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Responsible Tourism Made Easy: Carbon Footprint Tracked by your Bank for Sustainability

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Abstract
The legacy we leave to future generations is shaped by the way we consume, move and inhabit our environment. Despite increasing climate commitments, household carbon emissions remain a major blind spot in Spain's sustainability transition. This study addresses the problem of identifying the main drivers of individual emissions and their linkage with tourism-related behavior. Using a dataset of 1,017 individuals with detailed sociodemographic, professional and behavioral variables, total household emissions are disaggregated into mobility, restaurants, housing and shopping categories and cross-referenced by age, gender, region, employment status, income, telework days, nationality and household composition. Statistical analyses, including ANOVA and t-tests, are employed to highlight significant differences and patterns across demographic groups, taking into account indicators of sustainability-related attitudes and behaviors. The research aims to understand the underlying factors and inequalities of household carbon footprints, with a focus on implications for the tourism sector, which contributes significantly to national emissions, particularly through transport. Results show that variables such as age, income and household size shape carbon footprints and tourism demand patterns. Its originality lies in combining automatic carbon assessment tools with digital banking data to track consumption-based emissions at the individual level. Practically, the study offers data-driven recommendations for policymakers and businesses to design tailored sustainability interventions and theoretically, it advances the discussion on behavioral and technological pathways to low-carbon tourism. The findings underscore the need for targeted, data-driven sustainability policies that integrate technological innovation and behavioral insights. By empowering citizens through digital monitoring and awareness, the sector can foster environmental stewardship and strengthen Spain's transition toward a competitive, net-zero future.

Key Words: sustainable tourism; carbon footprint; green banking; greenhouse gas (GHG) emissions; digital tools for sustainability; climate awareness in tourism; socioeconomic factors.

JEL Classification: Q54, L83, R11, C81

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1. Introduction

One of the main challenges facing society today is climate change. Individuals are beginning to recognize the need to change some of their consumption habits to reduce their carbon footprint. In this effort, banking apps can become important allies. The growing concern for sustainability and the environment is encouraging financial institutions to seize the opportunity to contribute to the cause. To do so, many banks are not only reducing their own emissions but also helping their customers reduce theirs. Specifically, an increasing number of European banks are introducing features in their banking apps that allow users to track the carbon emissions associated with their behavior. It is evident that individuals' financial transactions can effectively reflect the behaviors and lifestyles they follow. This information can then be used to guide consumers on the sustainability of their activities during both work and leisure time. These functionalities are especially useful for the tourism sector, as they can help travelers track, compare and improve the environmental impact of their recreation choices, aligning the industry with global sustainability goals.

Tourism has become a major driver of global GHG emissions through energy-intensive transport, accommodation and hospitality services, making the decarbonisation of tourism demand a central policy challenge in many destinations (Gössling & Peeters, 2015). Existing studies document substantial tourism-related carbon footprints at the destination level, yet there is still limited understanding of how household-level consumption patterns translate into tourism emissions across different sociodemographic groups (Dong et al., 2024; Devkota et al., 2023). Within this context, analysing household carbon footprints linked to tourism-relevant spending provides a timely contribution to debates on sustainable tourism transitions and low-carbon travel behaviour. In this regard, tourism has developed into one of the most influential industries underpinning the global economy. As the climate crisis intensifies, mitigating its effects and limiting global warming to 1.5°C through reductions in carbon footprint have become urgent imperatives for the leisure industry (Higham et al., 2021). The tourism sector has faced major disruptions due to the COVID-19 pandemic but is now recovering and evolving to meet new consumer preferences oriented toward sustainability and resilience (Abou-Shouk, 2023; Carlisle et al., 2023). Santos et al. (2024) provide essential insights for the event industry by focusing on the design and promotion of more sustainable tourism in the post-pandemic era. It attracts tourists interested in experiences that stimulate green initiatives (Güneş, 2022). However, Toscani et al. (2024) examines the rapidly expanding field of environmental sustainability, highlighting that despite its growth, the tourism industry often incurs significant environmental impacts such as carbon emissions, waste generation and resource consumption.

