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How marine plastic debris shapes tourist behavior: Willingness to return and economic losses in Galapagos

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ABSTRACT

Marine plastic pollution poses a growing threat to tourism-dependent economies, particularly in regions reliant on pristine beach environments such as the Galapagos Islands, a UNESCO World Heritage Site. We estimate the potential economic losses from plastic debris on beaches by surveying 445 tourists in the Galapagos National Park. We modeled changes in tourists' willingness to visit and return under varying pollution scenarios. Estimated annual losses range from US$ 29.2–303.8 million in a conservative scenario to US$ 73–458.7 million in a severe case, with visitor numbers potentially declining by up to 70%. Using XGBoost and logistic regression, we identified key factors influencing willingness to return, including plastic consumption per capita and tourist education level. Our findings highlight how environmental degradation can reduce tourism demand and provide economic justification for policy actions to protect natural assets and sustain tourism revenues.

1. Introduction

Marine plastic pollution is one of the most urgent environmental challenges of the 21st century, with 19–23 million tons leaking into aquatic ecosystems each year (UNEP, 2025; Bertolazzi et al., 2024). Plastics persist because of their durability, low cost, and widespread use (Forleo and Romagnoli, 2021; Li et al., 2016). threatening marine biodiversity, human health, and the recreational and aesthetic value of coastal areas (Jang et al., 2014; Thushari and Senevirathna, 2020). Beaches are especially valued for their scenic and recreational importance (Williams and Rangel-Buitrago, 2022; Ritchie, 2023), and cleanliness consistently ranks among the top attributes shaping visitor satisfaction and destination choice (Asensio-Montesinos et al., 2019; Chen and Bau, 2016). The visual quality of coastal environments is therefore critical for tourism, particularly in naturally attractive island destinations where unmanaged plastic waste diminishes aesthetic appeal and discourages visitation (Smith and Garaba, 2025)

Beach debris is now documented worldwide. Haseler et al. (2025) reported macro- and mesoplastics on Mediterranean beaches in Egypt, Morocco, and Tunisia, while microplastics dominated Malta's Golden Bay and Riviera Beach (Jachimowicz et al., 2024). Microplastic contamination has also been recorded in Patos Lagoon, Brazil's largest lagoon (Silva and de Sousa, 2021), and even protected sites such as Los Frailes beach in Ecuador show anthropogenic litter (Gaibor et al., 2020). Visible debris reduces tourist satisfaction and willingness to return (Ballantyne et al., 2009; Dzitse et al., 2024) and generates substantial economic losses by degrading environmental quality and tourism revenue (Krelling et al., 2017); natural capital losses have been valued at up to US$33,000 per ton of marine plastic waste (Beaumont et al., 2019). Yet few studies have quantified the economic effects of marine plastic pollution on tourism, particularly in ecologically sensitive and tourism-dependent regions such as the Galápagos Islands.

The Galapagos exemplify Latin America's waste management crisis, where inadequate disposal and limited recycling fuel pervasive marine debris (do Sul and Costa, 2007) Regional evidence highlights the scale of the problem, with contamination levels reaching 490 microplastic items m^{-2} on Lima's beaches and extensive plastic accumulation documented in Punta del Este, Uruguay (De-la-Torre et al., 2020; Lozoya et al., 2016)

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In Ecuador, waste generation amounts to roughly 58,829 tons per week, yet only 20 % is properly managed, while the remainder is dumped, burned, or discharged into rivers; recycling remains limited to an estimated 14 %, often through informal systems operating in nearly half of municipalities (Torres, 2015) These national shortcomings are acute in the Galápagos, where per-capita waste generation averages 0.7 kg inhab^{-1} day^{-1}, —among the country's highest—placing heavy pressure on disposal infrastructure (Poma et al., 2025). Given that tourism underpins the islands' economy, plastic pollution threatens both fragile ecosystems and the sustainability of nature-based tourism.

Our study provides a novel contribution by offering the first empirical estimates of potential tourism revenue losses from marine plastic debris in the Galápagos Islands while moving beyond traditional loss assessments. Unlike most studies that only value economic impacts, we integrate scenario-based plastic pollution data with XGBoost machine learning and binomial logistic regression to examine how pollution shapes tourist preferences and visitation patterns and identify the heterogeneous factors driving these responses. This combined framework quantifies revenue losses while uncovering the behavioral mechanisms behind tourists' decisions, offering actionable insights for targeted conservation and management in ecologically sensitive destinations.

2. Background

The Galapagos Islands, located 500 nautical miles off mainland Ecuador, are renowned for their biodiversity and status as a leading ecotourism destination (Taylor et al., 2009). Until the 1970s, the islands received fewer than 5000 visitors annually. However, Ecuador's oil boom led to infrastructure investments that tripled tourist numbers within a decade. Since then, tourism has surged, reaching a record 329, 475 visitors in 2023 (GNP, 2024). This growth has transformed the Galapagos from an exclusive destination into a dynamic tourism economy. Today, the archipelago supports hundreds of tourism-related businesses and a growing population, 80 % of whom rely on tourism for their livelihood (Taylor et al., 2009; Epler, 2007; Walsh and Mena, 2023).

Tourism growth in the Galapagos has triggered complex social and ecological feedback. According to a system dynamics model by Pizzitutti et al. (2017) rising tourist demand has driven population growth as workers migrate to support the expanding industry. This demographic shift places mounting pressure on infrastructure, housing, freshwater resources, and waste management systems. As tourism revenues grow, so too does the demand for imported goods, energy, and services, intensifying environmental stress across both terrestrial and marine ecosystems.

These dynamics create feedback loops that degrade ecosystem services, introduce invasive species, and undermine conservation goals. A visible consequence of this expansion is the rise in plastic pollution, fueled by increased consumption and inadequate waste management. While tourism has bolstered local economies and conservation funding (Boley and Green, 2016), it has also intensified environmental degradation, especially through plastic debris. Studies report plastics on both tourist and remote beaches (Benito-Kaesbach et al., 2024; Jones et al., 2021; Sánchez-García and Sanz-Lázaro, 2023) with tourist sites particularly vulnerable due to high foot traffic and ocean-borne litter, despite regular cleanup efforts (Metilelu et al., 2022).

Environmental degradation, particularly beach pollution, undermines the experience of key tourist segments in Galapagos. "Estheticians," who value sensory and aesthetic experiences, are especially sensitive to visible litter, while segments like "Nature" and "Want It All" also react negatively to environmental degradation (Carvache-Franco et al., 2025a; Carvache-Franco et al., 2025b). Perez Loyola et al. (2021) found visitors were willing to pay up to US $111.20 per trip for cleaner environments—far more than for air quality or infrastructure improvements.

Despite recognition of the negative effects of marine debris, few studies quantify the resulting economic losses. In South Africa, Balance et al. (2000) estimated that beach litter in South Africa could reduce up to 97 % of beach value, deterring 40 % of international and 60 % of domestic tourists. Similarly, Krelling et al. (2017) reported that stranded litter in beaches could potentially lead to a 39.1 % decrease in local tourism revenue, resulting in annual losses of up to US$ 8.5 million at two Brazilian subtropical beaches. In South Korea, a 2011 debris wash-up on Geoje Island reduced visitors by over 50 %, with losses between US$ 29–37 million (Jang et al., 2014). On U.S. beaches Leggett et al. (2014) projected $67 million in benefits from a 50 % reduction in marine debris over three months in Orange County, while Ofiara and Brown (1999) estimated losses between $379 million and $1.6 billion following major pollution events in New Jersey. In the Asia-Pacific region, marine litter was estimated to cost the tourism sector US$ 622 million annually (McIlgorm et al., 2011).

To assess potential impacts in the Galapagos, we applied a scenario-based approach inspired by Balance et al. (2000) and Krelling et al. (2017). As no major pollution events have occurred in the archipelago, we developed hypothetical contamination scenarios featuring common debris—bottles, caps, fishing lines, and microplastics (Jones et al., 2021). Surveys with departing tourists captured their willingness to visit or return under varying pollution levels.

3. Methods and materials

3.1. Study site

The Galapagos Archipelago comprises 124 islands and islets covering 8011 km^2. Influenced by ocean currents, its tropical location yields a cooler, semi-arid climate. Renowned for active volcanoes, unique evolutionary history, and iconic wildlife, the islands are a major ecotourism destination. Their striking landscapes and relaxed pace consistently place the Galapagos among the world's top travel destination (Moore, 2021). With a population of just 28,583 (INEC, 2025), the Galapagos ranks third in Ecuador for tourism-generated revenue, recording $109 million between January and May 2022—behind only Pichincha and Guayas, which each have over 3 million residents (GTO, 2022). During the same period, the archipelago collected $2.4 million in value-added tax, 79 % of which came from tourism-related sectors. Accommodations contributed 10.7 %, food services 5.7 %, and maritime transport 4.5 % (GTO, 2022).

