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Using multilevel models to evaluate the attitude of separate waste collection in young people

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Abstract
Separate waste collection represents one of the necessary conditions to guarantee an efficient protection of the environment. In particular, raising awareness of young people towards eco-sustainable behaviors, such as waste sorting and waste recycling, is an essential target that institutions should pursue in order to contribute to the reduction of the environmental impact of waste. Thus, an appropriate assessment of the determinants which influence environmentally responsible practices is of wide interest, not only for its implications in environmental science, but also in other scientific fields, such as Sociology, Chemistry and Engineering. This paper is focused on an innovative analysis based on the use of multilevel models suitable to evaluate the young people's attitudes towards waste sorting in three different daily life contexts, i.e. school, family and spare time. A data set regarding a survey on a sample of students attending upper secondary schools, in the Province of Brindisi (Apulia Region), is used.

Keywords Waste sorting habit · Separate waste collection · Odds ratios · Multilevel binary logit model

1 Introduction

The improper management of solid waste disposal is one of the world's most critical environmental issues, which has received growing attention in recent years from both scholars and policy makers [4,5,23,27]. In this context, waste sorting and waste recycling represent relevant actions currently available to reduce the environmental impact of waste and to improve the waste management performances [3,8]; in addition, they also encourage the expansion of economic activities and the development of green technologies as well as the job generation by fostering a recycling industry [47,48]. Since the early 1990s the European Union

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has issued specific guidelines and directives to stimulate the adoption of practices to recover materials and reduce waste production; however, the percentage of recycled waste is still low in the world [29].

In the literature there are several studies which tried to assess the main determinants of waste sorting and recycling behaviors and significant contributions which recalled the theory of planned behavior for describing environmentally responsable attitudes from various viewpoints [10,28,45]. Nevertheless, only few of them put their attention on the specific reasons that can push the waste sorting on, such as the work written by Fan et al. [14], who implemented a theoretical model which included motivational, contextual and habitual factors useful to analyze the attitude towards waste sorting. In some studies, binary or multinomial logit or probit regression models were used to explain the determinants which could influence the environmentally responsible behavior. Among these, it is worth mentioning Fiorillo [15], who analyzed, through a probit regression model, the role of non-economic factors in the household recycling in Italy. Minelgaite and Liobikien [26] explored the determinants which could affect the habit of waste sorting in separate EU countries, by applying the binary logistic regression. In addition, Agovino et al. [1] applied a multinomial probit model able to explain the relationship between cultural factors and household level of recycling.

Some advanced approaches based on multilevel models can be also found in some references, such as in Guerin et al. [20], who proposed a cross-national two-level random intercept binary regression model, useful to analyze social and institutional factors that interact with some individual variables (referred to the European Union citizens of 15 countries) and influence waste sorting and recycling practice. Similarly, Pirani and Secondi [30] examined, through a multilevel approach, the differences in pro-environmental behaviors (that is individual behaviors devoted to environmental sustainability) among European countries. Furthermore, Tabernero et al. [46] considered a two-level model to identify the individual, collective, and organizational factors that institutions can control in order to increase the recycling rates in their communities. Recently, Degli Antoni and Vittucci Marzetti [13] implemented a multilevel model capable of explaining the relation between waste and recycling, by providing estimates of the source reduction effect of recycling policies and pointing out the key role of curbside collection programs.

Nevertheless, the focus of most of the works available in the literature was concentrated on empirical evidences at a macroscopic geographical level without highlighting the specific dynamics related to local contexts. Moreover, the role of eco-friendly inclination of young people and the effects of the surrounding environment have never been considered. Thus, differently from the previous works, this paper aims to provide a geographical detailed analysis (at municipality level) of the probability of young people's attitudes towards separate waste collection, by considering the impact of the social context on their behavioral choices. Note that the microscopic geographical level is of particular interest in some countries, such as Italy, where local communities have the authority to manage solid waste collection and disposal. In addition, the novelty of this contribution concerns the implementation of a multilevel analysis, based on a binary logit model, where the key role played by three different daily life contexts (school environment, family environment and spare time environment) on the habits of young people, has been pointed out. In other terms, this paper can be considered as one of the few attempts to evaluate the significance of civic participation of the future leading actors (that is young people), as also in [18,23], but with the further endeavor to find out their behavioral disparity with respect to the surrounding environment. This study intends to support the common belief that waste sorting is a type of pro-environmental behavior, which is simultaneously influenced by social norms, moral obligations, affective and instrumental attitudes, but partially it is also guided by habit or automated cognitive processes.

After a brief review on multilevel modeling (Sect. 2), a description of the survey results regarding the waste sorting habits of young people has been proposed (Sect. 3). Then, different multilevel logit models have been implemented in order to determine the probability of having an environmental friendly behavior towards waste sorting in the three scenarios under study. Estimates of fixed and random parameters, together with the associated *p value*s, the standard errors and the odds ratios for the models, have been discussed (Sect. 4).

2 Brief theoretical background on multilevel binary models

The multilevel approach is a statistical methodology for the analysis of hierarchical data structure with complex patterns of variability [16,37,40]. This structure classifies the cases into known groups, with their own set of explanatory variables at each group level. For this reason, these models can be interpreted as a natural extension of classical linear models or generalized linear models. Nevertheless, unlike traditional regression models, explanatory variables in multilevel models can be specifically identified for each group level and the variability at different levels of hierarchy is also computed. As a consequence, the effects of groups on the response variable are evaluated and unbiased estimates of standard errors are determined. Nowadays, various software packages can support the fitting procedure of these models [32,41].

Multilevel regression models are also known as *Variance components models* [6], *Hierarchical linear models* [33], and *Random coefficient models* [12,24]. Grilli and Rampichini [19] provided a review concerning the specification of random effects in multilevel models.

In the last few decades, various researchers have been demostrating interest in the development of multilevel regression models, as shown by a variety of monographs [16,39,40], together with their applications on a wide range of fields [34,35]. As discussed in Khan and Kamal [22], an extensive literature is also referred to multilevel models in education.

In the following, the theoretical background of multilevel models is briefly introduced and some specific formulations based on different combinations of within-group and between-group relations are highlighted. Without loss of generality, three common variants of three-level models, with random intercept and/or random slope, are presented.

