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ORIGINAL ARTICLE

Prediction of Middle School Students' Recycling Behaviors with Machine Learning Algorithms

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ABSTRACT

Recycling waste is essential to mitigate environmental damage caused by human activity. Environmentally responsible behaviors, shaped during early ages, are closely linked to environmental attitudes, as demonstrated by prior research. This study aims to predict middle school students' recycling behaviors using machine learning algorithms. A correlational survey model was employed, involving 574 middle school students in Turkey. Data were collected using the Environmental Attitude Scale, Recycling Knowledge Test, and Plastics Recycling Information Test. Logistic regression analysis was conducted to determine relationships among environmental behavior, environmental emotion, plastics recycling knowledge, and recycling behavior. Results revealed that recycling behavior is positively and significantly predicted by plastics recycling information, environmental behavior, and negatively significant relationship with environmental emotion. These variables emerged as strong and reliable predictors of students' recycling behaviors. This study highlights the importance of fostering environmental knowledge and emotional engagement to encourage responsible recycling practices among young learners.

KEY WORDS: Environmental behavior, environmental emotion, machine learning, middle school students, recycling behavior

INTRODUCTION

The advancement of technology and science as well as the uncontrolled and irregular rise of the human population, have increased consumption. The limited natural resources have been rapidly depleting while an excessive amount of waste has accumulated. Consumption and waste production are way above nature's capacity to renew itself. As a result, natural resources have started to deplete, habitats have been destroyed, and nature has started to become incompatible with human life. Various environmental problems such as pollution cause numerous health issues, even death (Uglietti et al., 2015; Mensah and Casadevall, 2019). This negative impact has prompted countries to design policies to eliminate, prevent, or resolve these environmental problems.

Since Turkey is a member of United Nations, it signed the United Nations Climate Change Framework Convention, Kyoto Protocol, and the Paris Agreement signed in 2015 and ratified in 2021 (Paris Agreement, 2021). These international agreements play a role in Turkey's determination of environmental policies. Moreover, European Union (EU) progress reports, which are published each year and provide recommendary road maps for membership, are also important in Turkey's determination of environmental policies since Turkey is in talks with the EU for EU membership. These reports underline waste management and recycling along with environmental protection (Dağıdır and Yaylı, 2020).

Emotional affinity to nature and ecological beliefs are known to be related to children's willingness to take ecological action (Collado et al., 2015). Studies on children's environmental attitudes point at the importance of cognitive factors. To improve environmentalist behavior, practical environment-friendly behavior training should be encouraged, and eco-awareness should be reinforced (Šorytė and Pakalniškienė, 2021). However, there are few studies on the processes which lead children to thinking, behaving, and feeling in environment-friendly ways (Collado et al., 2017). In this respect, there is need for investigating the connections between students' environmental emotion and behavior including the cognitive and sensory aspects of attitudes. However, although traditional statistical methods contribute to understanding the relationships between variables, their power to predict future behavior with high accuracy is limited (Shmueli, 2010). Therefore, in this study, machine learning (ML) was employed to examine the complex and multidimensional interactions between environmental emotions and behaviors. ML provides more accurate predictions and allows for the design of data-driven educational interventions that go beyond traditional methods (Jordan and Mitchell, 2015). Based on these perspectives, the aim of this study is to predict middle school students' recycling behavior using ML, within the framework of their environmental emotions, environmental behaviors, and knowledge of plastic recycling.

LITERATURE REVIEW

Recycling

Environment policies, which are based on the sustainability of the environment and development, and which make waste management compulsory, have resulted in the emergence of the circular economy. Circular economy, first brought forward by the EU, is an economy model which aims to increase both environmental and economic gains by recycling waste materials into resources so that they cease to be waste (Sapmaz Veral and Yiğitbasıoğlu, 2018). In this model, waste management and zero waste approach are on the fore. According to the Regulation of Waste Management (2015), waste management is defined as "*acts of preventing the formation of waste, reducing it at its source, re-using it, separating it according to type and quality, storing it, collecting it, storing it on a temporary basis, moving it, recycling it, reclaiming it including energy return, disposing it, following it up after disposal, its control and regulation.*" Zero waste, which has an important place in circular economy, is an approach that aims to use resources effectively, to prevent waste, and to appropriately gather, recycle, and dispose of waste. Zero waste approaches are encouraged to be popularized to serve sustainable development objectives (Yıldız, 2019).