In 2024, the Galapagos Islands received 279,277 tourists—a 15 % drop from the post-pandemic surge in 2023 but a 4 % increase over 2022 and 3 % above pre-pandemic levels in 2019 (GNP, 2025). Foreign tourists made up 55 % of arrivals, rising by 6 % compared to 2022, while domestic tourism grew by 2 %. Most visitors (72 %) entered via Baltra Island; the rest arrived through San Cristóbal. The tourism sector is largely composed of accommodation and travel agencies (65 %), followed by boat tours (20 %), food services (13 %), and transportation (1 %). Santa Cruz hosts the majority of tourism businesses (54 %), with San Cristóbal (23 %), Isabela (21 %), and Floreana (2 %) trailing behind (GTO, 2022).

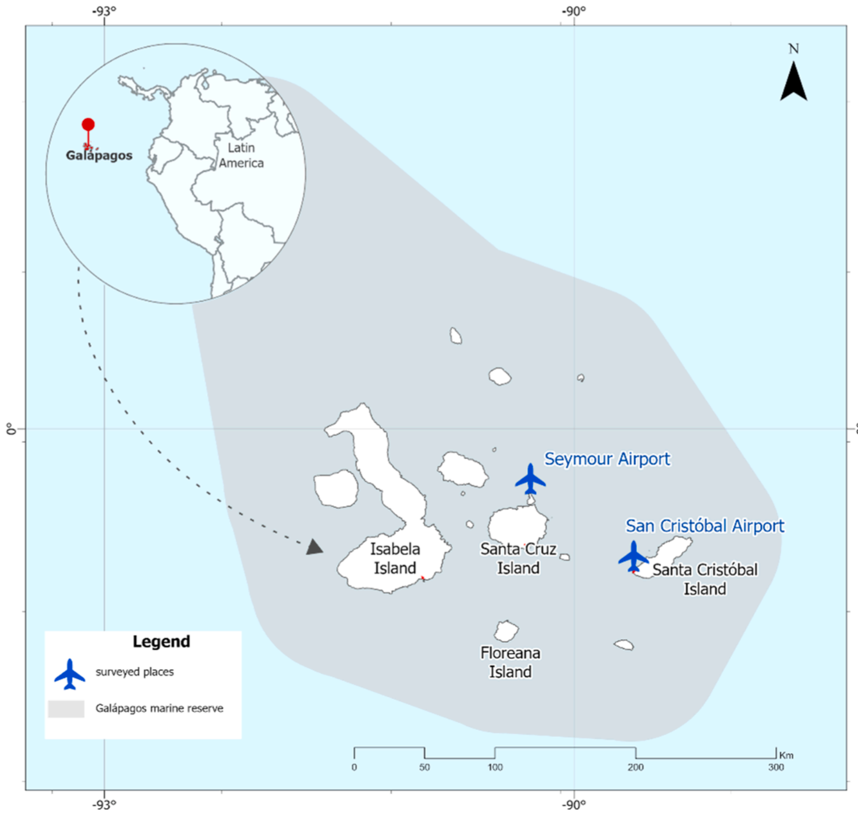


Fig. 1. Study area map.

3.2. Sample

Using the 2023 Galapagos National Park tourist arrivals (N = 329,475) as our population, we initially aimed for 384 surveys to achieve a 5 % margin of error at a 95 % confidence level. We completed 445 surveys, reducing the margin of error to 4.64 %. Surveys were distributed across Seymour Airport in Baltra (73 %) and San Cristobal Airport (27 %). Of the respondents, 54.6 % were foreign tourists, 42.5 % domestic, and 2.9 % did not specify their origin.

3.3. Survey design and data collection

The survey design was informed by three focus group discussions with recent Galapagos visitors, whose input helped refine content and presentation. Two versions—in English and Spanish—were administered to domestic and foreign tourists visiting the Galapagos National Park in February–March 2024. The survey was self-administered with field staff available for assistance, and informed consent was obtained. Visual aid cards were included to support responses to hypothetical plastic pollution scenarios (see Annexes 1 and 2). Eligible participants were adults (18+) visiting the Galapagos for leisure and staying no more than 60 days, as permitted by law. Residents were excluded.

Surveys were conducted in the pre-boarding areas of Baltra and San Cristóbal airports with approval from the Civil Aviation Authority. To ensure random sampling, specific lounge seats were pre-selected, and only individuals seated there were approached. Seat selection varied across the week to reduce location and timing biases. Pre-selecting seats in pre-boarding areas enhances the randomness of sampling and minimizes biases by preventing interviewer discretion. Each tourist's chance of selection depends solely on occupying a designated seat. Varying seat choices across times and locations further reduced spatial and temporal biases, making the sample more representative (Lohr, 2021).

Despite the effectiveness of this approach, conducting surveys in pre-boarding areas presented logistical challenges, as some tourists were in a hurry to board their flights. Consequently, 141 surveys (21.3 %) were declined—primarily for this reason, though some tourists were simply not interested—and 76 surveys (11.5 %) were incomplete, resulting in a final total of 445 complete questionnaires (67.2 %).

3.4. Variables

Table 1 shows the main variables we used in the study, categorized into four groups. The *Sociodemographic* variables capture tourists' profiles, including education, employment status, age, gender, nationality, and household income. The *Overall trip* variables measure trip-related factors such as trip satisfaction, the influence of information on marine plastic debris and the number of beaches visited. The variable expenditure represents the average per-person spending by tourists exclusively for their visit to the Galapagos, including round-trip airfare from mainland Ecuador and the Galapagos National Park entrance fee. We controlled outliers by excluding observations below the 1st and above the 99th percentiles.

Environmental attitudes were measured using *New Ecological Paradigm* (NEP) variables. Two dimensions—Limits to Growth (LG) and Anti-Exclusion (AE)—were included in the binary logistic model. LG reflects concerns about human-driven environmental degradation, while AE questions beliefs in unlimited resources and perpetual growth (Dunlap et al., 2000; Zeqir et al., 2019). Some statements were reverse-coded to standardize a 1–5 Likert scale, where "5″ indicates pro-environmental attitudes. Averages were then calculated for each dimension.

The *Pollution Scenarios* variables capture tourist perceptions and behaviors under different plastic pollution levels. Willingness to Accept (WTA) reflects the level of plastic contamination a tourist would tolerate when visiting a Galapagos beach (see Annex 1). Willingness to Visit (WTV) assesses the likelihood of visiting a beach given varying amounts of plastic per square meter, while Satisfaction Level (SL) measures anticipated satisfaction under those conditions. Willingness to Return (WTR) gauges the likelihood of returning if a certain percentage of

Table 1
Variables description.

Variable	Description
Sociodemographic	
Education	Highest education level attained; ordered 1–6 scale
Employment status	Current employment status
Age	Tourist age
Gender	1 = Female, 2 = Female
Nationality	1 = Domestic (Ecuadorian), 0 = Foreign
Household income	Annual household income (US$)
Overall trip	
Satisfaction	Overall level of satisfaction with the trip; 1–5 Likert scale (1 "Not satisfied".. 5 "Extremely satisfied)
Information	How much does the information on marine plastic debris pollution influence destination choice? 1–5 Likert scale (1 "none".. 5 "extremely)
Beach	Number of beaches visited in Galapagos
Expenditure	Tourist average expenditure (USD)
New ecological paradigm	
Limits to Growth (LG)	LG dimension (average) from the NEP (New Ecological Paradigm); 1–5 scale (1 "strongly disagree".. 5 "strongly agree")
Anti-Exclusion (AE)	AE dimension (average) from the NEP; 1–5 scale
Pollution scenarios	
Willingness-to-accept	Amount of plastic waste that a tourist is willing to accept when visiting a beach 1–5 Likert scale (1 "pristine beach".. 5 "high polluted beach")
Willingness-to-visit	Quantity of debris per square meter that a tourist would accept (1 "would visit"; 0 "would not visit or do not know")
Satisfaction level	Satisfaction level from visiting a beach; 1–5 Likert scale (1 "very low".. 5 "very high")
Willingness-to-return (WTR)	Willingness to return to Galapagos given different scenarios of polluted beaches; 1–5 Likert scale (1 "would not return".. 5 "would return")
Bottle caps	Corresponds to the WTR for bottle caps at 30 % of beaches contaminated; 1 if WTR = 1 or 2; and 0 if WTR = 3,4,5
Microplastics	Corresponds to the WTR for microplastics at 30 % of beaches contaminated; 1 if WTR = 1 or 2; and 0 if WTR = 3,4,5
Attribute	Beach characteristics most valued by tourists; 1–5 Likert scale (1 "not important".. 5 "extremely important")
PPC_kg_capita	Yearly plastic consumption per capita (kg) by country

beaches exceed a tourist's willingness to accept threshold. The Attribute variable identifies the beach features tourists value most. Finally, PPC_kg_capita captures per capita annual plastic consumption by country (WPR, 2023).

3.5. Methodology

To estimate the decrease of tourists due to plastic pollution, we developed two distinct scenarios. The first one is the *conservative* scenario, where we considered only those tourists with a willingness to return score of "1″—those who indicated they would not return. The second one is the *severe* scenario, where we included tourists with willingness to return scores of "1″ or "2"—those who said they would not return and would probably not return. To calculate potential economic losses under each scenario, we multiplied the percentage decrease in tourists by the total number of visitors to the Galapagos and then by the average expenditure per tourist (Jang et al., 2014; Krelling et al., 2017).

$$ELS_c = (D_c * N_c)*Exp_c \tag{M1}$$

Where,
ELS represents the total economic losses.
D, the percentage decreased of tourists.
c, domestic or foreign tourists.
N, Total number of tourists visited Galapagos in 2024.
Exp, average expenditure per tourist.