2.1 Random intercept model

Let $Y_{ijk} \sim Ber(\pi_{ijk})$ be the binary response variable which takes values 0/1 (response categories), with the index i ($i = 1, \ldots, n_{jk}$) representing the level 1 unit, the index j ($j = 1, \ldots, N_k$) corresponding to the level 2 unit and the index k ($k = 1, \ldots, K$) indicating the level 3 unit.

The random intercept three-level model is a simple multilevel logit model where only the intercept varies across the 2nd level and the 3rd level and the slopes are assumed to be constant for each covariate. Given the set of covariates $\{X_1., X_2., \ldots, X_H.\}$, which influence the dependent response variable $Y_{ijk} \sim Ber(\pi_{ijk})$, this model is defined as follows:

$$\eta_{ijk} = \beta_{0jk} + \sum_{h=1}^{H} \beta_h \cdot x_{hijk}, \tag{1}$$

where link between the mean π_{ijk} and the linear predictor η_{ijk} is given by the $logit$ function (well-known as link function),

$$\eta_{ijk} = \log it(\pi_{ijk}) = \ln \frac{\pi_{ijk}}{1-\pi_{ijk}} \quad \text{and} \quad \pi_{ijk} = \frac{\exp\{\eta_{ijk}\}}{1+\exp\{\eta_{ijk}\}} \tag{2}$$

with

- $\beta_{0jk} = \beta_0 + \varepsilon_{0k} + \delta_{0jk}$;
- $[\varepsilon_{0k}] \sim N(0, \Omega_\varepsilon), \quad \Omega_\varepsilon = [\sigma^2_{\varepsilon 0}]$;
- $[\delta_{0jk}] \sim N(0, \Omega_\delta), \quad \Omega_\delta = [\sigma^2_{\delta 0}]$.

It is worth pointing out that, given a binary response Y_{ijk}, the *logit* link function is a mathematical function used to transform the dependent outcome Y_{ijk}, so that it can be modeled as a linear function of a set of predictors. Since the outcome variable Y_{ijk} follows a Bernoulli distribution taking values 0/1 (where the value 0 corresponds to the reference category), it is convenient to transform its expected value (by using a logit transformations) into a latent variable that corresponds to its predicted value, given the set of predictors.

The parameters of such a model can be estimated through the marginal maximum likelihood estimation, where the marginal likelihood of the observed data, obtained by integrating out the distribution of the random effects, is maximized.

Each regression coefficient represents the changes in the log-odd (logit) and its exponential corresponds to the odds ratio (OR) which can assume any value from 0 to infinity. The ORs highlight multiplicative effects rather than additive effects and are more complicated to understand than probabilities. As a consequence, many researchers prefer to interpret a model in terms of predicted probabilities [38], which can be calculated by replacing the parameters with the estimates obtained from the fitted model and from the estimated group effects of the model.

2.2 Random slope model

Let $Y_{ijk} \sim Ber(\pi_{ijk})$ be the same binary response variable previously defined. Another variant of the multilevel models can be characterized by random slopes whose variability can be different at each level. In particular, given the set of covariates $\{X_{1\cdot}, X_{2\cdot}, X_{3\cdot}\}$, a random slope three-level model is expressed as follows:

$$\eta_{ijk} = \beta_0 + \beta_1 x_{1ijk} + \beta_{2j} x_{2ijk} + \beta_{3k} x_{3ijk} \tag{3}$$

where the link function is specified in (2) and

- $\beta_{2j} = \beta_2 + u_{2jk}$;
- $\beta_{3k} = \beta_3 + \nu_{3k}$;
- $[\nu_{3k}] \sim N(0, \Omega_\nu), \quad \Omega_\nu = [\sigma^2_{\nu 3}]$;
- $[u_{2jk}] \sim N(0, \Omega_u), \quad \Omega_u = [\sigma^2_{u2}]$.

Note that the model in (3) allows the slope β_2 and β_3 to vary across the 2nd level and the 3rd level, respectively; on the other hand, the intercept and the slope β_1 are assumed to be constant for each level.

2.2.1 Random intercept and random slope model

Given the same binary response variable $Y_{ijk} \sim Ber(\pi_{ijk})$ and a set of covariates $\{X_{1\cdot}, X_{2\cdot}, X_{3\cdot}\}$, the following three-level logit model presents random intercept and random slopes, that is:

$$\eta_{ijk} = \beta_{0jk} + \beta_{1jk}\, x_{1ijk} + \beta_{2jk}\, x_{2ijk} + \beta_{3jk}\, x_{3ijk} \tag{4}$$

where the link function is specified in (2) and

- $\beta_{0jk} = \beta_0 + v_{0k} + u_{0jk}$;
- $\beta_{1jk} = \beta_1 + v_{1k} + u_{1jk}$;
- $\beta_{2jk} = \beta_2 + v_{2k} + u_{2jk}$;
- $\beta_{3jk} = \beta_3 + v_{3k} + u_{3jk}$;
- $\begin{bmatrix} v_{0k} \\ v_{1k} \\ v_{2k} \\ v_{3k} \end{bmatrix} \sim N\left(\mathbf{0}, \boldsymbol{\Omega}_v\right), \quad \boldsymbol{\Omega}_v = \begin{bmatrix} \sigma^2_{v0} & & & \\ \sigma_{v01} & \sigma^2_{v1} & & \\ \sigma_{v02} & \sigma_{v12} & \sigma^2_{v2} & \\ \sigma_{v03} & \sigma_{v13} & \sigma_{v23} & \sigma^2_{v3} \end{bmatrix};$
- $\begin{bmatrix} u_{0jk} \\ u_{1jk} \\ u_{2jk} \\ u_{3jk} \end{bmatrix} \sim N\left(\mathbf{0}, \boldsymbol{\Omega}_u\right), \quad \Omega_u = \begin{bmatrix} \sigma^2_{u0} & & & \\ \sigma_{u01} & \sigma^2_{u1} & & \\ \sigma_{u02} & \sigma_{u12} & \sigma^2_{u2} & \\ \sigma_{u03} & \sigma_{u13} & \sigma_{u23} & \sigma^2_{u3} \end{bmatrix}.$

It is worth pointing out that the model in (4) allows the intercept and the slopes to vary across both the 2nd level and the 3rd level.