Concerns over solid waste have brought forth the notion of zero waste within the frame of a holistic approach. Zero waste approach has a special importance since it ensures that waste ceases to be a burden in city life and becomes a resource (Zaman and Ahsan, 2020). By implementing zero waste strategies, waste will provide energy transformation, emissions and the amount of waste will decrease (Castigliego et al., 2021). The zero waste approach focuses on the reuse of solid waste, including metals, to preserve resources and to decrease the impact on the environment, thereby recycling these materials (Dong et al., 2022).

At the beginning of waste management, the 3R rule, "Reduce, Reuse, Recycle," was adopted (Yıldız, 2019). Later on, based on the 2006/12 Waste Framework Directive of the European Commission, these principles were increased to five. The priority in waste management is to decrease waste at the production level so that it is the least harmful for the environment. The next step is to reuse the waste, recycle it, and to reclaim it for energy. If reclaim is not possible, the last step would be to burn it without harming the environment or dispose of it by safely storing it. This hierarchy of waste prevention can be explained as follows in Figure 1 (Sapmaz Veral and Yiğitbaşıoğlu, 2018):

These five principles are also known as the 4R rule: Preventing and Reducing waste, Reuse, Recycle, Recover, and Disposal (Can, 2009). The disposal of waste is a global problem. People buy and use waste-producing goods. The amount of waste increases with the ever-increasing number of consumers. This brings forth waste policies for waste management. Reduce, reuse, recycle, and recover are means of decreasing the negative impact of waste on the environment (Yu et al., 2021).

Plastic Recycling Knowledge

Plastic is used everywhere from homes to industries, from construction to daily tools; and it has replaced various traditional materials and products (Plastics Europe, 2019). Due to its high market value and demand, large amounts of plastic are disposed every day, and some of this plastic remains unrecycled (Thompson et al., 2009; Velis, 2014). Plastic bags are banned in many countries, especially in developing countries, depending on their thickness; in developed countries, areas, and states, there is a minimum charge for them (Miller, 2012). Furthermore, consumers are recommended to use alternative bags; however, they still show a greater preference for plastic bags due to their durability, lightweight nature, hygienic properties, and low cost (Dikgang et al., 2012; He, 2012).

Plastic pollution is truly a global problem, and it poses an environmental threat to the planet. Globally, 348 million tons of plastic are produced, and the number keeps going up. Consumers play a significant role in reducing pollution caused by plastic waste (De Marchi et al., 2020). While there are many studies analyzing individuals' recycling intentions and behavior, there are comparatively fewer studies addressing specifically on plastic. To positively affect consumers' intentions of plastic recycling, one needs to focus on perceived control and attitude brought about by peer effect (De Fano et al., 2022).

Environmental Attitudes and Behavior

Environmental attitude is defined as society and individuals developing values concerning the environment, showing concern for the environment, and having the motivation to be active participants in conserving and rehabilitating the environment (UNESCO Tbilisi Declaration, 1977). It is also the sum of intended behaviors, beliefs, or effects a person has on environment-related activities or matters (Schultz et al., 2004). Thurstone (1967) indicates that attitude is difficult to measure because it is abstract and maintains that attitude can be determined by looking at people's thoughts, emotions, and reaction tendencies (as cited in Tavşancıl, 2010).