We applied the XGBoost machine learning algorithm to identify the variables most strongly influencing willingness-to-return outcomes. XGBoost was selected over alternative methods such as Random Forests, Support Vector Machines (SVM), and Structural Equation Modeling (SEM) because it combines superior predictive accuracy with high computational efficiency relative to other tree-based and kernel approaches (Chen and Guestrin, 2016; Zhang et al., 2018). Unlike SEM, which requires a priori specification of causal pathways, XGBoost flexibly captures nonlinear relationships and high-order interactions—patterns that are common in behavioral responses to environmental change (Sarker, 2021). In addition, the algorithm provides robust feature-importance metrics, enabling transparent identification of the most influential predictors of willingness to return (Parsa et al., 2020; Zheng et al., 2017).

XGBoost is a scalable implementation of the gradient boosting framework, noted for its speed, accuracy, and adaptability in regression and classification across fields such as health, meteorology, energy, traffic safety and others (Zhang et al., 2018; Sarker, 2021; Parsa et al., 2020). The algorithm constructs an ensemble of weak learners—typically decision trees—that sequentially reduce prediction errors by iteratively minimizing a loss function. It supports custom objective functions and evaluation metrics, providing both flexibility and precision (Chen and Guestrin, 2016; Leo Breiman et al., 2017). In our analysis, we used a logit-binomial objective for binary classification, allowing the model to classify observations into two categories and generate probabilities between 0 and 1 via a sigmoid transformation:

$$P\left(y_i = 1 \,\middle|\, x_i\right) = \frac{1}{1 + e^{-\hat{y}_i}} \tag{M2}$$

For this objective, the logistic loss function was used during training:

$$l(y_i, \hat{y}_i) = -[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] \tag{M3}$$

In Eqs. (M2) and M3, y_i corresponds to the true label (0 or 1), and $\hat{y}_i$ is the predicted probability.

The binary classification error rate was selected as the evaluation metric (Eq. (M4)). The 0.5 threshold for predicted values was used to define negative and positive instances.

$$Error = \frac{number\ of\ wrong\ cases}{number\ of\ all\ cases} \tag{M4}$$

We used XGBoost to evaluate and rank the importance of input features. Feature importance was measured by *gain*, which captures the reduction in the loss function achieved when a feature is used to split the data at a node in the decision tree (Chen and Guestrin, 2016; Zheng et al., 2017). A higher gain indicates a greater contribution of that feature to the model's predictive accuracy. At each decision node, the algorithm tests all possible splits and selects the one that maximizes gain; the cumulative gain across all trees provides a comprehensive ranking of feature importance. This ranking identifies the variables that most strongly influence model performance. To examine how these key factors affect tourists' probability of returning to the Galápagos under different scenarios, we then applied a binary logistic regression model, where the dependent variable *PR* equals 1 if an individual intends to return and 0 otherwise, and the independent variables are denoted as X_1, X_2,…, X_k.

The general form of the binary logistic regression model is expressed as:

$$logit(PR) = ln\left(\frac{PR}{1 - PR}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k \tag{M5}$$

Where, *PR* represents the probability of return to Galapagos ($PR = 1$); ($1 - PR$) represents the probability of no return ($PR = 0$); β_0 is the intercept term; $\beta_1, \beta_2, \ldots, \beta_k$ are the coefficients of the independent variables X_1, X_2,…, X_k.

The logistic function, which maps the linear predictor to the probability of return (*PR*), is defined as:

$$PR = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k)}} \tag{M7}$$

Although binomial logistic regression does not require a perfectly balanced dependent variable, achieving a balanced outcome distribution is desirable to minimize model bias and ensure robust predictive performance.[1] When one outcome class dominates, the model can achieve deceptively high overall accuracy by simply predicting the majority class, thereby failing to learn the underlying patterns of the minority class (Buda et al., 2018; He and Garcia, 2009). This imbalance can compromise the model's calibration, reduce sensitivity, and limit its ability to generalize to new data (Menardi and Torelli, 2014). Foundational studies in predictive modeling emphasize that addressing class imbalance improves both discrimination and reliability (Kuhn, 2013). Techniques such as SMOTE were developed precisely because balanced data lead to more equitable learning across classes, even when such methods are not directly applied (Chawla et al., 2002).

Consequently, balancing the dependent variable strengthens the validity and interpretability of logistic regression models by reducing majority-class bias and enabling accurate estimation of relationships for both outcomes (Buda et al., 2018; He and Garcia, 2009). In this sense, we selected two outcome variables—*Caps_P30 and Microplastics_P30*—as they offered the most balanced distributions of 1 s and 0 s.[2] These represent willingness to return when 30 % of beaches are contaminated with bottle caps or microplastics. We employed a binary logit model as the primary analytical framework due to its suitability for dichotomous outcomes and its capacity to accommodate both continuous and categorical predictors (Hosmer et al., 2013). For robustness, we also estimated ordinary least squares (OLS) and ordinal logistic models to assess the consistency and sensitivity of the results.

Independent variables were selected based on their relative importance in the XGBoost algorithm. To guide the specification of the binomial logistic regression models, we used the feature importance scores from XGBoost. Specifically, we ranked all 28 predictors by their average gain across the contamination scenarios and retained those variables that consistently appeared among the top predictors. This approach ensured that only variables with the highest contribution to reducing model error were considered in the logistic regressions. This procedure avoids overfitting by excluding weak predictors, while still allowing inferential testing of the strongest predictors identified through XGBoost. All steps of this procedure, including annotated R code and its results, are provided in the supplementary materials for reproducibility. We used the XGBoost library (version 1.7.7.1) in R (version 4.3.2) to evaluate 28 predictors and SPSS (v21.0, IBM Corp.) was used for data preprocessing and regression analysis.

4. Results

4.1. Tourist demographics

Table 2 presents the demographic profile of the tourists surveyed. Regarding education level, the majority held a graduate degree (40 %) or a 4-year university degree (33 %), while smaller proportions reported other levels of education. In terms of employment status, half of the participants were employed full-time (50 %), followed by self-employed individuals (16 %) and retirees (14 %). The age distribution indicates that the largest group of respondents was aged 26 to 35 years (32 %), followed by those aged 36–45 years (15 %), while the rest of age groups distribution rages between 10 % and 14 %. Gender was nearly evenly distributed, with 50 % identifying as female and 45 % as male, while 5 % did not report their gender. Most participants are foreign tourists (55 %) compared to domestic visitors (42 %), with 3 % nonresponses. Lastly, annual household income was diverse, with the largest segment reporting earnings of $100,000 or more (21 %), followed by 14 % in the $50,000–99,999 bracket, while 16 % chose not to disclose their income

Table 2
Tourist demographics.

Variable	Description	n	%
Education	Some high school	16	4 %
	High school diploma or equivalent	26	6 %
	Some university/ technical school	46	10 %
	2-year university or college degree	19	4 %
	4-year university or college degree	146	33 %
	Graduate degree	180	40 %
	NR*	12	3 %
Employment status	Self-employed	69	16 %
	Employed full-time	221	50 %
	Employed part-time	27	6 %
	Unpaid domestic worker	4	1 %
	Student	25	6 %
	Retired	62	14 %
	Currently unemployed	25	6 %
	NR	12	3 %
Age group	18 - 25 years	53	12 %
	26 - 35 years	143	32 %
	36 - 45 years	68	15 %
	46 - 55 years	46	10 %
	56 - 65 years	61	14 %
	More than 65 years	60	13 %
	NR	14	3 %
Gender	Male	200	45 %
	Female	224	50 %
	NR	21	5 %
Nationality	Foreign	243	55 %
	Domestic	189	42 %
	NR	13	3 %
Annual household income	< US$ 4999	38	9 %
	5000 - 9999	42	9 %
	10,000 - 19,999	54	12 %
	20,000 - 29,999	42	9 %
	30,000 - 49,999	42	9 %
	50,000 - 99,999	63	14 %
	100,000 or more	92	21 %
	NR	72	16 %

* NR = Nonresponse.