Remarks

- Variability in multilevel data has a complex structure, since several populations are involved in multilevel modelling (one population for each level). Explaining variability in a multilevel structure must be achieved by considering variability among individuals and groups.
- By analysing multilevel data, it is interesting to evaluate the amount of variation that can be attributed to the different levels in the data structure, as well as the part of variation explained by independent variables at each level.
  For multilevel models with random coefficients, the intra-class correlation coefficient (ICC) is often used to this aim.
  For example, by considering the model in (3), the ICC can be defined for each level separately [36], as follows:

$$ICC^{(2)} = \frac{\sigma^2_{u2}}{\sigma^2_{v3} + \sigma^2_{u2} + \left(\frac{\pi}{3}\right)^2}$$
$$ICC^{(3)} = \frac{\sigma^2_{v3}}{\sigma^2_{v3} + \sigma^2_{u2} + \left(\frac{\pi}{3}\right)^2}$$

  where $\frac{\pi}{3}^2 \simeq 3.29$ is the fixed error variance, thus, no level-1 variance has to be estimated. The ICC assesses the degree of homogeneity of the dependent outcome within clusters and may range from 0 (perfect independence of residuals) to 1 (perfect interdependence of residuals).
- The three-level models above-mentioned can be easily extended to logit models with higher levels.

3 Descriptive analysis of waste sorting habits

The data used in this paper have been collected through a questionnaire-survey carried out on a stratified sample of students enrolled in upper secondary schools located in the Province of Brindisi. The survey has been realized by considering:

- the municipalities where the schools are located;
- the territorial organizations of the urban waste cycle management in the Province of Brindisi. In particular, the Province of Brindisi is divided into two Optimal Territorial Areas (O.T.A.), as regulated by the regional planning (Regional Law No. 17/1993, Commissioner's Decree No. 296/2002 and Regional Law No. 24/2012), i.e.:
  - O.T.A. BR/1 delimiting the coastal area of the province, which is composed of 11 municipalities, i.e. Brindisi, Carovigno, Cellino San Marco, Cisternino, Fasano, Mesagne, Ostuni, San Donaci, San Pietro Vernotico, San Vito dei Normanni, Torchiarolo;
  - O.T.A. BR/2 including the inland area of the province, which is composed of 9 municipalities, i.e. Ceglie Messapica, Erchie, Francavilla Fontana, Latiano, Oria, San Michele Salentino, San Pancrazio Salentino, Torre Santa Susanna, Villa Castelli.
- the number of public upper secondary schools distributed in the Province of Brindisi, classified by the type of institute:
  - lyceum, i.e. high school dedicated to scientific studies, or humanities, sometimes with artistic, music, psycho-social curricula;
  - technical college, which is oriented to Economics and Management, sometimes with agricultural, industrial or nautical curricula;
  - professional school (or vocational college), which includes a lot of practical activities relating to industry and crafts, hotel and catering services, with social services curricula.

Taking into account the significance level α equal to 0.04, the optimal sample size for the inference on the proportion π has been computed as follows:

$$n = \frac{z_{\alpha/2}^2 \; \pi(1-\pi)}{\dfrac{N-1}{N}\varepsilon^2 + z_{\alpha/2}^2 \dfrac{\pi(1-\pi)}{N}} = 1108$$

where the centile $z_{\alpha/2}$ is 2.05, $\pi(1-\pi)$ is prudentially assumed equal to the maximum 0.25, the margin of error ε is fixed equal to 0.03 and the school population of the Province of Brindisi N is 17438. Then, the optimal sample size has been proportionally stratified by the type of school (375 for technical school, 240 for professional school and 493 for lyceum) and the O.T.A. (743 for BR/1 and 365 for BR/2), as reported in Table 1.

The survey has been conducted, through a direct face-to-face interview, on clusters of students belonging to five classes (from the first to the fifth year), randomly selected, for each school.

The random sample of students, aged 14–19 years, is composed of 50.9% of females and 49.1% of males. With respect to the school attended, 45% of respondents are enrolled at a lyceum, 34% at a technical institute and 21% at a professional institute. Moreover, 33% of students is resident in O.T.A. BR/2, the 66% in O.T.A. BR/1 and the remaining 1% in other municipalities. Note that only the sample of students residing in the Province of Brindisi has been retained for the subsequent analysis; despite this, the effective sample size (1098) has remained satisfactory, taking into account that the negligible number of excluded observations (less than 1%).

In detail, the habits of respondents towards separate waste collection have been assessed by considering three different contexts, i.e. family, school and spare time.

With reference to the family environment, the descriptive analysis has highlighted that 74.4% of the respondents are used to practice waste sorting at home and, among of these, the

Table 1 Student population, population proportion for each stratum, proportional stratified sample with respect to the O.T.A. and type of school

Type of school	BR/1			BR/2			Total		
	Nr. of students	Prop. (%)	Optimal sample size	Nr. of students	Prop. (%)	Optimal sample size	Nr. of students	Prop. (%)	Optimal sample size
Technical	3852	22	245	2050	12	130	5902	34	375
Professional	1955	11	124	1817	10	115	3772	21	240
Lyceum	5883	34	374	1881	11	120	7764	45	493
Total	11690	67	743	5748	33	365	17438	100	1108

45.4% specify that it is done for habit and the 32.7% justify it because they believe in eco-sustainable development. On the other hand, the reasons given by those who do not collect waste separately at home are related to carelessness (56.5%) or to the belief that the separate waste collection service is inefficient (28%).

Regarding the school and spare time environments, the percentages of young people who implement waste sorting at school (53.2%) or during their free time (38.3%) are lower than the one in the family context. Carelessness, enforced in some cases by the belief of the inefficiency of waste collection service, is the main motivation given by those who do not respect the guidelines in terms of waste sorting at school and in free time contexts.

As a consequence, it would be advisable to start awareness campaigns based on the importance of good practices in every context of daily life; these campaigns should also be associated to an efficient improvement in the separate collection service, as well as to a widespread allocation of collectors through the streets of municipalities.

A further evaluation of the habits towards separate waste collection, in the three contexts examined, has been performed by classifying the answers of the respondents with respect to the O.T.A.