Environmental attitudes and behavior increase from age 7 to 10; therefore, mid-childhood or primary school age is especially important for the formation of environmentalism in children (Otto et al., 2019) because children can take on other people's viewpoints at these ages (Eccles, 1999). Determining environmental attitudes is significant to make sure students acquire positive attitudes and to determine educational precautions to change negative attitudes (Yücel and Özkan, 2014). People's commitment to environmental protection and making light of climate change, in other words, their environmental attitude is mental. This can be observed directly in what they do or do not do to protect the climate or other aspects of the environment (Kaiser et al., 2020). People with a strong environmental attitude would display behaviors that would result in serious financial sacrifice or serious self-limitations (Kaiser, 2021).

Applications of ML in Education

Situated at the heart of artificial intelligence and data science, ML is a fast-growing technique and is a fundamental tool to optimize learning and to realize in-depth education. ML focuses on how to form computer systems that learn automatically from past experiences without open programming (Jordan and Mitchell, 2015). ML also focuses on complex reasoning and the use of information to support improving the evaluation of large-scale measuring results (Krajcik, 2021). The use of ML in education has recently gained traction (Gobert and Sao Pedro, 2017; Zhou et al., 2018). Using ML in education can dynamically alter ways of learning, and these ways can be personalized based on students' progress and pace (Kuch et al., 2020). In this respect, personalized learning adapted to the needs of an individual in real time has become a point of interest for education researchers (Lu et al., 2018).

The main objective is to be able to make effective predictions about a data set with unknown results based on the classification done created by a data set whose results are known (Aydın and Özkul, 2015). ML proceeds in the form of testing and verification. Here, a separate data set is used for the testing step, and the desired variable is predicted based on this data set. Then, the generalization ability of the prediction success in the previous step is evaluated based on a data set aside for the verification step. ML is preferred over classical analysis methods because it performs a multi-step testing process (Yang et al., 2020). ML has been used in a variety of ways in education. For instance, ML was used in science education to measure the effectiveness of science education (Zhai et al., 2020), to examine the change in scientific argumentation (Pei et al., 2019), and to identify the progress in students' learning through the applied method (Gerard and Linn, 2016). Evaluating students' participation in science application has several challenges. ML can be used to encode students' written answers and create a structure map in science education. Here, one of the advantages of ML is instead of simplifying information obtained from bigger samples, it structures that information in a way to reveal its importance and focus (Rosenberg and Krist, 2021). ML is a data-centered approach, and it provides a strong and new frame for data analysis. ML helps modeling culture to be directed towards a more reliable science for education researchers, and it focuses on revealing stronger predictions from data. In this respect, it is used as a new understanding to form models in education research (Hilbert et al., 2021). In ML, factors such as the number of samples and the calibration of the evaluator are important problems and impact the performance (Maestrales et al., 2021). These problems can be alleviated by working with larger sample sizes or by "training sets" so that the machine constructs its own algorithmic model (Cheuk et al., 2019).

ML techniques are used to scrutinize a structure. ML methods can be supervised or unsupervised. Supervised learning structures models by label samples; when a data sample and the required outputs are given, it is the best model to predict the relationship between the input and the output. Unsupervised learning, on the other hand, models by categorizing close results in unlabeled samples (Hastie et al., 2009). Regression belongs to supervised learning. ML algorithms have become an important aspect of model applications due to having high practical impact and algorithmic fairness. The reason regression is preferred in ML is that there is a linear relationship between predictors and responses, and it is simple and easy to interpret (Chouldechova and Roth, 2018). Steps followed in ML are according to the Cross-Industry Standard Process (CRISP) in Figure 2 (Shearer, 2000).

Recent studies have demonstrated the effectiveness of ML in predicting student academic performance, learning outcomes, and behavioral patterns. Studies have also highlighted the potential of ML to improve learning outcomes (Gerard and Linn, 2016; Mehenaoui et al., 2022; Su et al., 2022; Yan and Au, 2019). In this study, unprecedented possibilities offered by ML methods were utilized to explain students' recycling behaviors, and supervised ML was used.

METHODS

Research Design

This quantitative study was based on the correlational survey design. Correlational survey design studies try to determine the unknown value of a variable from a known value of one variable. Correlational survey studies are research models that aim to identify the presence of change between two or more variables (Fraenkel et al., 2012).