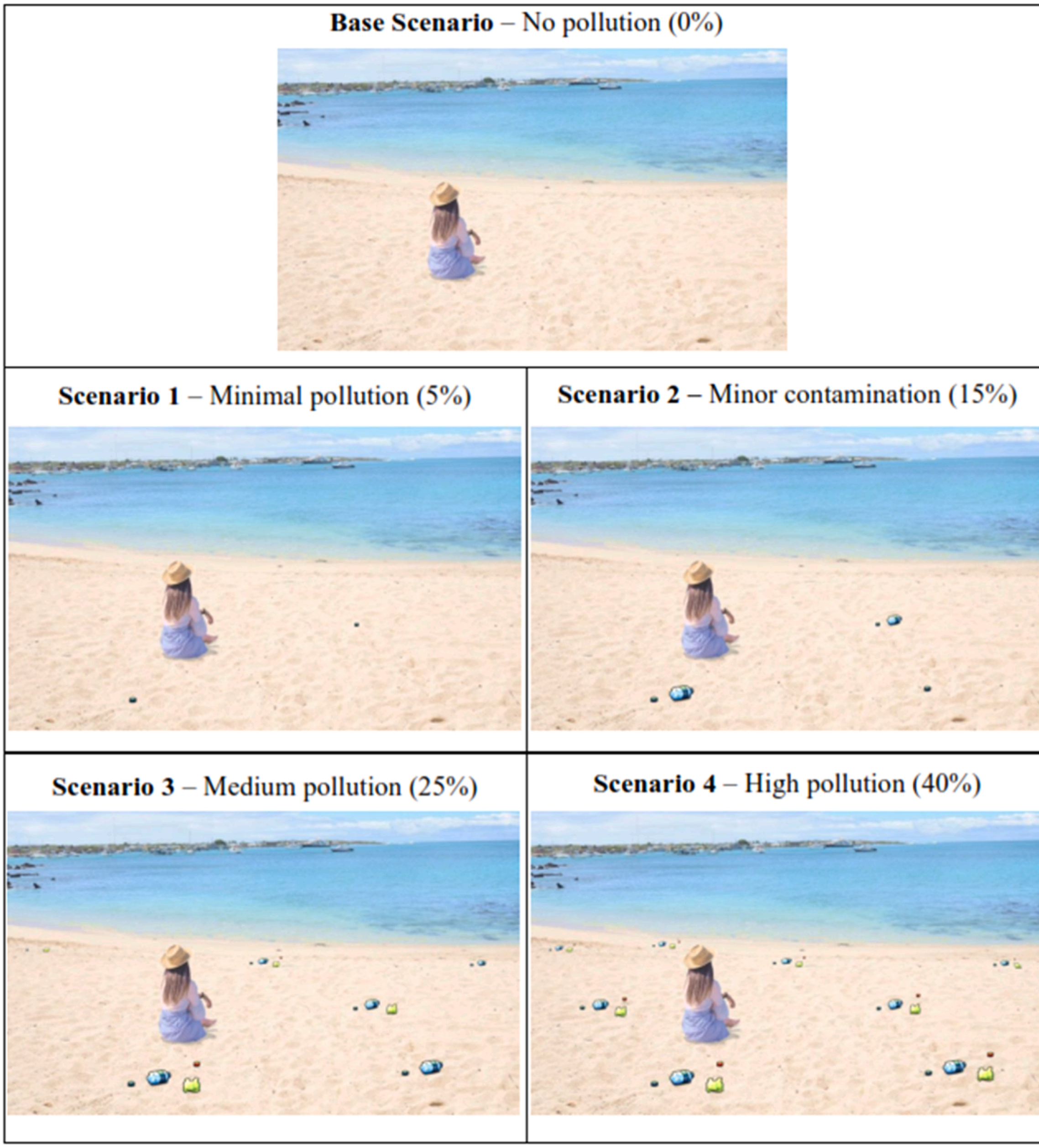
Table 3
Beach attributes (1 – 5 Likert scale).

	Near			Far/Uninhabited		
	Mode	Mean	SD	Mode	Mean	SD
Cleanliness (natural/organic waste)	5	4.23	0.92	5	4.35	0.95
Cleanliness (plastic waste)	5	4.51	0.67	5	4.63	0.64
Opportunity to observe wildlife	5	4.61	0.66	5	4.69	0.58
Vegetation of the place	5	4.21	0.87	5	4.39	0.81
Observable landscapes	5	4.35	0.78	5	4.49	0.75
Number of people on the beach	4	3.71	1.04	5	3.86	1.18

[1] Table A1 presents the results for testing various assumptions of our binary logistic models. The Durbin-Watson test confirms that the data meet the assumption of independence of observations. Since our independent variables include continuous data, we tested for a linear relationship between these variables and the log odds, with non-significant *p*-values indicating compliance with this assumption. Finally, the Variance Inflation Factor (VIF) values for all variables are below 10, confirming that the models do not suffer from multicollinearity.

In addition, the corresponding ordinal logit models satisfied the test of parallel lines, with p-values of 0.196 and 0.808 for Outcomes 1 and 2, respectively, supporting the proportional odds assumption.

[2] The results of the binomial logistic regression for the imbalanced outcomes are provided in the online supplementary material.



Annex 1. Plastic pollution scenarios.

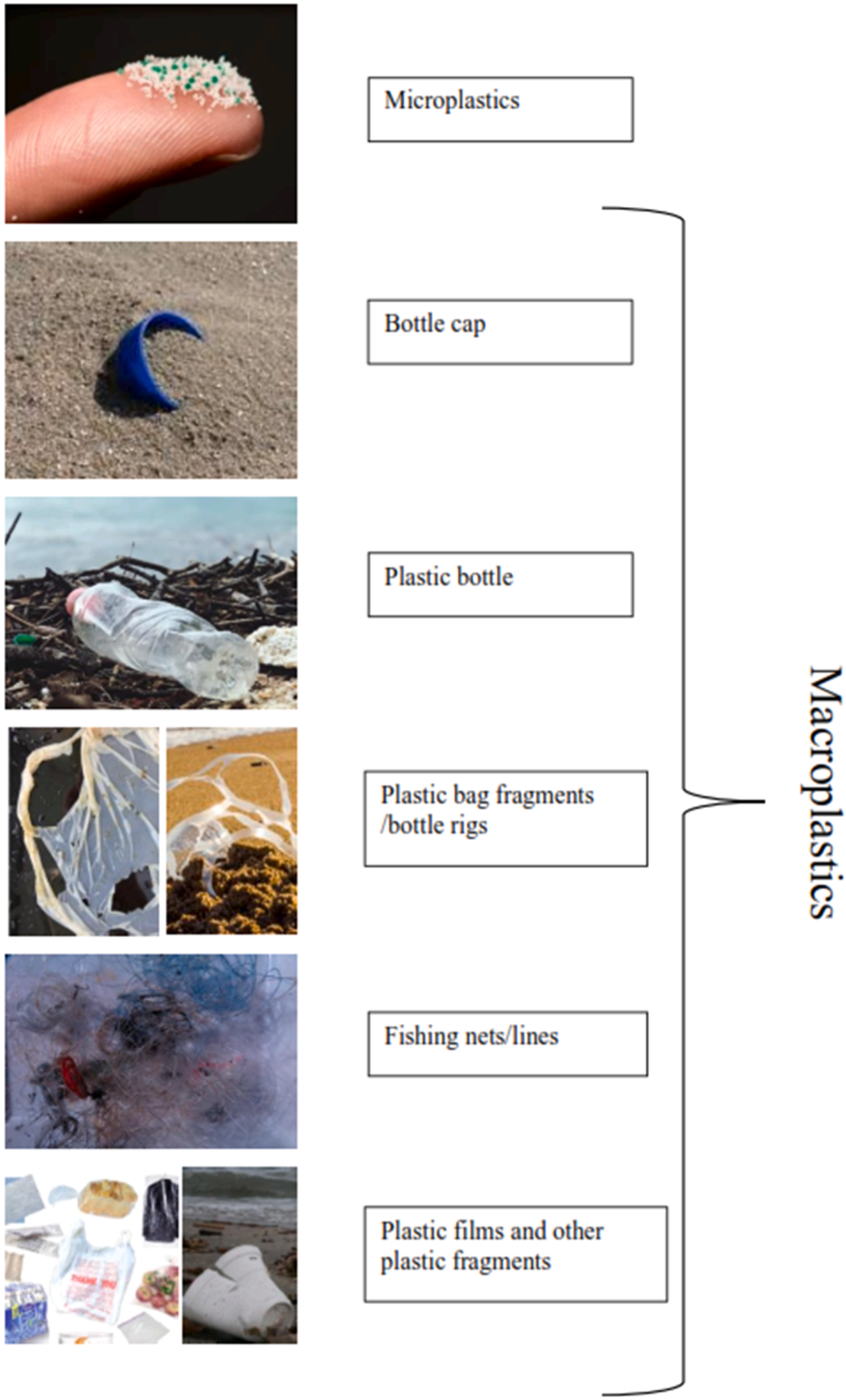
4.2. Beach attributes

Tourists stated high importance on environmental cleanliness (organic and plastic waste), as well as on opportunities for wildlife observation, vegetation of the place, and observable landscapes (see Table 3). Both remote beaches and those near populated ports have a mode score of 5 (extremely important) for these attributes, with mean ratings exceeding 4 (very important). While the number of visitors at the beach is also considered important, it was rated lower than the other attributes, with an average score below 4. For beaches near populated areas, the mode was 4, compared to a mode of 5 for remote beaches.

4.3. Plastic pollution scenarios

Using hypothetical beach pollution scenarios (see Annex 1), we applied a 1–5 Likert scale, where “1″ indicates no pollution and “5” the highest contamination level. Tourists selected their willingness to accept thresholds for different plastic types (see Annex 2). Results show an overall low willingness to accept, with a mode of 1 and mean values below 2 for macroplastics (see Fig. 2). Microplastics had the highest willingness to accept, with a mode of 2 and mean of 2.24. Chi-square and Mann-Whitney U tests showed significant differences *($P < 0.01$)* between domestic and foreign tourists, with domestic tourists showing lower willingness to accept levels across all plastic types. The instrument showed excellent reliability, with a Cronbach’s alpha of 0.94.