Achieving real impact relies on a unified effort among governments, businesses, financial institutions and society at large, alongside millions of individual choices (Séraphin & Chaney, 2023). Today's travelers are increasingly motivated to align their spending with environmental values. Access to reliable carbon footprint data empowers individuals to make informed and responsible decisions, driving the transition toward a low-carbon economy (Dong et al., 2024). Schleich and Alsheimer (2024) suggest that raising awareness about personal emissions can motivate more climate-friendly behavior, but emphasizing climate targets alone may have limited influence. Promotional marketing strategies, including the use of digital channels such as social media, play a crucial role in increasing awareness and promoting sustainable tourist behavior in destinations. Devkota et al. (2023) confirm that sustained promotional efforts enhance the connection between tourists and the destination, which positively influences sustainable behaviors like waste reduction, energy conservation and support for local businesses. Furthermore, Dávid and El Archi (2024) underscore the role of smart solutions in promoting sustainability within tourism management by enabling resource optimization, waste reduction and environmental risk mitigation. Their work highlights how technologies like AI, IoT and blockchain facilitate ecological practices that align tourism with environmental protection, as evidenced by studies on eco-friendly technologies and carbon emissions in high-tourism countries. Streimikiene and Kyriakopoulos (2024) also highlight the critical role of policy, technology adoption and efficiency improvements in achieving decarbonization goals within tourism destinations. The study focuses on the transport and hospitality sectors, which are the primary contributors to GHG emissions in tourism. Kanwal et al. (2024) provide a critical analysis of the carbon footprint associated with tourism activities, also highlighting transportation, accommodation and infrastructure as major contributors to GHG emissions. It is noteworthy that Tothova et al. (2022) highlights the substantial carbon footprint of the tourism sector, noting that tourism generates significant emissions, consumes vast amounts of energy and water and produces waste, with the hotel industry projected to account for up to 21% of tourism's ecological footprint by 2035.

Nevertheless, previous research has mostly relied on self-reported travel surveys and aggregate tourism statistics to estimate emissions, which constrains the precision and behavioural granularity of existing evidence. While these studies confirm that factors such as income and household composition are key drivers of tourism emissions, there is still a lack of empirical research using consumption data to quantify how different sociodemographic profiles shape tourism-related carbon footprints at the household level (Jack & Ivanova, 2021). This study contributes to the literature by linking banking transaction data to tourism-relevant emission categories and exploring how sociodemographic characteristics may help predict household carbon footprints, incorporating indicators reflecting sustainability-related attitudes and behaviors.

On this matter, the ecological footprint (or eco-footprint) and the carbon footprint are both essential metrics for quantifying the environmental impact of individuals, organizations and nations. The ecological footprint is a comprehensive indicator that measures the total impact of human activities on the planet by quantifying the amount of natural resources and land area required to sustain a given lifestyle and absorb the waste produced, including GHG emissions (Global Footprint Network, 2024). In contrast, although a widely accepted and concrete definition of a carbon footprint does not exist at present, the notion of what a footprint is does exist. A mostly recognized concept was proposed by Wiedmann and Minx (2008) and the carbon footprint specifically refers to the total GHG emissions, expressed in carbon dioxide equivalent tonnes (CO_2-equivalent), generated directly or indirectly by an individual, organization, product, or event through daily activities that contribute to climate change. For organizations, these emissions are categorized as direct emissions from sources owned or controlled by the organization, such as fuel combustion or company vehicles and indirect emissions, like those from purchased electricity (GHG Protocol, 2024). For individuals, understanding both metrics is crucial for recognizing not only how personal habits contribute to climate change but also how they affect overall global sustainability, enabling more responsible choices to reduce total environmental impact.