Sampling

The sample of the research consists of 574 middle school students in Turkey. The sample was determined by the convenience sampling method because this method ensures a fast and easy access to the sample (Yıldırım and Şimşek, 2013). Information about the sample is presented in Table 1.

Data Collection Tools

Recycling knowledge test-dependent variables

It was developed by the researchers. It consists of 10 items that include recycling symbols covered in the middle school curriculum, with each question having four or five answer choices. Students are required to identify the meaning of the recycling symbol by selecting one of the given options. The

Table 1: Characteristics of sampling

Variables	f	%
Gender		
Female	356	62.0
Male	218	38.0
Age		
10	136	23.7
11	169	29.4
12	116	20.2
13+	153	26.7
Class		
5. class	155	27.0
6. class	141	24.6
7. class	178	31.0
8. class	100	17.4

correct answer is coded as 1, whereas all incorrect answers are coded as 0. The highest possible score on the test is 10, while the lowest is 0. The recycling knowledge test items were created based on the Ministry of National Education (MoNE) science curriculum. Two science teachers and one academic expert provided expert opinions on the test items. Based on the expert opinions, language corrections were made to the test items. The test was administered to a pilot group of 148 middle school students. The data obtained from this group was used to conduct reliability studies on the test. The KR-21 reliability coefficient of the test is 0.710. In a test, a reliability coefficient of 0.70 or above is expected and indicates that the test is reliable. (Büyüköztürk, 2006; Fraenkel et al., 2012).

Environmental attitudes scale

It was designed by Yücel and Özkan (2014). The 5-point Likert-type scale has a two-factor structure, consisting of 14 items measuring environmental behavior and 21 items measuring environmental emotion.Cronbach alpha reliability coefficient of the behavior dimension of the scale is 0.845, while that of the emotions scale is 0.757. Reliability coefficients obtained from sample data are 0.852 and 0.817, respectively.

Plastics recycling knowledge test

It was developed by the researchers. It contains 7 items on plastic recycling symbols. The plastic recycling knowledge test items were created based on the MoNE science curriculum. Two science teachers and one academic expert provided expert opinions on the test items. Based on the expert opinions, language corrections were made to the test items. The test was administered to a pilot group of 148 middle school students. The data obtained from this group was used to conduct reliability studies on the test. Students are asked to mark one of the choices to show their knowledge of the symbol. While the correct answer is coded as 1, all incorrect answers are coded as 0. The highest score to get from the test is 7, and the lowest is 0. KR-21 reliability coefficient of the test is 0.720.

Data Analysis

When one of the variables of a study is dependent (Y) and the other is independent (x), if the relationship between these variables is presented as Y being a function of X, it is called regression. Regression analysis is an analysis method that makes it possible to identify the cause-effect relationship between variables. In this study, logistic regression analysis was employed to examine the relationships between environmental behavior, environmental emotion, and plastics recycling knowledge, and recycling behavior. Logistic regression is used to analyze the probability of an event or behavior to happen based on several explanatory variables (Tabachnick and Fidell, 2013). Logistic Regression (LR) model is one of the most frequently applied multi-variable regression analysis methods due to its algorithmic efficiency and its ability to deal with complex non-linear problems by adding a link function appropriate for the normal linear regression model (Allison, 2001, pp. 288; Atkinson and Massari, 1998; Bai et al., 2010). Logistic regression is more flexible compared to other techniques. Logical regression analysis does not require assumptions such as the normal distribution of independent variables, linearity, and equal variance-covariance matrices (Tabachnick and Fidell, 2007). The dependent variable examined in this study is middle school students' recycling behavior. Recycling behavior is a categorical dependent variable (Y), and its probability to happen was coded as (1 = yes, 0 = no). Independent variables are environmental behavior x_1, environmental emotion x_2, and plastics recycling knowledge x_3.