By analyzing the descriptive statistics, it is worth noting that 58.6% of students resident in O.T.A. BR/1 do not sort waste at school. On the other hand, there is a reversal in the behavior of students resident in O.T.A. BR/2 with respect to O.T.A. BR/1: more than half of the students residing in O.T.A. BR/2 declare to collect waste separately at school (61.4%). It is likely that this discrepancy is due to the different perception of the efficiency of the public waste collection service in the two territorial areas. Indeed, 62.0% of the students (who do not practice separate waste collection in the school environment) residing in the O.T.A. BR/1, against the 39.3% of the ones residing in the O.T.A. BR/2, claim that the collection service does not work. This tendency is also confirmed in the other two environments.

The 61.9% of the interviewees, belonging to the O.T.A. BR/1, carry out waste sorting in the family; whilst, with reference to the interviewees belonging to the O.T.A. BR/2, a larger percentage of students (86.4%) performs waste sorting in the family. Furthermore, for the two O.T.A.s, waste sorting in family environment is done for habit (respectively 44.1% for O.T.A. BR/1 and 46.3% for O.T.A. BR/2) or because they believe in eco-sustainable development (35.5% for O.T.A. BR/1 and 30.9% for O.T.A. BR/2); on the other hand, those who do not practice, declare as motivations carelessness and inadequacy of the public waste collection service (respectively 98% and 75.4%).

The free time environment is characterized by a decrease of the percentages of practicing waste sorting for both O.T.A. BR/1 and O.T.A. BR/2: students who do not usually apply waste sorting are 71.0% for O.T.A. BR/1 and 52.7% for O.T.A. BR/2. Among the motivations that support the waste sorting there are the habit (respectively 47.5% and 60.5%) and the belief in eco-sustainable development (37.5% and 25.5% respectively), whilst among the reasons against waste sorting there are carelessness (respectively 57.5% and 47.3%) and the persuasion that the collection service does not work (respectively 28.6% and 29.1%).

4 Multilevel models for young people's attitudes towards waste sorting

In this section, the young people's attitudes towards waste sorting has been evaluated through the use of multilevel models with three hierarchical levels:

- the first level, where the units are the students enrolled in upper secondary schools, in the Province of Brindisi (1098 students out of 1108 respondents, because the students residing in other districts were excluded from the analysis);
- the second level, where the units are the upper secondary schools in the Province of Brindisi, classified by type of institution and by class of attendance (15 types of schools per class of attendance);
- the third level, where the units are the municipalities where the schools under study are located (20 municipalities).

The choice of these levels is justified by the intrinsically hierarchical structure of the school education, where the municipalities are considered as the highest level, in which the schools are located; on the other hand, the students represent the lowest level of nesting [7]. As already specified, the novelty of the following analysis regards the focus on the effects of the surrounding environment on the eco-friendly behavior of young people. Indeed, unlike other contributions on this subject essentially limited to the school environment [17,18,23], in this paper three different multilevel logit models have been implemented in order to assess the influence of three different daily life contexts (school, family and spare time) on the behavioral choices of young people.

On the basis of this exploratory data analysis presented in the previous section, the covariates shown in Table 2 have been selected and recoded for modeling purposes.

Note that some covariates are derived variables, such as:

- the information level towards waste sorting, which is assumed to be dependent on the knowledge of following aspects reported in the questionnaire administrated to the sample of students:
  - the notion of separate waste collection;
  - the presence of community bins to store specific waste (such as organic waste; used paper napkins; newspapers/notebooks; glass containers; light bulbs; pens and similar; tin cans; plastic plates/cups; plastic bottles);
- the sensitivity level, which is assumed to be dependent on the following issues:
  - concerns towards urban waste disposal;
  - habit of adopting a pro-environmental behavior;
  - purchase of products made from recycled material;
  - participation in educational workshops to learn how to reuse materials;
  - sharing of good practices concerning the separate waste collection;
  - habit of raising awareness towards separate waste collection, in the case of a friend does not adopt a pro-environmental behavior;
  - true interest in waste topics.

Starting from a full model which includes, as covariates, the variables in Table 2, the backward deletion procedure has been used in order to select the right pattern of covariates. At the end of this process, the covariates not statistically significant (that is the gender, the number of family members' per household, the parents' occupation, the parents' educational level) have been neglected.

Table 2 Individual covariates selected for the study

Questionnaire variables or derived variables	Questionnaire modality/derived modality
Gender	"0" = male
	"1" = female
Number of family members' per household	"0" = fewer than 3 members
	"1" = 3 members
	"2" = 4 members
	"3" = 5 members or more
Parents' occupation	"0" = unemployed
	"1" = worker
	"2" = farmer
	"3" = craftsman
	"4" = teacher
	"5" = technicians and managers
	"6" = sales and family services
	"7" = retired
	"8" = intellectual profession
	"9" = other
Parents' educational level	"0" = Literate
	"1" = Primary school
	"2" = Secondary school
Information level	"0" = low information level;
	"1" = high information level
Sensitivity level	"0" = low sensitivity level;
	"1" = high sensitivity level
O.T.A.	"0" = O.T.A. BR/1
	"1" = O.T.A. BR/2

4.1 A binary multilevel model for the three contexts under study

Let $Y_{ijk} \sim Ber(\pi_{ijk})$ be the binary response variable which takes values 0 for "not practicing waste sorting" with probability $(1-\pi_{ijk})$ and 1 for "practicing waste sorting" with probability π_{ijk}, where

- the index i $(i = 1, \ldots, 1098)$ represents the students (units of level 1),
- the index j $(j = 1, \ldots, 15)$ corresponds to the upper secondary schools, classified by type of institution and class of attendance (units of level 2) and
- the index k $(k = 0, \ldots, 19)$ indicates the municipalities (units of level 3).

Moreover, let $\{X_1., X_2., X_3.\}$ be a set of covariates (that is, O.T.A., sensitivity level, information level), which can help in explaining the dependent response variable. Thus, the binary logistic regression model in (4), characterized by the intercept and the slopes that vary across the upper secondary schools (the 2nd level) and municipalities (the 3rd level), has been reasonably adopted in order to estimate the probabilities of having an environmental friendly behavior towards waste sorting, in the three contexts under study (family, school, spare time). Computational aspects associated to the fitting process have been faced by using a specific statistical software for multilevel analysis, called *MLwiN* [32].

4.2 Results of multilevel binary logit models

Table 3 shows the maximum-likelihood estimates of the coefficients for the relevant covariates, O.T.A., sensitivity level, information level, while the covariates which were not statistically significant (that is the gender, the number of family members' per household, the parents' occupation, the parents' educational level) have been left out from the models.