For the willingness to visit estimation we also used visual aids (see Annex 3). We tested three types of plastic waste: bottle caps, plastic bottles, and other plastic fragments. The results show that when there is one item m^{-2}, 80.1 % of tourists would still visit the beach if the item were bottle caps, 72 % for plastic bottles, and 74.5 % for other plastic fragments. However, despite their willingness to visit, tourists reported only average satisfaction. The average satisfaction level score for all three waste types was approximately 3 over 5 (see Fig. 3). As the amount of waste increases, both the percentage of willingness to visit and their satisfaction level decline. When there are 2 to 4 items m^{-2}, only 39 % to 48 % of tourists would visit the beach, with satisfaction level falling to



Annex 2. Types of plastic pollution.

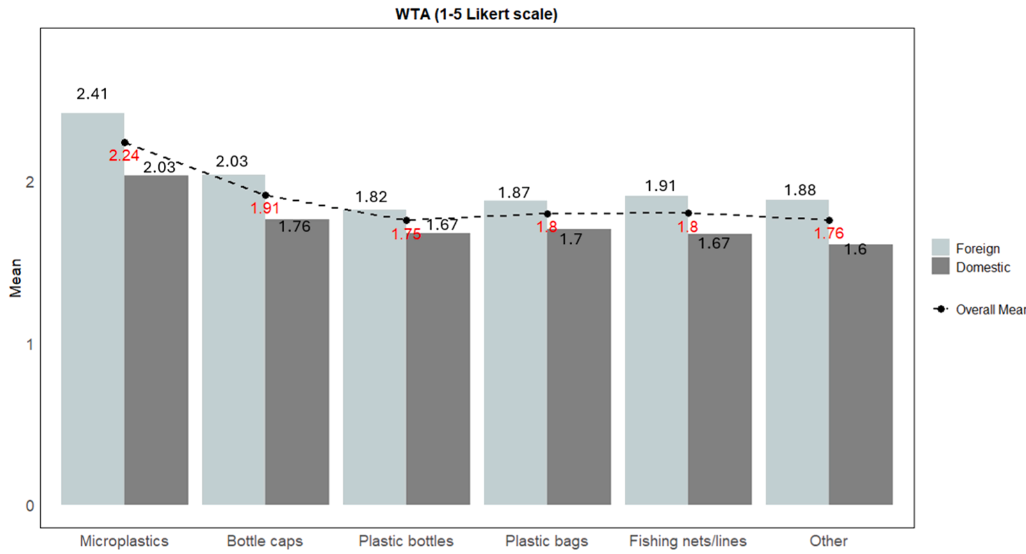
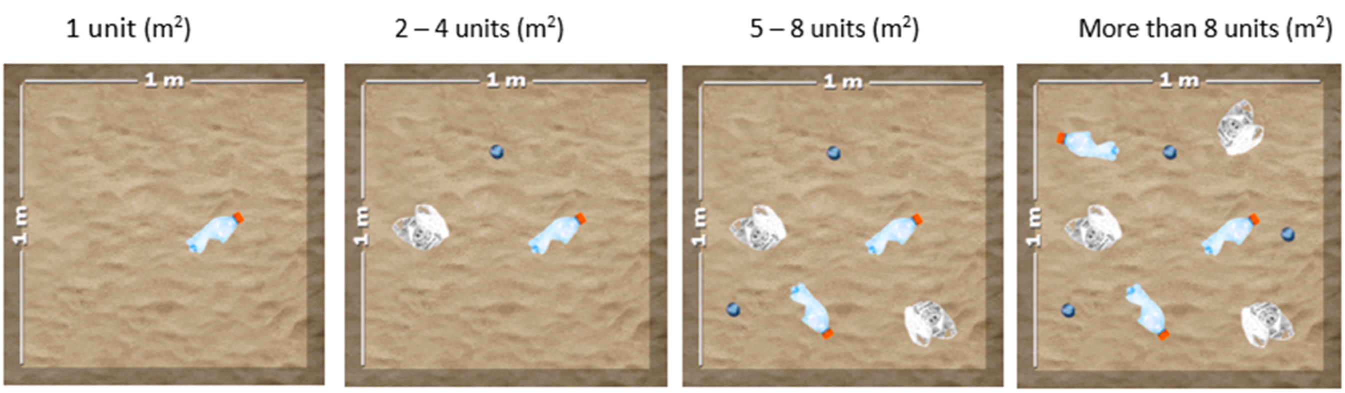


Fig. 2. Tourists' willingness to accept (average).



Annex 3. Willingness to Visit - visual AIDs.

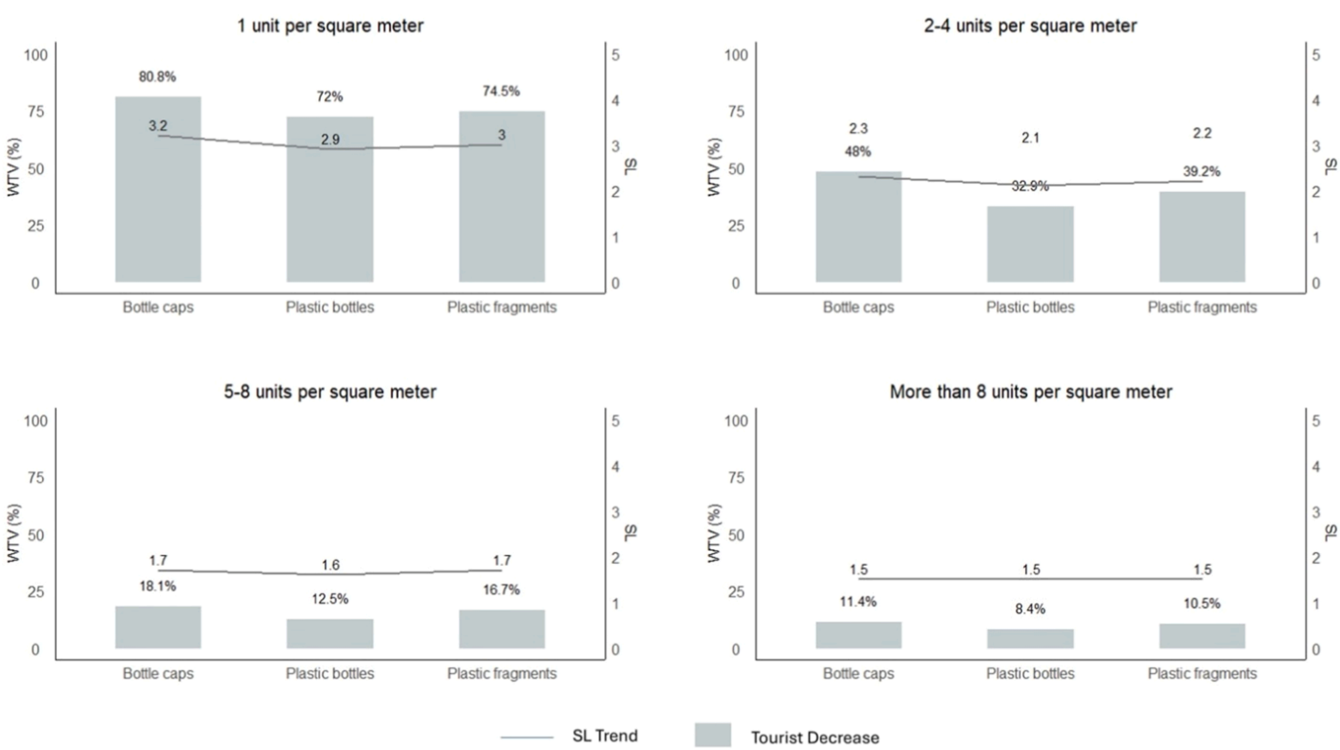


Fig. 3. Tourists' willingness to visit (WTV) and satisfaction level (SL).

Table 4
Willingness to return (1 – 5 Likert scale average).

	Microplastics	Bottle caps
Scenario (10 %)	3.89	3.71
Scenario (20 %)	3.28	3.05
Scenario (30 %)	2.70	2.42
Scenario (40 %)	2.20	1.96
Scenario (50 % >=)	1.94	1.71

around 2.1. At 5 to 8 items m^{-2}, the proportion drops to between 12.5 % and 18.1 %, with a satisfaction level of approximately 1.7. Finally, when the quantity of waste exceeds 8 items m^{-2}, fewer than 12 % of tourists would visit the beach, with a satisfaction level of 1.5 indicating very low satisfaction.