Recycling behavior was determined by a recycling knowledge test. The test consists of 10 items on recycling symbols covered in the middle school curriculum. Students are asked to identify the recycling symbol by marking one of the options. While the correct answer is coded as 1, all incorrect answers are coded as 0. The highest mark one can get from the test is 10, and the lowest is 0. If the total mark received from the test is 5 or below, it is coded as 0 since the student cannot perform the behavior. Students who receive 6 or above are coded as 1 since they will perform the recycling behavior. All analyses were conducted using R software version 4.2.0.

The logistic regression model is the most frequently used multivariance regression analysis methods. When the dependent variable is a categorical variable (especially a binary dependent variable), the method can effectively predict the occurrence of probability or implement the classification of a dependent variable (Ayalew and Yamagishi, 2005). Simply put, it can be expressed as follows:

$$P = \frac{1}{1+e^{-z}} \tag{1}$$

where P is the estimated probability of an event occurrence varying from zero to unity, and z is defined as:

$$z = \ln(\frac{P}{1-P}) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n \tag{2}$$

Here, β_0 is the intercept of the model, n is the number of independent variables, β_i (i = 1, 2, 3., n) is the slope coefficient of the model, and x_i (i = 1, 2, 3,…, n) is the independent variable.

FINDINGS

Descriptive statistics and regression analysis results for the variables of recycling behavior, environmental behavior, environmental emotion, and plastics recycling knowledge were presented in Table 2.

To determine the variables of environmental behavior, environmental emotion, and plastics recycling knowledge, all of which were thought to be influential on recycling behavior, logistic regression analysis was carried out in this study. The analysis result is presented in Table 2. According to this, the most fundamental finding is that recycling behavior is related to these reported three variables. The recycling behavior dependent variable has a 95% reliable positive and significant relation with plastics recycling knowledge, environmental behavior, and environmental emotion. Consequently, plastics recycling knowledge, environmental emotion, and environmental behavior are strong predictors of recycling behavior.

According to Table 2, there is a positive relation between plastics recycling knowledge and recycling behavior. Plastic recycling knowledge increases the log odds of recycling behavior by 0.35. Environmental emotion has a negative relation with recycling behavior. The reported relationship between recycling behavior and environmental emotion is inverse because their relation is negative. In other words, people with low environmental emotions display more recycling behavior. Environmental behavior has a positive and significant relation with recycling behavior. Environmental behavior decreases the log odds of recycling behavior by 0.50.

Table 2: Descriptive analyses

Variables	n	%	Mean	SD	Depended variable β (Standard error)
Recycling behaviour	0 208	36.2	0.6376	0.4811	
	1 366	63.8			
Plastics recycling knowledge	574	100	1.7509	1.548	0.35*** (0.077)
Environmental behaviour	574	100	3.4679	0.6847	0.50*** (0.148)
Environmental emotion	574	100	4.1229	0.4679	−1.10*** (0.27)

Significant codes. "***" 0.001

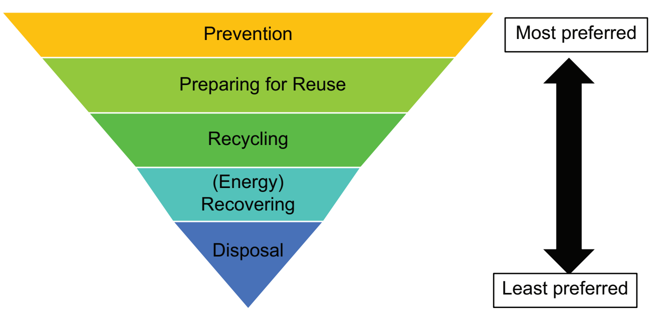

Figure 1: European union waste prevention hierarchy (Sapmaz Veral and Yiğitbasıoğlu, 2018)