Indeed, as expected, the territorial area, the information and sensitivity levels influence the response variable, hence the null hypothesis that the corresponding coefficients β are nil, is rejected. In particular, among the covariates in Table 2, both the O.T.A and the sensitivity level have the greatest impact on the probability of practicing waste sorting in the three social contexts.

In addition, in order to evaluate the covariates effect on the probability of collecting waste separately, the ORs have been computed. From the ORs, given in the last column of Table 3, it can be pointed out that:

– being habitually resident in the O.T.A. BR/2 leads to increase the probability of implementing waste sorting of 134% in the school context, of 254% in the family context and of 105% in the spare time context, with respect to the O.T.A. BR/1; one can observe that young people resident in the O.T.A. BR/2, contribute more virtuously to the separate waste collection than in the O.T.A. BR/1, as also highlighted in the exploratory data analysis;
– a high sensitivity level in young people leads to increase the probability of practicing waste sorting of 76% in the school context, of 210% in the family context and of 288% in the spare time, compared with a low sensitivity level;
– a high information level increases the same probability of 48% in the school, of 101% in the family context and of 71% at free time, compared to a low information level; indeed, real awareness campaigns based on waste sorting should be supported by the authorities, in order to instill positive willingness of respondents to practice separate waste collection.

It is also of particular interest to assess the amount of variation explained at each level and in the three contexts under study.

By analyzing the random effects of the models shown in Table 3, it is clear that the variability is larger among the municipalities (3rd level) with respect to the groups of secondary schools and class of attendance (2nd level) for the three environments. The ICC (measured in %) gives a further confirmation of this evidence, that is

– 41.2% for the 3rd level and 10.6% for the 2nd level, in the family environment;
– 28.3% for the 3rd level and 26.3% for the 2nd level, in the school environment;
– 24.3% for the 3rd level and 10.4% for the 2nd level, in the free time environment.

However, in the school environment, differently from the other contexts, the percentage of variation explained at the 2nd level (26.3%) is almost equal to the percentage of the 3rd level (28.3%); this is because this specific social context feels the effects that the eco-friendly strategies, adopted by the different types of institute, determine on the waste sorting attitude of their students (of all classes).

The sociological implications associated with the ORs results can be explained by taking into account that waste sorting is a type of pro-environmental behavior, which is simultaneously influenced by personal pro-social norms, moral obligations, affective and instrumental

Table 3 Estimates of fixed and random parameters, together with the standard errors (SE), the *p value* and the odds ratios for the model (4)

Covariate's and estimates for fixed parameters	$\hat{\beta}$	$SE(\hat{\beta})$	Wald statistic	*p-value*	$OR = \exp(\hat{\beta})$
1st variant of the Model (4)-school context					
Constant	−1.021	0.215	−4.749	0.000**	0.360
O.T.A. ($x_{1\,ijk}$)	0.849	0.206	4.121	0.000**	2.337
Sensitivity level ($x_{2\,ijk}$)	0.564	0.185	3.049	0.002**	1.758
Information level ($x_{3\,ijk}$)	0.391	0.213	1.836	0.066*	1.478
Random parameters	$\mathbf{\Omega}_v = \begin{bmatrix} 0.931 & & & \\ -0.239 & 0.482 & & \\ 0.109 & 0.207 & 0.346 & \\ 0.193 & 0.265 & 0.149 & 0.290 \end{bmatrix};$				
	$\mathbf{\Omega}_u = \begin{bmatrix} 1.301 & & & \\ -0.202 & 0.340 & & \\ 0.022 & 0.023 & 0.143 & \\ 0.011 & 0.024 & 0.131 & 0.125 \end{bmatrix}.$				
2nd variant of the Model (4)-family context					
Constant	−0.381	0.173	−2.202	0.028**	0.683
O.T.A. ($x_{1\,ijk}$)	1.264	0.207	6.106	0.000**	3.540
Sensitivity level ($x_{2\,ijk}$)	1.133	0.204	5.554	0.000**	3.105
Information level ($x_{3\,ijk}$)	0.697	0.198	3.520	0.000**	2.008
Random parameters	$\mathbf{\Omega}_v = \begin{bmatrix} 0.623 & & & \\ -0.111 & 1.807 & & \\ 0.121 & 0.212 & 0.181 & \\ 0.222 & 0.347 & 0.032 & 0.201 \end{bmatrix};$				
	$\mathbf{\Omega}_u = \begin{bmatrix} 0.352 & & & \\ -0.272 & 0.243 & & \\ 0.023 & 0.019 & 0.043 & \\ 0.013 & 0.023 & 0.035 & 0.089 \end{bmatrix}.$				

Table 3 continued

Covariate's and estimates for fixed parameters	$\hat{\beta}$	$SE(\hat{\beta})$	Wald statistic	*p-value*	$OR = \exp(\hat{\beta})$
3rd variant of the Model (4)-free-time context					
Constant	−1.941	0.199	−9.754**	0.000**	0.144
O.T.A. (x_{1ijk})	0.716	0.180	3.978	0.000**	2.046
Sensitivity level (x_{2ijk})	1.355	0.174	7.787	0.000**	3.877
Information level (x_{3ijk})	0.538	0.197	2.731	0.000**	1.713
Random parameters	$\boldsymbol{\Omega}_{v} = \begin{bmatrix} 0.586 & & & \\ -0.092 & 0.407 & & \\ 0.111 & 0.183 & 0.147 & \\ 0.116 & 0.089 & 0.051 & 0.085 \end{bmatrix};$				
	$\boldsymbol{\Omega}_{u} = \begin{bmatrix} 0.264 & & & \\ -0.169 & 0.140 & & \\ 0.027 & 0.021 & 0.099 & \\ 0.009 & 0.018 & 0.030 & 0.019 \end{bmatrix}.$				

$*p$ *value* < 0.1; $**p$ *value* < 0.05

attitudes, as also illustrated by the theory of planned behavior and its applications [14,44]. However, although individuals can adopt reasoned choices according to this theory, in many other cases behavior is habitual and guided by automated cognitive processes instead of rational action [42].

As reported by Stern [43], the habit is the fourth variable besides the attitude, personal capability and contextual factors, which affects the behavioral choice. Hence, the assessment of the habits towards separate collection is crucial for improving the policy strategies, based on theory of environmental interventions into the municipalities.