We assessed the willingness to return using microplastics and bottle caps as test debris. Our findings show that when 10 % of the touristic beaches in Galapagos are contaminated with either pollutant, the mode is 5, with an average willingness to return of 3.89 for microplastics and 3.71 for bottle caps, which falls between "3″ (would probably return) and "4″ (would likely return). However, as the percentage of contaminated beaches increases, the likelihood of tourists returning decreases (see Table 4). For instance, when 50 % or more of the beaches are polluted, the mode drops to 1, with an average willingness to return of 1.94 for microplastics and 1.96 for bottle caps, indicating a range between "1″ (would not return) and "2" (probably would not return). After conducting the Chi-square test and Mann-Whitney U test, we found no significant differences in willingness to return between national and foreign tourists, except when the contamination represents 20 % of the beaches for both pollutants. The reliability of the scale was high, with Cronbach's alpha values of 0.90 for microplastics and 0.89 for bottle caps.

4.4. Economic losses

Tourist spending in the Galapagos averages US$ 2671.15, including the Galapagos National Park entry fee and round-trip flights from mainland Ecuador. A *t*-test revealed significant differences between foreign and domestic tourists: $t(373) = -9.873$, $p < 0.000$. Foreign tourists spend an average of US$ 3851.33, while domestic tourists spend US$ 1085.52. For estimating economic losses from plastic pollution, we excluded flight costs (US$ 400 for foreigners, US$ 300 for Ecuadorians), resulting in adjusted averages of US$ 2419.47 overall, US$ 3520.79 for foreigners, and US$ 871.66 for domestic tourists. The differences between groups remain statistically significant after this adjustment and we used them alongside the willingness to return scores to estimate revenue losses under conservative and severe scenarios.

In the conservative scenario, we found that if 10 % of the beaches were contaminated with microplastics beyond the tourists' willingness to accept threshold, 4.1 % of foreign tourists would not return to Galapagos, resulting in an annual estimated economic loss of US$ 22.3 million (see Fig. 4). For domestic tourists, the reduction would be 6.3 %, leading to losses of US$ 7 million. With bottle caps as the contaminant, losses rise to US$ 35.6 million from a 6.6 % decline in foreign tourists and $ 9.3 million from an 8.5 % decline in domestic tourists. Therefore, under the conservative scenario, with 10 % of beaches contaminated, total economic losses would amount to US$ 29.2 million for microplastic contamination and US$ 44.9 million for bottle cap contamination (see Table A2 for detailed values).

As the percentage of contaminated beaches increases, so does the number of tourists choosing not to return to Galapagos, amplifying the economic impact. If contamination from microplastics affects 50 % or more of tourist beaches, we estimate a 39.1 % decline in foreign tourists and a 42.3 % decline in domestic tourists, resulting in projected losses of US$ 211.4 million and US$ 46.4 million, respectively. For contamination by bottle caps, the decrease would be 45.7 % of foreign tourists and 51.9 % of domestic tourists, with corresponding losses estimated at US$ 247 million and US$ 56.8 million.

In the severe scenario, the decline in tourists—and the resulting economic losses—grows significantly. If 10 % of the beaches were contaminated with microplastics, we estimate a 10.3 % decline in

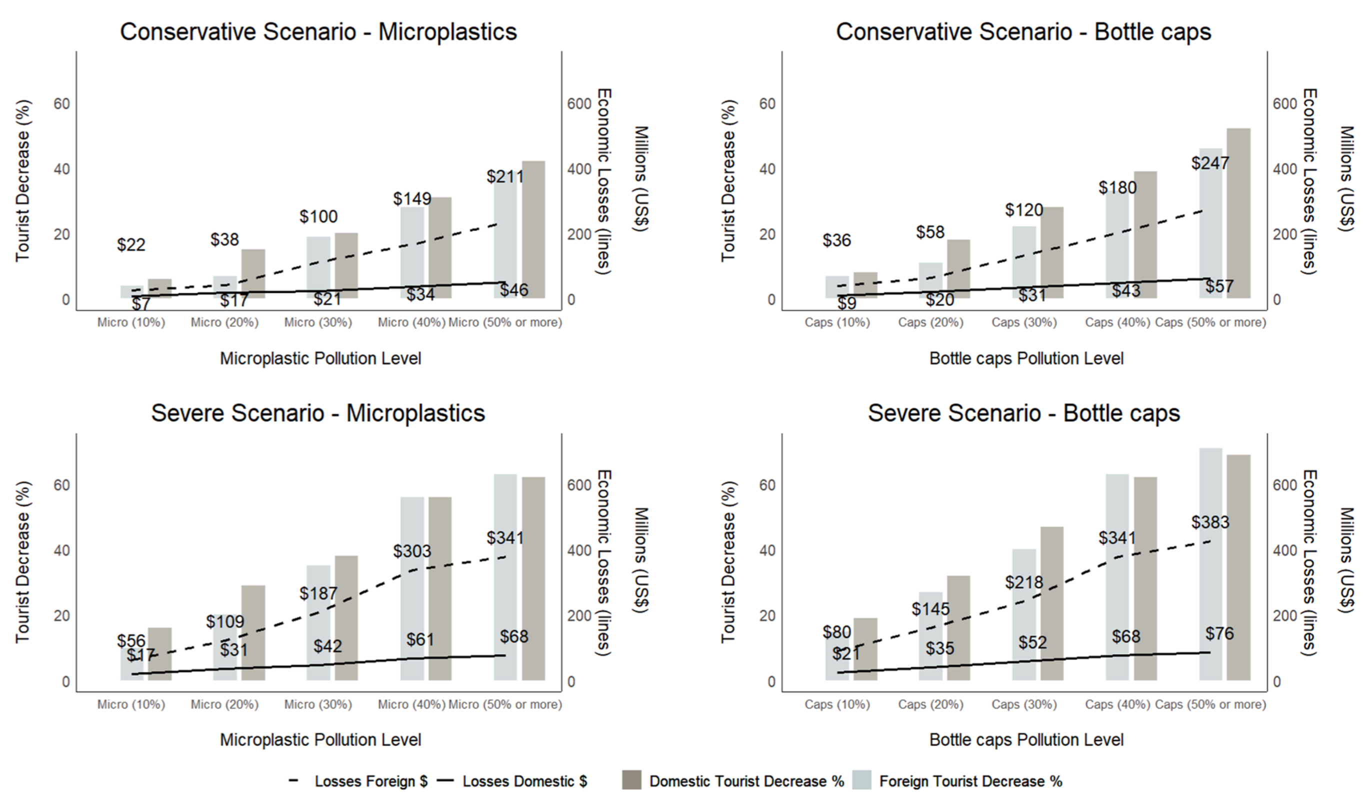


Fig. 4. Annual economic losses scenarios (US$).

foreign tourists and an 15.9 % in domestic tourists, resulting in losses of US$ 55.6 million and US$ 17.4 million, respectively. If the contamination consists of bottle caps, we estimate a 14.8 % reduction in foreign tourists and a 19 % reduction in national tourists, generating losses of US $ 80.1 million and US$ 20.9 million respectively. At 50 % of beaches contaminated with microplastics the decrease of foreign tourists will be 63 % and 61.9 % of domestic generating losses of US$ 340.5 million and US$ 67.8 million. For bottle caps we estimate a 70.8 % decrease in foreign tourists and 69.3 % of domestic ones with losses of US$ 382.8 million and US$ 75.9 million.

4.5. Model results

We applied the XGBoost algorithm to identify the independent variables with the highest gain across the different beach contamination scenarios, indicating their strongest contribution to reducing model error in the subsequent logistic regressions. Among the 28 candidate predictors (see supplementary material), we ranked variables by their average gain and grouped them by frequency of appearance within the top three ranks across scenarios, thereby isolating those consistently demonstrating the greatest predictive importance (see Fig. 5). In the first position, the top-ranked variables were *Expenditure* (33.3 %), *Age* (30 %), and *AE* (10 %). For the second position, the most important variables were *PPC_kg_capita* (16.7 %), *Age* (13.3 %), and *Expenditure, Income, Information*, and *LG*, each at 10 %. In the third position, the top variables were *Age* (30 %), *Information* (16.7 %), and *Expenditure* (13.3 %).

We incorporated the predictors identified by XGBoost into the binomial logit regression models.[3] As reported in Table 5, for the bottle-cap contamination outcome PPC_kg_capita, Information, and Education were significant ($p < 0.05$), whereas for the microplastic outcome PPC_kg_capita, Education, and Satisfaction were significant ($p < 0.05$). To assess robustness, we re-estimated the same models using ordinal logit and OLS regressions; the results, also presented in Table 5, were largely consistent across specifications, with Education losing significance only in the ordinal logit for the microplastic scenario.

As an additional robustness check, we re-estimated the binomial logit models by adding five predictors from the XGBoost ranking (see Table A3), expanding the covariate set from rank 3 to rank 5. In this extended specification, PPC_kg_capita remained significant for both outcomes, while Education retained significance only in the bottle-cap scenario compared to our initial binomial logit model.

In this sense after robustness checks our results show that PPC_kg_capita has a negative and statistically significant effect on both outcomes, indicating that tourists from countries with higher per-capita plastic consumption are more likely to return to the Galapagos when 30 % of beaches are contaminated with bottle caps or microplastics—levels exceeding the stated willingness-to-accept threshold; also, higher education reduced the probability of returning under bottle-cap contamination. It is important to emphasize that these models are designed to assess associations rather than establish causal relationships.