Building on this framework, the research aims to achieve two main objectives: (1) to identify how demographic, socioeconomic and behavioral factors drive household carbon footprints in Spain and (2) to examine the role of digital banking tools in enhancing individual awareness and facilitating sustainable travel and entertainment decisions. Specifically, the study seeks to answer two research questions (RQ1 and RQ2) through the following formal hypotheses (H1a-H1h, H2a and H2b), which provide the explicit theoretical framework guiding the statistical analyses:

RQ1: How do factors such as age, gender, income, profession, employment status, telework days, region, nationality and household composition influence the carbon footprint?

H1a: Higher income levels are positively associated with larger carbon footprints, particularly in mobility domains.

H1b: Younger age groups exhibit higher emissions in restaurants and leisure domains due to frequent social/tourist activities.

H1c: Males show higher emissions across all domains vs. females

H1d: Self-employed individuals have higher carbon footprints than employed/salaried workers, especially mobility/housing.

H1e: Households with fewer telework days show elevated mobility and housing emissions

H1f: Larger households (more dependents) show elevated total emissions, particularly housing/transport due to increased resource needs.

H1g: Carbon footprints significantly vary across regions (autonomous communities), reflecting territorial differences in energy sources, infrastructure and mobility patterns.

H1h: Nationality influences carbon footprint levels, with foreign residents potentially showing different emission patterns linked to lifestyle and consumption habits.

RQ2: What differentiated incentive mechanisms best reduce emissions in tourism sectors with varied consumer behavior and sociodemographic characteristics?

H2a: Self-perceived sustainable individuals have lower emissions across domains.

H2b: Individuals willing to follow tourism recommendations generate significantly lower emissions across all domains.

Answering these questions provides actionable insights for policymakers, financial institutions and tourism stakeholders to collaboratively design data-driven, equitable and effective sustainability strategies. These strategies aim to maximize environmental performance, promote responsible tourism and support Spain's commitments to achieving net zero emissions in line with global climate goals. The study also contributes theoretical advancements and outlines future research avenues in sustainable tourism development leveraging technology and behavioral insights.

To address these aims, the study uses a sample of 1,017 Spanish households and exploits anonymised digital banking transaction data to construct tourism-relevant carbon footprint indicators across multiple consumption categories. The empirical analysis relies on validated one-way analysis of variance (ANOVA) and post-hoc tests to identify statistically significant differences between sociodemographic groups, as well as independent t-tests. This data-driven approach is original in that it combines high-resolution financial data with carbon accounting to study tourism-related emissions at the household level, offering new insights for both theory and practice. For researchers, the findings refine understanding of how sociodemographic segmentation can explain tourism emission patterns; for policymakers and industry practitioners, they inform the design of targeted, carbon-differentiated tourism instruments.

The paper is organised as follows: the next section reviews the relevant literature on tourism emissions, household carbon footprints and digital consumption data; the methods section describes the dataset, variables and statistical procedures; the subsequent sections present and discuss the empirical results; and the final section outlines the main conclusions, policy implications, the study's limitations and avenues for future research. Several appendices have been included containing detailed statistical results to support the main findings.

2. Literature review

2.1 Digital tracking of carbon footprints

The carbon footprint, it has been widely used to monitor the degree of human pressure on the ecological environment and to measure climate change and environmental sustainability. Yan and Meng (2020) present a comprehensive bibliometric analysis of carbon footprint research, applying knowledge mapping techniques to explore the field's evolution and research framework. According to a more recent bibliometric study by Dong et al. (2024), carbon footprint research has undergone significant growth and diversification between 2007 and 2022. The field covers a broad range of academic disciplines, notably environmental sciences, sustainable technology and engineering. Methodologically, life cycle assessment (LCA), input-output analysis (IOA) or hybrid approaches (Han et al., 2022; Gao, 2013) and the Intergovernmental Panel on Climate Change (IPCC) accounting methods are predominant in carbon footprint calculations together with emission mitigation strategies across multiple scales, including products, organizations and regional to national levels (IPCC, 2022).