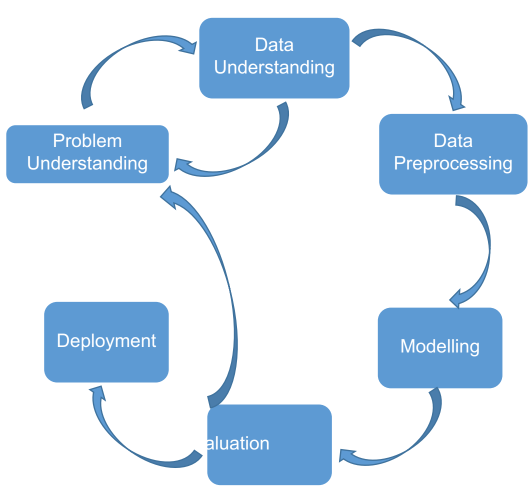

Figure 2: The cross-industry standard process for machine learning

Receiver Operating Characteristic (ROC) and area under the curve (AUC)

To evaluate classification performance in the data cluster of ML, ROC curve and the AUC were used. This curve provides a visual tool to reveal the result of the analysis carried out within the frame of the research problem. If the area value under the curve is around 0.50, it shows that the model performance is low; if this value is about 1, then it means the performance is high. Generally speaking, over 0.9 is classified as Excellent, between 0.8 and 0.9 as Good, between 0.7 and 0.8 as Fair, between 0.6 and 0.7 as Poor, and between 0.5 and 0.6 as Fail for AUC (Nahm, 2022; Muller et al., 2005). The area under the ROC curve for the test data obtained in this study is presented in Figure 3, and the area under the ROC curve for the full data is presented in Figure 4.

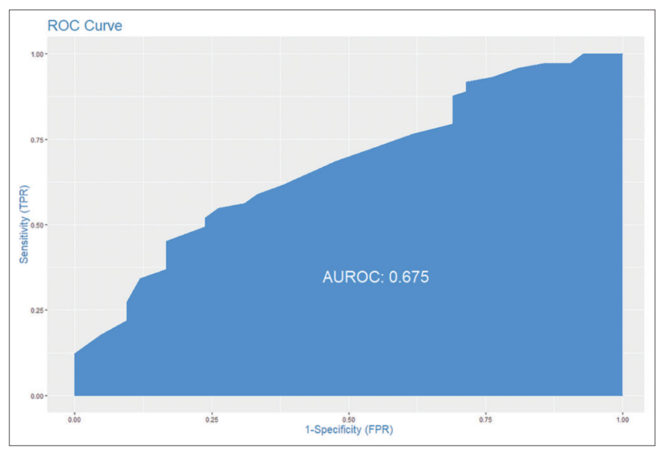

Figure 3: AUC: Area under the receiver operating characteristic curve for test data

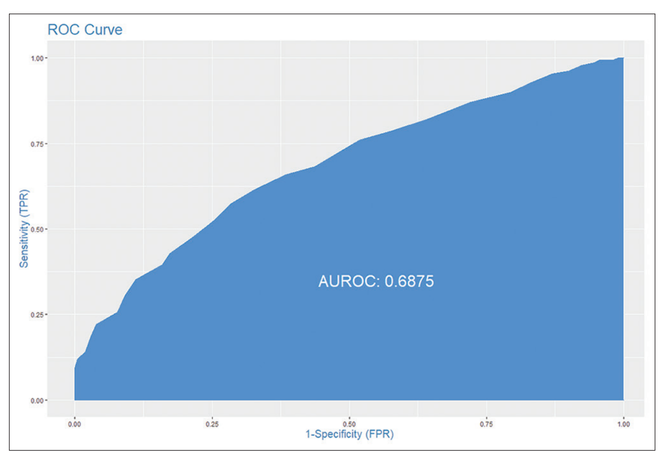

Figure 4: AUC: Area under the receiver operating characteristic curve for full data

The curve can be interpreted using the rule "the farthest the curve is from the diagonal line, the better the model fits the data. According to this, the AUC area in test data was 0.675, while it was 0.6875 in full data. The AUC value obtained in the study was accepted as 0.7, which is primarily a limitation, and this value is considered acceptable according to the literature. In other words, the model performs better in distinguishing between individuals who display and do not display recycling behavior. The fit between test data and full data is 70%.