[3] For Outcome 1 (caps) and Outcome 2 (microplastics), the Omnibus tests yielded p-values of 0.000 and 0.005 (9 df), confirming the overall significance of both models. The Hosmer–Lemeshow goodness-of-fit test returned p-values of 0.013 and 0.930 (8 df), indicating an acceptable fit. Classification accuracy was 58.1% for Outcome 1 and 63.2% for Outcome 2, while the area under the receiver operating characteristic curve (AUC) was 0.661 and 0.644, reflecting limited but meaningful predictive power—both models generally rank positive cases above negatives, though not by a wide margin. The Nagelkerke R^2 values were 0.112 and 0.091 respectively.

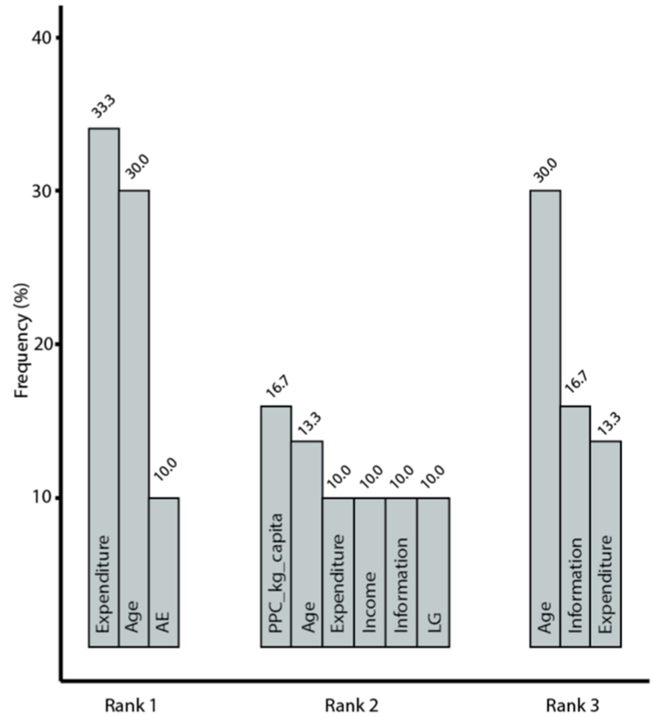


Fig. 5. XGBoost results by rank.

5. Discussion

Our research shows that tourists place a high value on cleanliness and natural features of Galapagos beaches. Cleanliness, specifically regarding plastic waste, has an average rating of 4.51 out of 5 (SD = 0.67) for beaches near populated areas, and 4.63 (SD = 0.64) for more remote beaches. It was the second most valued attribute, just behind the opportunity to observe wildlife attribute. This result aligns with previous studies emphasizing the critical importance of beach cleanliness to tourists. For example Chen and Bau (2016) identified environmental cleanliness as the most valued factor for tourists visiting Taiwanese beaches. Similarly, Lukoseviciute and Panagopoulos (2021) found that, irrespective of the season, beach cleanliness combined with infrastructure remained the most critical factor for visitors in Portugal. Comparable findings have been reported in Italy (Marin et al., 2009) and in Brazil (Rodella and Corbau, 2020).

Moreover, we observed that domestic tourists exhibited a lower willingness to accept compared to foreign tourists. This finding is particularly striking given that higher educational profile would generally suggest greater environmental awareness (Abdul-Wahab and Abdo, 2010; Tikka et al., 2000). We found significant differences in educational levels, significant differences in educational attainment, with foreign tourists exhibiting higher levels of education compared to domestic visitors ($\chi^2(5, N = 430) = 35.16$, $p < 0.001$). One possible explanation for the lower willingness to accept among domestic tourists could be a stronger sense of attachment or belonging to their country's tourist destinations (Kim and Lee, 2022; Kabote, 2020) which make them less tolerant to pollution in emblematic tourist destinations of their own country. However, our findings contrasts with Krelling et al. (2017), who reported no significant differences in pollution tolerance levels between Second Home Owners/Users (SHOU)—representing domestic tourists—and other tourists on Brazilian beaches

Regarding the willingness to visit, Balance et al. (2000) found that if pollution exceeds more than 10 large item per linear meter on Cape Town beaches, 97 % of surveyed tourists would choose not to visit. Similarly, Krelling et al. (2017) reported that on Brazilian beaches, more than 85 % of beachgoer would avoid visiting if pollution reached more

Table 5
Model results.

	Outcome: Bottle caps			Outcome: Microplastics		
	Binomial logit	Robustness check		Binomial logit	Robustness check	
		OLS[a]	Ordinal logit[b]		OLS[a]	Ordinal logit[b]
PPC_kg_capita	−0.019***	−0.004***	0.019***	−0.014**	−0.003**	0.013**
	(−0.007)	(−0.002)	(−0.006)	(−0.007)	(−0.002)	(−0.006)
Age	0.015*	0.003*	−0.018**	0.013	0.003	−0.017**
	(−0.008)	(−0.002)	(−0.007)	(−0.008)	(−0.002)	(−0.007)
Information	0.209**	0.049**	−0.182**	0.198*	0.046*	−0.173*
	(−0.106)	(−0.024)	(−0.091)	(−0.106)	(−0.024)	(−0.092)
Education	0.268***	0.061***	−0.248***	0.171**	0.038**	−0.104
	(−0.086)	(−0.019)	(−0.076)	(−0.087)	(−0.019)	(−0.074)
Satisfaction	−0.331*	−0.074*	0.348**	−0.414**	−0.095**	0.433***
	(−0.19)	(−0.043)	(−0.165)	(−0.188)	(−0.043)	(−0.161)
Anti-Exclusion	−0.045	−0.003	−0.049	0.09	0.021	−0.142
	(−0.171)	(−0.013)	(−0.145)	(−0.171)	(−0.039)	(−0.147)
Beach	0.031	0.009	−0.028	0.031	0.007	0.001
	(−0.045)	(−0.011)	(−0.039)	(−0.045)	(−0.01)	(−0.038)
Limits to Growth	−0.0004	−0.0001	0.07	0.072	0.016	−0.027
	(−0.145)	(−0.011)	(−0.125)	(−0.146)	(−0.034)	(−0.123)
Expenditure	0.00004	0.00001	−0.00003	0.00002	0.00001	−0.00004
	(−0.00005)	(−0.00001)	(−0.00004)	(−0.00005)	(−0.00001)	(−0.00004)
Constant	−0.446	0.365		−0.654	0.355	
	(−1.128)	(−0.251)		(−1.12)	(−0.258)	
Observations	339	339	339	337	337	337
Adjusted R^2		0.059			0.042	
Log Likelihood	−220.121	−231.082	−486.863	−217.903	−228.854	−505.305
Akaike Inf. Crit.	460.241	484.163	999.73	455.806	479.708	1036.61
Residual Std. Err.	0.486 (df = 329)			0.484 (df = 327)		
F Statistic		3.370*** (df = 9; 329)			2.643*** (df = 9; 327)	

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.
[a] Binary outcome: 1: won't return; 0: will return.
[b] Ordinal outcome: 1–5 Likert scale; 5: will return.

than 15 items m^{-2}. In our worst-case scenario—where pollution exceeds 8 items m^{-2}—over 88 % of tourists would avoid the beach: 88.4 % for bottle caps, 91.6 % for plastic bottles, and 89.5 % for plastic fragments.

Satisfaction levels, measured in a 1–5 Likert scale would fall from around 3 when the scenario is 1 item m^{-2} to around 1.5 for the worst scenario (more than 8 items m^{-2}). This decline could have adverse effects, as studies have shown that low satisfaction reduces the likelihood of returning to the place (Hosany et al., 2017; Dodds and Holmes, 2019; Hasan et al., 2024) and recommending the destination (Triantafillidou and Petala, 2016; Prebensen et al., 2010). Additionally, Qiang et al. (2020) reported that dissatisfaction due to plastic and can waste on beaches along the East China Sea led to shorter stays, negatively impacting tourism revenue.

As pollution levels increased, both the willingness to accept and willingness to return declined. Our findings align with those of Hayati et al. (2020), who used six hypothetical pollution scenarios to estimate visitors' acceptance levels and found that higher pollution levels corresponded to lower acceptance scores, indicating reduced tolerance. In our study, we estimate that tourists spend an average of US$ 2671 per trip to the Galapagos, including round-trip airfare to Ecuador mainland and the Galapagos National Park entrance fee, with an average stay of seven days. This figure is lower than the estimate by Perez Loyola et al. (2021) who reported an average expenditure of US$ 4690 for the same duration.

However, compared to earlier data, our estimate represents a nominal increase: in 2011, the Galapagos Tourism Observatory reported an average expenditure of US$ 1807 (excluding airfare and the Galapagos National Park entrance fee), which rose to US$ 2206 in 2012 when these costs were included (GTO, 2011) (GTO, 2012). For calculating economic losses from plastic pollution, we excluded the average cost of round-trip airfare, resulting in an adjusted average expenditure of US$ 2419. This adjustment reflects the fact that airlines servicing the Galapagos (e.g., Avianca and LATAM) are international carriers, meaning that most of the airfare revenue does not remain in the local Galapagos economy.