In addition, personal consumption choices significantly contribute to climate change and can be estimated at the population level by calculating an individual's carbon footprint, which in Spain can be done using data from the National Statistics Institute (INE, 2024), specifically the Household Budget Surveys (HBS). The HBS is based on a carefully designed sampling process: INE selects 2,275 census tracts based on socioeconomic factors, then randomly chooses ten dwellings in each tract, inviting all households to participate. Each household is surveyed for two years in a rotating panel design. During the survey, households record their spending over two weeks using standardized notebooks, with purchases categorized according to the standard five-digit Classification of Individual Consumption by Purpose (COICOP) system and including quantity and price data. This method was explored in Victoria's (2016) study, which confirms that carbon footprint increases with income—higher income leads to greater consumption and, consequently, higher emissions.

Furthermore, Spain's National Inventory of Greenhouse Gases (GEI), published by the Ministry for the Ecological Transition and the Demographic Challenge (MITECO), provides detailed data on total national emissions and removals of GHG from all sectors—not just household or individual emissions. The inventory includes emissions from transportation, industry, electricity generation, agriculture, residential use and more, along with carbon sinks such as forests. The latest edition, approved on December 20, 2024, covers data up to 2023 (MITECO, 2024a). In 2023, Spain's gross GHG emissions amounted to approximately 270 million tons of CO_2-equivalent, a 7.6% decrease compared to 2022. After accounting for land use, land-use change and forestry, net emissions were around 218.9 million tons. The transportation sector was the largest emitter (around 32% of the total), followed by industry, electricity generation, agriculture and residential energy use. Spain offers open access to an interactive emissions data portal (MITECO, 2024b), allowing users to explore emissions by year, gas and economic sector.

In this regard, carbon footprint information plays a significant role in consumer decision-making processes. Studies show that providing consumers with clear, contextualized carbon footprint data—especially when presented using traffic-light color codes or monetary terms—can effectively reduce the purchase of high-carbon products and lower overall carbon emissions related to food choices (Beyer et al., 2023). Pérez and Vargas (2018) investigate how providing consumers with information about the carbon footprint of food products influences their purchasing decisions. The findings suggest that carbon footprint labeling can effectively promote more sustainable consumption patterns by encouraging environmentally conscious food choices. Meyerding et al. (2019) also highlight the potential of carbon footprint information as a tool for guiding consumer behavior towards sustainability. However, despite general awareness of carbon labels, a gap remains between consumer knowledge and actual behavior change, highlighting the importance of how information is communicated (Imran et al., 2025).

Household carbon emission patterns derived from banking transaction data reveal direct tourism relevance, as mobility and restaurant spending constitute primary tourism expenditure categories (Trendl et al., 2022; Higham et al., 2021; Gössling & Peeters, 2015). High-income households exhibit higher mobility emissions, correlating strongly with international travel propensity, while larger households show elevated restaurant emissions linked to domestic tourism (Becken, 2002). These patterns mirror tourism sector findings where transport dominates carbon footprints, confirming banking data's utility for tourism emission profiling (Tothova et al., 2022). Digital tracking thus enables targeted interventions—green loans for low-carbon destinations, emission-based tourism taxes—transforming household-level insights into sector-wide sustainability strategies (Dávid & El Archi, 2024).

In this sense, amid the pressing global challenge of the climate crisis, developing digital apps that offer feedback on consumers' consumption patterns represents a novel evolution of carbon footprint calculators (CFC), enhancing consumer awareness and fostering more informed, eco-friendly choices. These innovations underline carbon footprint digital feedback as promising strategy to guide consumers toward more environmentally responsible behaviors and support the transition to a low-carbon economy, although cost and personal preferences continue to influence final decisions (Bobert & Fofana, 2022). Hoffmann et al. (2022) examine the factors influencing consumers' intentions to adopt carbon footprint tracking apps. Their survey results from Germany reveal that perceived usefulness and ease of use are the strongest predictors of adoption intention, supported by consumers' environmental awareness and social influences. Trust in the app and concerns over data privacy also play vital roles in users' willingness to use such technologies. West et al. (2016) describe the development and use of REAP Petite, a household-level CFC designed to communicate the impacts of consumption and explore mitigation options, enabling users to compare their footprint with others in their community and receive tailored pledges to reduce their carbon impact. However, despite the potential of digital carbon footprint tools to promote sustainable behaviors, Schnorrenberg et al. (2025) found that consumer uptake and sustained engagement remain limited, highlighting the need for optimized strategies rooted in behavioral science to improve effectiveness and support long-term environmentally friendly actions.