In order to support the above mentioned results, the predicted probabilities of collecting waste separately have been calculated for the sample of students with respect to the municipalities (Table 4) and secondary schools classified by type of institute per class of attendance (Table 5).

From Table 4, it is worth highlighting that, for all municipalities, the probability of having an environmental friendly behavior (towards waste sorting) is higher at home than in the other two daily life contexts and, except one single case (that is the municipality of Carovigno), this probability is lower during the spare time than inside the school environment. Indeed, the minimum and the maximum estimated probabilities computed for the three contexts are 0.466–0.893 (family), 0.248–0.636 (school), 0.145–0.542 (spare time). Note that the particular performance of Carovigno with respect to the other municipalities is most likely due to the shortage of bins for separate waste collection in the school building and their inadequate placement, as complained by the students.

As reported in Table 5, it is confirmed that, for all types of institutes and classes of attendance, the probability of collecting waste separately is, on average, characterized by increasing values going from the spare time context to the school environment and then to the family context. In addition, for a fixed environment and O.T.A., the levels of probability do not present, on average, significant differences with respect to the type of institute (lyceum, technical or professional institutes); while for all types of school, the probability takes on higher values for the fifth class than for the first class. This last empirical evidence implies that the awareness towards eco-friendly behavior increases with the age. From both Tables 4 and 5, it is clear that this probability is, on average, higher for students residing in the O.T.A. BR/2 municipalities than for the students residing in the O.T.A. BR/1 municipalities in the three contexts under study. This discrepancy is reasonably due to the implementation of a door-to-door collection program extended to a wider range of waste (paper, glass, plastic, flat batteries, expired medicine, bins, organic waste) in the O.T.A. BR/2 with respect to the O.T.A. BR/1.

5 Concluding remarks

Separate waste collection is one of the most relevant actions to reduce the environmental impact of waste. According to the European Directive 2008/98/EC, Italy should have guaranteed the 50% separate waste collection rate target by 2020 [4], while with the most recent Directive 2018/851/EU, the following additional objectives have to be achieved by 2025 (55%), 2030 (60%) and 2035 (65%). These targets are surely more flexible than the ones fixed by the Legislative Decree 152/2006 (article no. 205—*Measures to Improve Separate Collection and Recycling*) in Italy (at least 35% by 31 December 2006; at least 45% by 31 December 2008; at least 65% by 31 December 2012); but thanks to this law, local authorities were pushed up to implement even better plans of waste collection. As reported by [21], the

Table 4 Predicted probabilities of collecting waste separately at school, home and free time, classified by municipality

Municipality (O.T.A.)	Est. Prob. for the 1st variant of Eq. (4) (school)	Est. Prob. for the 2nd variant of Eq. (4) (family)	Est. Prob. for the 3rd variant of Eq. (4) (free time)
Brindisi (BR/1)	0.564	0.647	0.300
Carovigno (BR/1)	0.282	0.673	0.306
Cellino San Marco (BR/1)	0.364	0.486	0.203
Cisternino (BR/1)	0.437	0.696	0.366
Fasano (BR/1)	0.365	0.613	0.297
Mesagne (BR/1)	0.331	0.558	0.257
Ostuni (BR/1)	0.329	0.610	0.307
San Donaci (BR/1)	0.384	0.591	0.287
San Pietro Vernotico (BR/1)	0.389	0.532	0.169
San Vito dei Normanni (BR/1)	0.248	0.466	0.145
Torchiarolo (BR/1)	0.501	0.568	0.272
Ceglie Messapica (BR/2)	0.625	0.875	0.518
Erchie (BR/2)	0.623	0.871	0.461
Francavilla Fontana (BR/2)	0.585	0.851	0.488
Latiano (BR/2)	0.590	0.854	0.430
Oria (BR/2)	0.622	0.893	0.542
San Michele Salentino (BR/2)	0.636	0.890	0.530
San Pancrazio Salentino (BR/2)	0.632	0.881	0.496
Torre Santa Susanna (BR/2)	0.561	0.801	0.395
Villa Castelli (BR/2)	0.614	0.867	0.448

national separate waste collection rate was 58.1% at the end of 2018, even if this promising evidence clashed with the wide disparities among Northern, Central and Southern regions (67.7%, 54.1%, 46.1%, respectively) [9,25,27]. Nevertheless, regarding this last aspect, it is worth highlighting the convergence process among macro-areas in terms of separate collection rates, favoured by the reduction of the existing gap between the more virtuous Northern regions and the others [2]. Thus, it is clear that there is still a pressing need to develop policy strategies aimed to improve the above mentioned rate by enhancing the efficiency of the waste collection service, monitoring the separate waste collection targets, as well as identifying and promoting best practices.

In this paper, a thorough analysis of the young people's attitude towards waste sorting was carried out by applying three-level binary logistic regression models. In particular, the eco-friendly behavior of young people was studied with reference to three social contexts: school, family and spare time. This idea was based on (a) the precondition that the living context, where the right behavior in pupils can be istilled, plays a significant role [31] and (b) the belief that waste sorting and recycling are often neglected since there are considered to be a time consuming and annoying activity to be avoided whenever possible [11]. Then, the probabilities of collecting waste separately in different daily life contexts were estimated through three variants of multilevel logit models and an interesting comparison among them was proposed, at municipality level, for the Province of Brindisi.

Table 5 Predicted probabilities of collecting waste separately at school, home and free time, classified by institute and class of attendance

Type of institute	Class of attendance	O.T.A. BR/1		
		Est. Prob. for the 1st variant of Eq. (4) (school)	Est. Prob. for the 2nd variant of Eq. (4) (family)	Est. Prob. for the 3rd variant of Eq. (4) (free-time)
Professional	First	0.393	0.569	0.274
	Second	0.343	0.562	0.234
	Third	0.413	0.620	0.293
	Fourth	0.345	0.575	0.252
	Fifth	0.529	0.691	0.340
Technical	First	0.454	0.587	0.276
	Second	0.426	0.559	0.243
	Third	0.427	0.615	0.299
	Fourth	0.422	0.559	0.249
	Fifth	0.484	0.617	0.299
Lyceum	First	0.301	0.651	0.314
	Second	0.360	0.638	0.330
	Third	0.290	0.650	0.298
	Fourth	0.298	0.661	0.321
	Fifth	0.360	0.657	0.338
Type of institute	Class of attendance	O.T.A. BR/2		
		Est. Prob. for the 1st variant of Eq. (4) (school)	Est. Prob. for the 2nd variant of Eq. (4) (family)	Est. Prob. for the 3rd variant of Eq. (4) (free-time)
Professional	First	0.578	0.837	0.439
	Second	0.616	0.822	0.401
	Third	0.653	0.883	0.518
	Fourth	0.607	0.885	0.538
	Fifth	0.656	0.839	0.487
Technical	First	0.558	0.863	0.476
	Second	0.557	0.840	0.483
	Third	0.655	0.893	0.537
	Fourth	0.500	0.844	0.466
	Fifth	0.597	0.884	0.477
Lyceum	First	0.634	0.884	0.515
	Second	0.601	0.873	0.495
	Third	0.585	0.845	0.412
	Fourth	0.626	0.871	0.489
	Fifth	0.639	0.894	0.525