DISCUSSION AND CONCLUSION

This study was conducted to reveal the recycling behaviors of middle school students aged 10–14 in Turkey in relation to environmental behavior, environmental emotion, and plastics recycling knowledge by using the ML technique. According to the results of the study, recycling behavior has a positively significant relationship with plastics recycling knowledge and environmental behavior, and it has a negatively significant relationship with environmental emotion. This finding of the study is consistent with the literature on environmental attitude (Awana et al., 2022; Rodríguez-Barreiro et al., 2013; Jezewska-Zychowicz and Jeznach, 2015) recycling behavior (Haj-Salem and Al-Hawari, 2021; Escario et al., 2020; Jekria and Daud, 2016; Hornik et al., 1995), and waste management behaviors (Corsini et al., 2018; Whitmarsh et al., 2018; Do Valle et al., 2004; Ojedokun, 2011).

In order to ensure that individuals exhibit recycling behavior, their attitudes should be adjusted. When attitudes are positively affected, the possibility of exhibiting recycling behavior will increase (Aboelmaged, 2021). People with high environmental attitudes are expected to participate in recycling; the correlation between these two behaviors is significant (Mason et al., 2022). Behavioral control is the strongest predictor of intention; this is followed by attitude (Raimondo et al., 2022). According to this, for someone to recycle, they are expected to have a high attitude. It supports this study's finding that there is a positive relationship between recycling and environmental behavior. Mid-childhood is characterized by important cognitive changes which enable children to be more flexible in their thinking compared to their pre-school years (Huston and Ripke, 2009). They can reason on concrete information (Piaget, 1963). Environmental attitudes and behavior increase from age 7 to 10; therefore, mid-childhood or primary school age is especially important for the formation of environmentalism in children (Otto et al., 2019). These changes ensure that children are aware of the environmentally harmful behaviors on the one hand, and on the other hand, they enable children to develop reasoning skills to think about the consequences of these harmful behaviors (Honig and Mennerich, 2012).

Recycling and plastics recycling knowledge are in a positively significant relationship according to findings. When we increase students' plastics recycling knowledge, we can also increase the probability of their displaying recycling behavior. Recycling is included in environmentally conscious behaviors. When people believe that the environment should be protected, they display environmentally conscious behavior. The strongest predictor of environmentally conscious behavior is environmental attitude (Casaló and Escario, 2018). Many people do not act environmentally consciously, and how to overcome this environmental attitude-behavior gap remains a mystery. Motivational tendencies underlying environmentally conscious behavior and structural factors should be considered. Environmentally conscious behavior takes place when a person's personal cost is low or the benefit to the environment is high. Another important finding is self-control. Self-control helps people to act in accordance with their own attitudes, and this is a significant factor in preserving people's long-term environmentally conscious behavior (Wyss et al., 2022).

Unexpectedly, research findings indicate a negative relationship between environmental emotion and recycling behavior. These results show that students with lower environmental emotion engage in recycling behavior more frequently. This outcome may be due to external factors such as school rules, habits, grade anxiety, or fear of social exclusion rather than environmental commitment or emotional awareness (Cialdini et al., 1990; Steg and Charles, 2009). In some societies, recycling may have become a social norm. Middle school students often tend to respond to social expectations and comply with the rules of their environment. Thus, even if their environmental emotion is low, they may engage in recycling behavior out of a sense of "doing the right thing" (Thøgersen, 2004). This finding demonstrates that the level of environmental emotion is not always directly proportional to recycling behavior and that environmental emotion alone may not sufficiently explain such behaviors. In educational environments, emphasis should be placed to include activities that not only promote recycling behavior but also aim to develop the underlying cognitive and affective awareness behind these actions.

Despite there are numerous studies analyzing and predicting people's recycling intentions or behaviors (Pakpour et al., 2014; Tonglet et al., 2004), there are only a handful of studies focusing specifically on behavior in relation to plastics (Heidbreder et al., 2019). This points at a gap in the literature. This study examined students' plastics recycling knowledge. It is highly important for the environment to know the types of plastics and how they could be recycled. It would be sufficient at the middle school level to know whether recycling is possible for plastic types such as PET, HDPE, LDPE, PP, and PS. This topic should be included in the middle school science curriculum.