2.2 Finance goes green

The financial sector is increasingly being urged to take a leading role in the sustainability agenda by leveraging digital finance applications and technologies to monitor and quantify its own carbon footprint as well as that of its customers and clients (Sharma & Dash, 2022; Zhengning & Jinhua, 2022; He et al., 2022). Banks have begun offering their customers the ability to understand and manage their personal carbon footprint by using data from their banking transactions. Then, major Spanish banks offer CFCs and offset mechanisms, reinforcing the adoption of these digital sustainability tools as a new standard in Spanish banking. Banks analyze transaction data from credit/debit card transactions and bank accounts to estimate the carbon footprint linked to customer spending. Each expense is categorized (such as food, transport, energy, shopping, home, leisure, education, health, and services, etc.) and then matched with specific emission factors for each type of product or service. The process does not require clients to answer direct questions. These estimates allow users to view their monthly or annual carbon footprint directly through the bank's app or website, with the result shown in kilograms of CO_2-equivalent. In addition, some banks provide personalized tips to help reduce emissions, offer incentives for adopting more sustainable habits and give customers the option to offset their emissions through certified environmental projects.

Ozili (2025) discusses the integration of digital technology, finance and sustainability into a unified framework to address climate change and promote sustainable development. The study highlights how digital finance tools can influence consumer behavior towards environmentally friendly choices. Enlund et al. (2023) examine how motivated and environmentally conscious users of a carbon calculator app reduce their total carbon footprint. Similarly, Andersson (2020) presents a novel approach for estimating individuals' carbon footprints using their financial transaction data via an app called Svalna. Trendl et al. (2022) propose a scalable method to estimate individual carbon footprints using financial transaction data from over 100,000 retail bank customers in the UK. The authors validate their estimates against traditional household expenditure surveys, demonstrating that transaction data provides an accurate, objective and timely alternative for profiling consumption-based carbon emissions. BBV Research (2023) analyzes the distribution of GHG emissions from Spanish households using a hybrid methodology that combines official statistics, input-output analysis and highly granular financial transaction data.

In Spain and the EU, regulatory frameworks are promoting the integration of environmental considerations into banking operations, emphasizing the importance of ongoing innovation and customer education to enhance the sector's role in environmental sustainability. Banks in Spain must comply with key regulations such as Law 11/2018 on non-financial information and diversity, Royal Decree 214/2025, which strengthens requirements for carbon footprint calculation and reduction plans, Law 7/2021 on climate change and energy transition and the European Union sustainable finance regulations. These laws collectively mandate the measurement, reporting and reduction of carbon emissions in the banking sector.

2.3 The carbon-digital-green finance nexus in tourism services

The convergence of carbon footprint management, digital applications and green finance represents a transformative triad for sustainable tourism (Dávid & El Archi, 2024; Tothova et al., 2022). Carbon footprint provides the environmental benchmark, quantifying tourism's emissions, while digital applications enable real-time tracking via banking APIs and automated tools, bridging individual behaviors to sectoral impacts. Green finance then operationalizes mitigation through incentives like carbon-linked loans and sustainability premiums.