On the basis of the modeling results, it was underlined that the good practice of waste sorting is observed, first of all, in the family environment and secondly in the school environment. On the other hand, during the free time pupils adopt a less virtuous behavior with respect to the other contexts under study. The prominent factors which might stimulate residents to implement waste sorting depend on the quality of the public waste collection service, the effective public informative campaigns and detailed guidelines from the authorities. In this context, raising the awareness of the future generations to have a pro-environmental behavior, such as the good practice of waste sorting and recycling [8], waste prevention at the source [25] and food wast reduction [9] are directions that the institutions must continue undertaking.

Moreover, it was shown that, with reference to the third level (municipalities of the Province of Brindisi), the predicted probabilities associated to the young people's attitudes towards waste sorting are, on average, higher for students residing in the O.T.A. BR/2 than in the O.T.A. BR/1 for each of the three contexts under study. The difference between the two O.T.A.s, is reasonably due to the implementation of a more intensive curbside collection policy in the O.T.A. BR/2 with respect to the O.T.A. BR/1. Regarding the second level (upper secondary schools, classified by type of institution and by class of attendance) of the models, the predicted probabilities tend to increase moving from the first to the fifth class of attendance in almost all cases. This empirical evidence can be presumably ascribed to the fact that the awareness towards eco-friendly behavior increases with the age.

For future works, it would be interesting to apply the multilevel approach in order to analyze the changes over time in the behavior of young people in the three contexts examined, according to guidance of the 2030 Agenda for Sustainable Development [49]. Among the goals of the 2030 Agenda, it is worth highlighting the Goal no. 12 "Ensure sustainable consumption and production patterns ", where are listed, among others, the following objectives:

– promote public procurement practices that are sustainable, in accordance with national policies and priorities,
– ensure that people everywhere have the relevant information and awareness for sustainable development and lifestyles in harmony with nature,
– substantially reduce waste generation through prevention, reduction, recycling and reuse,
– reduce food losses along production and supply chains.

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References

1. Agovino, M., Crociata, A., Sacco, P.L.: Cultural factors for household recycling behavior. A case study from Italy. Riv. Int. Sci. Soc. **129**(2), 137–160 (2015)

2. Agovino, M., Garofalo, A., Mariani, A.: Separate waste collection in Italy: the role of socio-cultural factors and targets set by law. Environ. Dev. Sustain. **19**(2), 589–605 (2017)
3. Agovino, M., D'Uva, M., Garofalo, A., Marchesano, K.: Waste management performance in Italian provinces: Efficiency and spatial effects of local governments and citizen action. Ecol. Indic. **89**, 680–695 (2018)
4. Agovino, M., Cerciello, M., Musella, G.: The good and the bad: Identifying homogeneous groups of municipalities in terms of separate waste collection determinants in Italy. Ecol. Indic. **98**, 297–309 (2019)
5. Agovino, M., Cerciello, M., Musella, G.: The effects of neighbour influence and cultural consumption on separate waste collection. Theoretical framework and empirical investigation. Ecol. Econ. (2019). https://doi.org/10.1016/j.ecolecon.2019.106440
6. Aitkin, M., Longford, N.: Statistical modelling issues in school effectiveness studies. J. R. Stat. Soc. Ser. A Stat. Soc. **149**(1), 1–43 (1986)
7. Bini, M., Grilli, L., Rampichini, C.: Contextual factors of the external effectiveness of the university education: a multilevel approach. Ital. J. Appl. Stat. **23**(1), 51–65 (2011)
8. Cavicchia, C., Sarnacchiaro, P., Vichi, M.: A composite indicator for the waste management in the EU via Hierarchical Disjoint Non-Negative Factor Analysis. Socio-Econ. Plan. Sci. **20**, 20 (2020). https://doi.org/10.1016/j.seps.2020.100832
9. Cerciello, M., Agovino, M., Garofalo, A.: Estimating urban food waste at the local level: are good practices in food consumption persistent? Econ. Polit. J. Inst. Econ **36**(3), 863–886 (2019)
10. Chan, L., Bishop, B.: A moral basis for recycling: extending the theory of planned behaviour. J. Environ. Psychol. **36**(36), 96–102 (2013)
11. Crociata, A., Agovino, M., Sacco, P.L.: Neighbourhood effects and pro-environmental behavior: the case of Italian separate waste collection. J. Clean. Prod. **135**(C), 80–89 (2016)
12. De Leeuw, J., Kreft Ita, G.G.: Random coefficient models. J. Educ. Stat. **11**(1), 55–85 (1986)
13. Degli Antoni, G., Vittucci Marzetti, G.: Recycling and waste generation: an estimate of the source reduction effect of recycling programs. Ecol. Econ. **161**, 321–329 (2019)
14. Fan, B., Yang, W., Shen, X.: A comparison study of "motivation-intention-behavior" model on household solid waste sorting in China and Singapore. J. Clean. Prod. **211**, 442–454 (2019)
15. Fiorillo, D.: Household waste recycling: national survey evidence from Italy. J. Environ. Plan. Manag. **56**(8), 1125–1151 (2013)
16. Goldstein, H.: Multilevel Statistical Models, 4th edn, pp. 1–384. Oxford University Press Inc., New York (2011)
17. Goldstein, H., Spiegelhalter, D.J.: League tables and their limitations: statistical issues in comparisons of institutional performance. J. R. Stat. Soc. Ser. A Stat. Soc. **159**(3), 385–443 (1996)
18. Gray, J., Jesson, D., Goldstein, H., Hedger, K., Rasbash, J.: A multilevel analysis of school improvement: changes in schools' performance over time. Sch. Eff. Sch. Improv. **6**(2), 97–114 (1993)
19. Grilli, L., Rampichini, C.: Specification of random effects in multilevel models: a review. Qual. Quant. **49**, 967–976 (2015)
20. Guerin, D., Crete, J., Mercier, J.: A multilevel analysis of the determinants of recycling behavior in the European countries. Soc. Sci. Res. **30**, 195–218 (2001)
21. ISPRA, Istituto Superiore per la Protezione e la Ricerca Ambientale. Rapporto rifiuti urbani, pp. 1–615, Rapporti n. 313 (2019)
22. Khan, R.A., Kamal, S.: Random intercept and random slope 2-level multilevel models. Pak. J. Stat. Oper. Res. **8**(4), 777–788 (2012)
23. Licy, C.D., Vivek, R., Kamath, S., Anies, T.K., Josphina, C.T.: Awareness, attitude and practice of school students towards household waste management. J. Environ. **2**(6), 147–150 (2013)
24. Longford, N.T.: Random Coefficient Models, pp. 1–270. Claredon Press, Oxford (1993)
25. Mazzanti, M., Montini, A., Zoboli, R.: Municipal waste generation and socioeconomic drivers: evidence from comparing Northern and Southern Italy. J. Environ. Dev. **17**(1), 51–69 (2008)
26. Minelgaite, A., Liobikien, G.: The problem of not waste sorting behaviour, comparison of waste sorters and non-sorters in European union: cross-cultural analysis. Sci. Total Environ. **672**, 174–182 (2019)
27. Musella, G., Agovino, M., Casaccia, M., Crociata, A.: Evaluating waste collection management: the case of macro-areas and municipalities in Italy. Environ. Dev. Sustain. **21**(6), 2857–2889 (2019)
28. Pakpour, A.H., Zeidi, I.M., Emamjomeh, M.M., Asefzadeh, S., Pearson, H.: Household waste behaviours among a community sample in Iran: an application of the theory of planned behaviour. J. Waste Manag. **34**(6), 980–986 (2014)
29. Pietzsch, N., Ribeiro, J.L.D., de Medeiros, J.F.: Benefits, challenges and critical factors of success for zero waste: a systematic literature review. J. Waste Manag. **67**, 324–353 (2017)
30. Pirani, E., Secondi, L.: Eco-friendly attitudes: what European citizens say and what they do. Int. J. Environ. Res. **5**(1), 67–84 (2011)