Using our willingness to return data, we developed two scenarios to estimate potential economic losses. In the *conservative* scenario, annual losses could range from US$ 29.2 to US$ 303.8 million, while in the *severe* scenario, losses could range from US$ 73 to US$ 458.7 million. Similar studies reflect these potential impacts as well: English et al. (2019) estimated that doubling marine debris could reduce annual tourism spending by US$ 414 million in Orange County, California; US$ 218 million in coastal Ohio; US$ 254 million in coastal Delaware and Maryland; and US$ 113 million in coastal Alabama. Qiang et al. (2020) found that cleaner beaches could increase tourist spending by 3.95 % to 32.23 %. In a worst-case scenario, Krelling et al. (2017) estimated losses of US$ 8.53 million due to pollution on Pontal do Paraná Beach, Brazil. Furthermore, following severe storms in 2011, debris accumulation on South Korea's Geoje Island beaches led to a 63 % drop in visitors, causing estimated losses of US$ 29 to 37 million (Jang et al., 2014).

After conducting binary logistic regressions with robustness checks, we found that tourists from countries with higher per capita plastic consumption exhibit greater tolerance or acceptance of plastic waste —an insight that has not been previously documented in this context. These tourists are more likely to consider returning to the Galapagos, even when contamination levels exceed their stated willingness to accept threshold. While comparative studies for direct analysis are lacking, one plausible explanation for this observation is that individuals from high-plastic-consumption environments may have heightened exposure to plastic waste, leading to increased acceptance or desensitization. Previous research has identified associations between plastic usage and environmental awareness or behavior (Senturk and Dumludag, 2022; Permana et al., 2020).

Finally, our model shows the higher the level of education of tourists, the greater the likelihood of not returning to the Galapagos due to potential contamination levels. This finding is significant, as in February 2024 the entry fee to the Galapagos National Park Galapagos National Park was increased (GCSRG, 2024) making the destination more expensive and potentially attracting higher-income individuals.

Typically, those with higher incomes also have higher levels of education (Gómez-Méndez and Amornbunchornvej, 2024; Lattimore et al., 2023), which suggests they may be less willing to visit the Galapagos if pollution on its beaches increases.

6. Conclusions

Despite local bans on single-use plastics[4] (e.g., straws, plastic bags, non-returnable bottles), the Galápagos Islands continue to face significant marine plastic pollution. Much of this waste originates outside the archipelago, underscoring the limits of local policies in addressing a global problem (Benito-Kaesbach et al., 2024; Sánchez-García and Sanz-Lázaro, 2023). The worldwide rise in plastic production and waste further increases the risk of accumulation in marine ecosystems, including those surrounding the Galápagos (Lebreton and Andrady, 2019). Estimating the ecological and economic impacts of this growing threat is therefore essential.

Our study provides the first in-depth assessment of how marine plastic pollution affects both tourist perceptions and economic outcomes in the Galápagos. Results show that tourists are highly sensitive to beach cleanliness: greater plastic waste significantly reduces both satisfaction and willingness to visit, with the likelihood of returning falling sharply as the share of polluted beaches increases. This effect is strongest among foreign visitors, whose spending constitutes a major share of tourism revenue.

Under a conservative scenario, annual economic losses could reach US$ 303.8 million, rising to US$ 458.7 million under severe contamination. Tourist numbers may decline by 50–70 % when more than half the beaches are polluted. Excluding atypical years such as 2020–2021 (COVID-19) and 2023 (post-reopening surge), tourism has shown steady growth, suggesting that future losses from plastic pollution will escalate as visitation rises. Using XGBoost and binary logistic regression, we identified key factors shaping willingness to return: tourists from nations with high per-capita plastic consumption exhibit greater tolerance for pollution, whereas those with higher education are less likely to return under degraded conditions.

This research represents the first in-depth study of its kind for the Galapagos, providing a foundation for informed policy-making. By underscoring the economic consequences of plastic pollution to the tourism sector, our findings seek to encourage a greater number of studies in this area that allow targeted interventions to reduce waste and enhance environmental protections. Sustaining the Galapagos as a premier ecotourism destination will require robust waste management strategies and public awareness initiatives that preserve both the islands' ecological integrity and economic viability, ensuring the Galapagos remain an iconic, sustainable destination for generations to come.

Data availability

The dataset and supplementary materials supporting the findings of this study are openly available at https://data.mendeley.com/datasets/f942zn23b2/2.

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Ethics approval statements

This study was approved by the Human Research Ethics Committee of the San Francisco University of Quito "CEISH-USFQ" (approval no.2023–142IN) on January 11, 2024. All participants provided written informed consent prior to participating.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT in order to improve the readability and language of the manuscript. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

CRediT authorship contribution statement

Pablo D. Llerena: Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Henry Cárdenas-Campoverde:** Writing – review & editing, Software, Methodology, Formal analysis. **Carlos F. Mena:** Project administration, Funding acquisition, Conceptualization, Resources. **Susana A. Cárdenas:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Pablo Llerena reports financial support was provided by University of Exeter. Carlos Mena reports financial support was provided by University of Exeter. Susana Cardenas reports financial support was provided by University of Exeter. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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[4] Resolution No.05-CGREG-2015

Appendix A

Table A1
Hypothesis testing for our outcome models.

	Bottle caps	Microplastics
Ho: Independence of observations		
Durbin-Watson	1.840	2.034
Ho: Linear relationship between continuous variables and the log odds		
P-Value		
Ln(PPC_kg_capita[a]) * PPC_kg_capita	0.949	0.430
Ln(Beach) by Beach	0.239	0.713
Ln(Expenditure) by Expenditure	0.243	0.265
Variance Inflation Factor (Multicollinearity)		
PPC_kg_capita	1.733	1.735
Age	1.475	1.479
Information	1.067	1.067
Education	1.094	1.098
Satisfaction	1.109	1.109
Anti-Exclusion	1.266	1.264
Limits to Growth	1.217	1.212
Beach	1.080	1.082
Expenditure	1.548	1.551

[a] PPC_kg_capita: Yearly plastic consumption per capita (kg).

Table A2
Tourist decreased and economic losses (US$ thousands).

	Conservative scenario				Severe scenario			
	Foreign decreased	Domestic decreased	Foreign losses ($)	Domestic losses ($)	Foreign decreased	Domestic decreased	Foreign losses ($)	Domestic losses ($)
Microplastics (10 %)	4.1 %	6.3 %	22,255	6955	10.3 %	15.9 %	55,638	17,388
Microplastics (20 %)	7.0 %	15.3 %	37,834	16,809	20.2 %	28.6 %	109,050	31,299
Microplastics (30 %)	18.5 %	19.6 %	100,148	21,446	34.6 %	38.1 %	186,944	41,732
Microplastics (40 %)	27.6 %	31.2 %	149,110	34,197	56.0 %	56.1 %	302,671	61,439
Microplastics (50 % ≥)	39.1 %	42.3 %	211,424	46,369	63.0 %	61.9 %	340,505	67,814
Bottle caps (10 %)	6.6 %	8.5 %	35,608	9274	14.8 %	19.0 %	80,119	20,866
Bottle caps (20 %)	10.7 %	18.0 %	57,864	19,707	26.7 %	32.3 %	144,659	35,356
Bottle caps (30 %)	22.2 %	28.0 %	120,178	30,719	40.3 %	47.1 %	218,101	51,585
Bottle caps (40 %)	33.3 %	39.2 %	180,267	42,891	63.0 %	62.4 %	340,505	68,394
Bottle caps (50 % ≥)	45.7 %	51.9 %	247,033	56,802	70.8 %	69.3 %	382,789	75,929

Table A3
Robustness check.

	Outcomes	
	Bottle caps (1)	Microplastics (2)
PPC_kg_capita	−0.026***	−0.021**
	−0.009	−0.009
Age	0.023**	0.017*
	−0.01	−0.01
Information	0.157	0.218*
	−0.117	−0.118
Education	0.262***	0.14
	−0.096	−0.096
Satisfaction	−0.338	−0.388*
	−0.209	−0.205
Limits to Growth	−0.205	−0.058
	−0.189	−0.189
Beach	0.032	0.019
	−0.052	−0.052
Limits to Growth	0.136	0.088
	−0.218	−0.219
Expenditure	0.00001	0
	−0.0001	−0.0001
Income	0.023	0.042
	−0.047	−0.047
Participation[a]	0.239	0.117
	−0.291	−0.295

(*continued on next page*)

Table A3 (*continued*)

	Outcomes	
	Bottle caps (1)	Microplastics (2)
BN[b]	−0.112	−0.058
	−0.17	−0.168
Gender	0.196	0.481*
	−0.255	−0.255
Statement[c]	0.13	0.017
	−0.144	−0.142
Constant	−0.312	−0.506
	−1.437	−1.417
Observations	296	295
Log Likelihood	−187.847	−186.744
Akaike Inf. Crit.	405.694	403.487

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

[a] Willingness to participate/support activities that reduce pollution (yes/no).

[b] Balance of nature dimension (Likert scale).

[c] Mandatory Use of Recycled Materials Despite Higher Production Costs (Likert scale).

Data availability

I have share the link to my data/code at the Attach File step Database2 (Original data) (Mendeley Data)

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