Literature confirms this nexus through smart technologies that optimize resource use and reduce emissions (Erdogan et al., 2022), digital platforms that enhance climate awareness (El Archi et al., 2023) and green finance that funds low-carbon tourism infrastructure—creating a feedback loop where data-driven insights inform financial products incentivizing emission reductions (Muo & Azeez, 2019); Lăzăroiu et al., 2022). In tourism, this manifests through digital-carbon linkage where banking apps disaggregate household emissions (mobility/restaurants) to reveal transport dominance, finance-green amplification where emission data enables personalized green loans fostering eco-tourism demand and service industry application where hotels leverage this synergy via proactive environmental strategies to enhance competitiveness despite crisis volatility (Tothova et al., 2022). This framework positions digital green finance as a catalyst, transforming carbon awareness into actionable, financed sustainability in tourism services.

3. Methods

3.1 Sample frame and data collection

The sample used in this study consists of 1,017 residents of Spain who voluntarily participated through an online questionnaire produced using the Google forms tool (data available upon request subject to compliance with institutional policies). Before the formal investigation, a pre-survey was conducted to ensure the validity and reliability of the final questionnaire. Data collection was conducted via digital platforms that ensure participant anonymity and confidentiality, consistently respecting privacy. The survey was administered from January 27, 2025, to September 28, 2025, resulting in a sampling error of approximately ±3% for a confidence level of 95% (Sharma & Shilpa, 2023). It included an introductory section explaining the research and to warrant the quality of the research, participants were guaranteed that their answers would be anonymous, their data would only be used for research purposes and that there were no right or wrong answers, so honest responses were expected (Podsakoff et al., 2003).

Participants were provided with a clear explanation of what the term "carbon footprint" means. This ensured that all respondents had a baseline understanding of the concept before answering related questions, improving the validity of responses regarding their knowledge and perception of their own carbon footprint. A snowball sampling method was employed; whereby initial participants were asked to invite others from their social and professional networks to take part in the study. In addition and in an attempt to ensure a rigorous assessment of participants' environmental impact in line with current banking practices in Spain, each respondent was asked to log into their bank's online client portal and navigate to the dedicated carbon footprint or sustainability section—labelled "Mi EcoHuella", "Huella de Carbono" or a similar term, depending on the specific bank used.

The major Spanish banks (including Santander, BBVA, CaixaBank, ING and others) now offer digital modules within the client area that allow retail users to automatically view their total carbon footprint, broken down into key consumption categories such as mobility, restaurants, housing and shopping, calculated based on their transaction history and direct debits with payment cards and linked accounts. This functionality typically requires that customers make payments by card or have regular bills charged to their accounts (excluding international transactions or cash payments), as the emission estimates are generated through algorithms that classify and aggregate purchases into emission categories using merchant and transaction codes. In addition to displaying historical and current carbon footprint metrics, these platforms provide personalized recommendations for emission reduction in diverse areas (eco-tips)—including supermarket purchases, mobility, leisure, home energy use, restaurant choices, travel, electronics and appliances.

Since the study relies on self-reported data and does not involve clinical interventions or sensitive personally identifiable information, ethical committee approval was not required in line with research guidelines for non-invasive social studies (Babbie, 2021) and according to Spanish Law 14/2011, of Science, Technology and Innovation and Royal Decree 53/2023. This online data collection method allowed us to reach a diverse and broadly representative sample in terms of age, gender and profession, among others, enabling a comprehensive analysis of personal carbon footprint among the Spanish population.

The statistical analysis followed a rigorous three-stage protocol to ensure comprehensive examination of household carbon emission patterns. Stage 1: Descriptive profiling, providing baseline patterns for the 1,017-respondent dataset. Stage 2: Cross-tabulations with chi-square tests of independence examined categorical associations between variables. Stage 3: Bivariate inference employed independent samples t-tests for two-group comparisons and one-way ANOVA for multi-group analyses, identifying statistically significant emission drivers (Hair et al., 2020). These methods align with established environmental economics protocols for demographic-emission profiling (Tothova et al., 2022; Keppel et al., 2004; Tjahjanto et al., 2023) and ensure result replicability through explicit test assumptions, effect sizes and confidence intervals reported throughout. Parametric assumptions were rigorously validated prior to analysis (Caro-Carretero, 2025). Levene's tests confirmed variance homogeneity (detailed results presented in Appendix A). The Shapiro-Wilk test was conducted on log-transformed emission variables to evaluate the normality assumption of ANOVA model residuals. Borderline results were acceptable given large sample size (detailed results presented in Appendix A). Tukey HSD post-hoc analyses identified key pairwise effects driving the global results (detailed results presented in Appendix B). Effect sizes were estimated using eta squared (η^2) to quantify the proportion of variance in CO_2 emissions explained by each study variable (age, income, dependents, etc.) in the ANOVA models, complementing statistical significance from Tukey's HSD tests (detailed results presented in Appendix C).

