactly the same type of washing machine is collected as the WEEE of the same brand then we have the same product
Transaction hour	The time at which a customer delivers a waste white appliance and receives a new white appliance or small household appliance

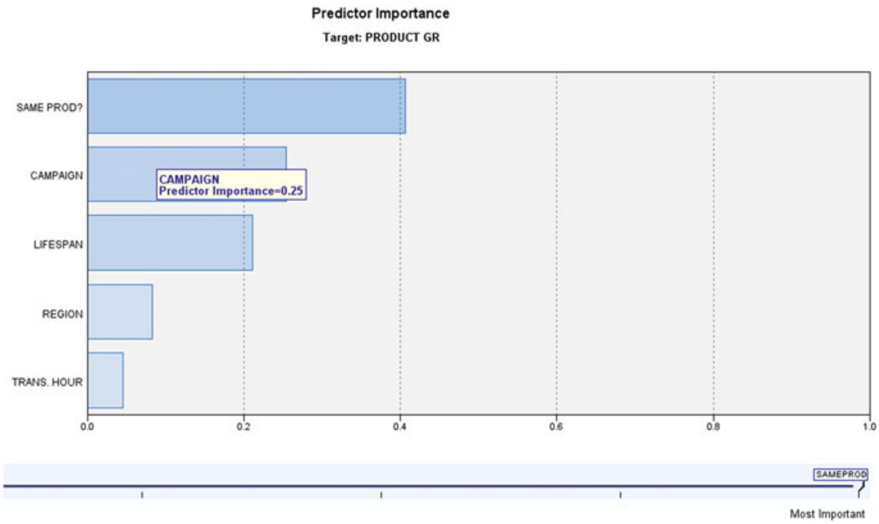

Fig. 3 Importance factors for product groups of waste white appliances

Research Question

The campaign is found to be the second most important predictor for the product groups. Therefore, we wanted to see whether a relationship between the number of waste white appliances collected and the campaign period exists. The transaction

Table 3 Pearson correlation test between transaction date and campaign time

		Trans. date	Campaign
Trans. date	Pearson correlation	1	0.983**
	Sig. (two-tailed)		0.000
	N	633,525	322,334
Campaign	Pearson correlation	0.983**	1
	Sig. (two-tailed)	0.000	
	N	322,334	322,334

**The correlation is significant at the 0.01 level (two-tailed)

date are considered to measure the effect of the campaign period since all cases are recorded in the transaction time (Table 3).

H_0: $\rho = 0$
H_A: $\rho \neq 0$

We can conclude that the result of the Pearson correlation test indicates a quite strong positive linear relationship between the transaction date and the campaign period for waste white appliances. This means that customers are prone to delivering their waste white appliances especially during the period of the campaign. On the other hand, when we look at the number of waste white appliances collected during a three-year period, we can clearly see from Fig. 4 that the increases at the end of each year indicate a seasonal effect (Fig. 5).

Meanwhile it is also important to see whether there are differences in customer behavior by region. Therefore, firstly we questioned whether brand preferences differ between regions. Afterwards we also questioned whether the lifespans of