31. Rada, E.C., Bresciani, C., Girelli, E., Ragazzi, M., Schiavon, M., Torretta, V.: Analysis and measures to improve waste management in schools. Sustainability **8**(9), 1–12 (2016)
32. Rasbash J., Steele F., Browne W.J., Goldstein H.: A User's Guide to MLwiN Version 2.10, 3rd edn. Centre for Multilevel Modelling, University of Bristol, United Kingdom, pp. 1–314 (2009)
33. Raudenbush, S.W., Bryk, A.S.: A hierarchical model for studying school effects. Sociol. Educ. **59**(1), 1–17 (1986)
34. Raudenbush, S.W., Bryk, A.S.: Hierarchical Linear Models: Applications and Data Analysis Methods, 2nd edn, pp. 1–512. Sage Publications, Inc., Newbury Park (2002)
35. Reise, S.P., Duan, N.: Multilevel Modeling: Methodological Advances, Issues, and Applications, Multivariate Applications Series, 1st edn, pp. 1–276. Lawrence Erlbaum Associate Inc, New York (2003)
36. Rozi, S., Mahmud, S., Lancaster, G., Hadden, W., Pappas, G.: Multilevel modeling of binary outcomes with three-level complex health survey data. Open J. Epidemiol. **7**, 27–43 (2017)
37. Scott, M.A., Simonoff, J.S., Marx, B.D.: The SAGE Handbook of Multilevel Modeling. Jai Seaman Editor, Great Britain, pp. 1–696 (2013)
38. Skrondal, A., Rabe-Hesketh, S.: Prediction in multilevel generalized linear models. J. R. Stat. Soc. A. **172**(3), 659–687 (2009)
39. Skrondal, A., Rabe-Hesketh, S.: Generalized Latent Variable Modeling. Multilevel, Longitudinal, and Structural Equation Models, pp. 1–528. Chapman & Hall, Boca Raton (2004)
40. Snijders, T.A.B., Bosker, R.J.: Multilevel Analysis. An Introduction to Basic and Advanced Multilevel Modelling, pp. 1–368. Sage Publishers, London (2012)
41. Sommet, N., Morselli, D.: Keep calm and learn multilevel logistic modeling: a simplified three-step procedure using Stata, R, Mplus and SPSS. Int. Rev. Soc. Psychol. **30**(1), 203–218 (2017)
42. Steg, L., Vlek, C.: Encouraging pro-environmental behavior: an integrative review and research agenda. J. Environ. Psychol. **29**(3), 309–317 (2009)
43. Stern, P.C.: New environmental theories: toward a coherent theory of environmentally significant behavior. J. Soc. Issues **56**(3), 407–424 (2000)
44. Stern, P.C.: A value-belief-norm theory of support for social movements: the case of environmentalism. Res. Human Ecol. **6**(2), 81–97 (1999)
45. Stoeva, K., Alriksson, S.: Influence of recycling programmes on waste separation behaviour. Waste Manag. **68**, 732–741 (2017)
46. Tabernero, C., Hernández, B., Cuadrado, E., Luque, B., Pereira, C.R.: A multilevel perspective to explain recycling behaviour in communities. J. Environ. Manag. **159**, 192–201 (2015)
47. UNEP (United Nations Environment Programme): Green Jobs: Towards Decent Work in a Sustainable, Low-carbon World, Kenya, pp. 1–354 (2008)
48. UNEP (United Nations Environment Programme): Towards a Green Economy: Pathways to Sustainable Development and Poverty Eradication-A Synthesis for Policy Makers, Kenya, pp. 1–44 (2011)
49. United Nations-Sustainable Development Goals (Knowledge Platform), Transforming our world: the 2030 Agenda for Sustainable Development (2015). https://sustainabledevelopment.un.org/post2015/transformingourworld