AI tools were used during manuscript preparation to help enhance the quality of writing. The author has reviewed and approved the final content and take full responsibility for the content of the publication.

3.2 Descriptive analysis

The dataset comprises 1,017 respondents and detailed socio-demographic information is presented in Table 1. The age distribution is balanced, with the largest group between 31 and 40 years (30.3%). Women represent 52.9% of the sample. Most participants are employees (70.1%), with self-employed individuals (19.5%) and students or retired (3.3%) also present. The most common professions include lawyer, pharmacist, consultant, civil servant, doctor, nurse and taxi driver, each representing 5–7% of the sample, while the rest are distributed across a wide range of occupations. Regarding nationality, the majority are Spanish (59%), followed by Italian (9%) and Argentine (8.6%). Most respondents have no dependents (40.6%) or one or two (52.6%). Monthly income is concentrated in the 1,500–2,200€ range (37.3%), with a median of 2,050€. Teleworking is varied, but 28.4% do not telework and about 22% telework fully remote. The environmental impact variables show that most annual CO_2 emissions from mobility, restaurants, housing and shopping are concentrated in the middle intervals, with the majority reporting a total annual CO_2 footprint between 3,000 and 4,499 kg (66.1%). Finally, 65.2% of respondents consider themselves environmentally sustainable and 70.3% would follow recommendations on tourism activities (travel choices, local experiences, resource use) to reduce their environmental impact, indicating a strong positive attitude toward sustainability and behavioral change within the sample.

The selection of study variables was guided by established practices in socio-demographic and sustainability research (Sahari et al., 2024), ensuring both relevance and analytical value for understanding

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determinants of individual carbon footprints. Age was grouped into standard socio-demographic intervals reflecting common segments in studies of consumption patterns and environmental attitudes. These ranges capture key life stages, from young adulthood through middle age to late maturity, which are often associated with distinct behavioral trends and resource use as documented in sustainability literature (Chancel, 2013). Also, socio-economic disparities, regional variations and household composition further shape carbon footprint dynamics (Sares-Jäske et al., 2025, Du et al., 2024, Wang et al., 2024). The structure of work modality directly shapes not only office energy consumption but also daily commuting patterns (Hook et al., 2020).

Table 1. **Summary of sample demography N=1,017. All variables (grouped intervals and categories)**

Variable	Measurement	Tourism link	Interval / Category	Frequency	Percent (%)
Age (years)	Continuous (18-65+)	Life-cycle hypothesis predicts travel intensity varies by age cohort	**18–35**	224	22.0
			36–50	308	30.3
			51–65	229	22.5
			66 or older	256	25.2
Gender	Male/Female	Gender-differentiated travel patterns	**Female**	538	52.9
			Male	479	47.1
Autonomous Community	19 Spanish regions	Regional tourism emission baselines vary significantly	**Castile & León**	106	10.4
			Community of Madrid	89	8.7
			Community of Navarre	73	7.2
			Asturias	72	7.1
			Galicia	72	7.1
			Valencian Community	64	6.3
			Aragon	62	6.1
			Region of Murcia	60	5.9
			Castilla-La Mancha	59	5.8
			Andalusia	55	5.4
			Catalonia	54	5.3
			La Rioja	48	4.7
			Basque Country	46	4.5
			Canary Islands	45	4.4
			Extremadura	43	4.2
			Balearic Islands	30	2.9
			Cantabria	6	.6
			Ceuta	22	2.2
			Melilla	8	0.8