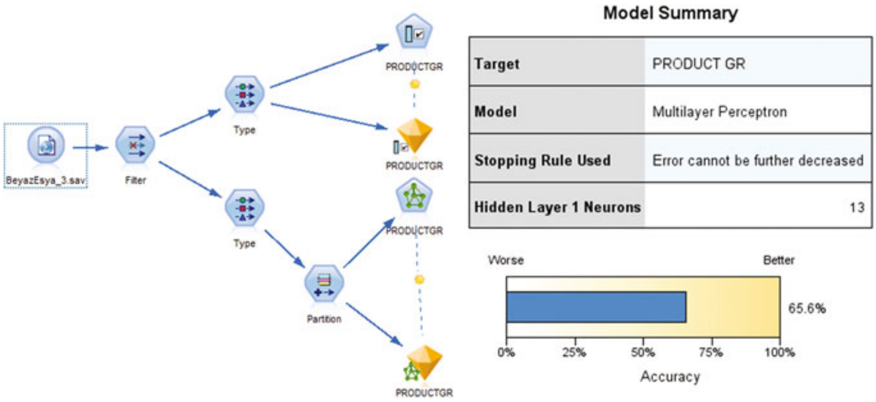

Fig. 4 Application design and model summary

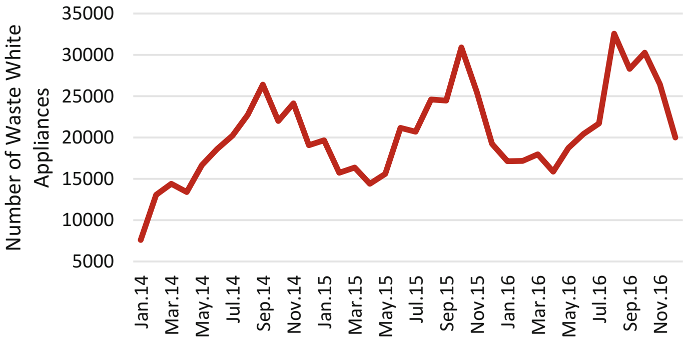

Fig. 5 Number of waste white appliances collected monthly

Table 4 ANOVA test result for brand of new product

	Sum of squares	Df	Mean square	F	Sig.
Between groups	1844.370	9	204.930	216.670	0.000
Within groups	262955.880	608029	0.946		
Total	264800.249	608020			

white appliances differ between regions. The following variance analyses were used to test our hypotheses regarding these questions.

H_0: On average, brands of new white appliances do not differ between regions.
H_A: On average, brands of new white appliances differ between regions.

According to the results of the F-test carried out with a 95% confidence interval, the significance value for the brand of new product was found to be $p = 0.000 < 0.05$. With regard to the brand of new product, hypothesis H_A is accepted (Table 4). In other words, brand preference differs significantly by region. Also, when we look at the brand preference table (Table 5), we can see that the upper-mass brand preference increases especially in the west of Turkey. In other words, more lower-mass brands are preferred by customers, especially in the East Anatolia region.

H_0: On average, the lifespans of waste white appliances do not differ between regions.
H_A: On average, the lifespans of waste white appliances differ between regions.

According to the results of the F-test for the lifespan of waste white appliances with a 95% confidence interval, the significance value was found to be $p = 0.000 < 0.05$. With regard to the lifespan of waste white appliances, hypothesis H_A is accepted (Table 6). In other words, the lifespans of waste white appliances differ significantly between regions. Also, Table 7 shows the average lifespan of

Table 5 Proportion of brand segments according to region

	Lower mass/upper mass
East Marmara region	0.067
North Aegean region	0.078
Central Anatolia region	0.114
Thrace region	0.116
Southeastern Anatolia region	0.133
Black Sea region	0.140
West Aegean region	0.146
Central Aegean region	0.157
West Mediterranean region	0.182
East Anatolia region	0.190

Table 6 ANOVA test result for lifespan of waste white appliances

	Sum of squares	df	Mean square	F	Sig.
Between groups	54283.137	9	6031.460	486.735	0.000
Within groups	3635717.567	633,516	12.392		
Total	3690000.705	633,525			

Table 7 Average lifespan of waste white appliances by region

	Lifespan
Southeastern Anatolia region	6.25
Black Sea region	6.31
West Aegean region	6.45
Central Aegean region	6.67
East Anatolia region	6.95
West Mediterranean region	6.97
Thrace region	6.98
East Marmara region	7.09
North Aegean region	7.09
Central Anatolia region	7.55

white appliances. It can be seen that white appliances have the longest lifespans in the Marmara and Central Anatolia regions.

Results and Conclusion

This study considers waste white appliances, a type of WEEE that is a cause of great concern all over the world. In order to understand the big data of reverse logistics operations, three-year product records were analyzed using different tools in SPSS. The main purpose of the work was to understand customer behavior according to different variables. Also, the results can lead the way for companies in a strategic manner. Initially, the most important factors wanted to be seen for product groups. Predictor importance results showed that being the same product was the most important predictor. This indicates that customers mainly prefer to buy the same brand again when they want to buy a new white appliance. This also indicates customer loyalty, considering one of the most dominant brands of the Turkish market. The second most important predictor for the product groups was campaigns. The Pearson correlation test results showed a strong positive linear relationship between campaign period and collected waste white appliances. Lifespan and region were the third and fourth most important predictors for the product groups, respectively. Therefore, we questioned whether there were differences in lifespan and choice of brand between regions. The results of both analyses indicated that significant differences exist. Also, the tables of lifespan and brand preferences show differences between regions. These results give a good indication of which regions prefer lower-mass or upper-mass brands. Besides, the lifespan of products can be a good indicator for forecasting sales.

With regard to future study, we would like to extend our research by rule mining since association rules can help companies to make strategic decisions on reverse logistics or marketing. Besides, demand for waste products has increased by approximately 10%, and seasonal effects exist. Thus forecasting future demand can be beneficial as well.

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