The role of environmental attitude in learning and acquiring information is not clear. For instance, some researchers regard environmental knowledge as the sole determiner to change people's environmental attitudes (Indriani et al., 2019; Smith and Paladino, 2010). However, there are those who contend the opposite. According to this, people's knowledge of the environment is actually dependent on their environmental attitude (Henn et al., 2019; Taube et al., 2021). Young people can be the representatives of sustainable change. To this end, environmental education programs should aim to improve these peoples' environmental information, attitude, intention, and behaviors (van de Wetering et al., 2022). People's pre-existing environmental attitudes support their acquiring new information. To effect change in adolescents' environmental attitudes, their developmental characteristics should be taken into account. In this respect, from age 11 to 16, their environmental attitudes can be improved by providing support (Baierl et al., 2022). Studies should be carried out to gather more information about the relationship between the level of education of environmental-friendly behavior such as recycling; and this relationship should be examined in detail (Wang et al., 2020). In this respect, it is important to start educating middle school students early so that they can develop recycling behavior.

The following should be done to develop recycling behavior. In the science curriculum, activities that enhance students' recycling knowledge and support recycling behaviors -such as types of recycling and correct waste separation methods- should be included. For example, virtual tours to recycling facilities can be organized to allow students to observe how recycling is carried out. Activities incorporating coping strategies for environmental concerns should be integrated into the science curriculum. Science textbooks should include animated scenarios, educational drama activities, and case studies that help students develop emotional awareness toward the environment. For instance, a success story emphasizing the impact of individual recycling efforts could foster a more meaningful connection between environmental sentiment and recycling behavior. A social image should be built promoting recycling is a useful, good, and important activity; this would increase its realization probability. One of the important predictors of recycling tendency is information. Students should be educated, recycling should be promoted properly, and recycling messages should be disseminated regularly (Miafodzyeva and Brandt, 2013). When the users who follow content related to plastics recycling on social media platforms were examined, it was determined that such information and content have an important effect on the occurrence of this behavior (De Fano et al., 2022). Students should be encouraged to become members of school clubs working on recycling; activities related to these should be shared on social media to make it appealing for other students.

Another result of people's conscious or unconscious behavior is global warming. Global warming results in creating unhealthy environments and sickness. To prevent this, school kids should be informed about preventive behavior, and they should be encouraged to exhibit such behavior (Banchonhattakit et al., 2022). People should be encouraged to buy products designed to decrease carbon emission during production, which would have both ecological and economic benefits. The ecological benefit would be the reduction of emissions, and saving on fossil resources; and the economic benefit would be the decrease in dependency on fossil resources through recycling and reuse (van Heek et al., 2017). Studies on individuals' environmental protection priorities also show that these can be explained by macroeconomic and psychological variables (Lou et al., 2022).

The use of ML technology in education is fairly new. Simply put, ML ensures that computers learn by being fed data in the form of observations and real-life interactions. ML is part of artificial intelligence research which provides information to computers through data, observation, and interaction with the world. The basic objective of the ML algorithm is to successfully interpret previously unseen data (Faggella, 2020). Evaluation based on ML provides feedback to teachers, students, and parents about how students learn, about the support they need, and about their progress concerning learning outcomes (Kucak et al., 2018). In this study, recycling behavior was attempted to be predicted using plastics recycling knowledge, environmental behavior, and environmental emotion. To do this using ML, recycling behavior was first attempted to be predicted using test data. Then, in the validation, it was tested whether generalization could be made on the selected data set, and the study's focus on predicting recycling behavior through ML is important because of its contribution to the field.

ETHICAL APPROVAL

The ethical approval authority was obtained from the Hacettepe University Institute of Education Sciences Research Ethics Committee, Türkiye (Approval No: E-51944218-050-00003773808).

DISCLOSURE STATEMENT

The authors declare no potential conflict of interest.

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