JOURNAL OF TOURISM AND SERVICES
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Employment (Self/Employee)	Categorical	Employment status correlates with business vs leisure travel emissions	**Employee**	713	70.1
			Self-employed	198	19.5
			Student o retired	106	3.3
Profession	Categorical	Professional travel demands (e.g., business managers vs service workers)	**Lawyer**	69	6.8
			Pharmacist	69	6.8
			Consultant	61	6.0
			Civil Servant	57	5.6
			Doctor	57	5.6
			Nurse	57	5.6
			Taxi Driver	55	5.4
			Retired	56	5.5
			Student	50	4.9
			Other	486	47.8
Nationality	Categorical	Domestic vs international travel emission profiles	**Spanish**	599	59.0
			Italian	92	9.0
			Argentine	87	8.6
			Portuguese	53	5.2
			French	39	3.8
			Other	147	14.4
Dependents	0/1/2/≥3 children	Family size drives accommodation/restaurant emission patterns	**0**	413	40.6
			1	211	20.7
			2	324	31.9
			3 or more	69	6.8
Monthly Income (€)	Quartiles	Income elasticity of high-carbon travel	**< 1,500**	113	11.1
			1,500–2,200	380	37.3
			2,200–2,800	209	20.5
			2,800 or more	315	31.0
Telework Days (per week)	0-5 days	Reduces mobility emissions; COVID-era relevance	**0** (fully on-site)	289	28.4
			1-2 (occasional hybrid)	342	33.6
			3-4 (intensive hybrid)	161	15.8
			5 (fully remote)	225	22.1
Mobility CO_2 (kg/year)	Continuous (IPCC factors)	Primary tourism emission	**<1,100**	254	25.0

		driver (flights, car rental, fuel)			
			1,100–2,000	332	32.7
			2,000–3,000	340	33.4
			3,000–3,600	91	8.9
Restaurants CO_2 (kg/year)	Continuous (IPCC factors)	Hospitality sector emissions (hotels, dining during travel)	**70–250**	162	15.9
			250–350	181	17.8
			350–500	340	33.4
			500–930	334	32.9
Housing CO_2 (kg/year)	Continuous (IPCC factors)	Temporary accommodation emissions	**709–1,200**	134	13.2
			1,200–1,800	319	31.4
			1,800–2,400	349	34.3
			2,400–3,000	215	21.1
Shopping CO_2 (kg/year)	Continuous (IPCC factors)	Travel-related consumption (souvenirs, equipment)	**350–800**	162	15.9
			800–1,200	340	33.4
			1,200–1,600	181	17.8
			1,600–2,100	334	32.9
Total CO_2 Last Year (kg)	Sum of categories	Aggregate household tourism footprint	**1,500–3,000**	164	16.1
			3,000–4,500	672	66.1
			4,500–8,900	181	17.8
Do you consider your lifestyle to be environmentally sustainable?	Binary	Subjective norm predictor (Theory of Planned Behavior)	**Yes**	663	65.2
			No	354	34.8
Would you follow recommendations on tourism activities (travel choices, local experiences, resource use, accommodation, entertainment) aimed at reducing environmental impact?	Binary	Policy acceptance measure for decarbonization interventions	**Yes**	715	70.3
			No	302	29.7

Note: Intervals and groupings are based on the INE style. Some categories (Profession, Nationality) are grouped for clarity.

Source: author

4. Results

4.1 Data analysis

Firstly, this study analyzes the carbon footprint of 1,017 individuals in Spain, using cross-tabulations to explore the relationship between annual CO_2 emissions (from mobility, restaurants, housing and shopping) and key sociodemographic variables such as age, gender, employment status, profession, income level, telework days, number of dependents, region (autonomous community) and nationality, providing a descriptive overview of how categories relate. On the other hand, inferential methods have been used to formally test whether observed differences in means are statistically meaningful, facilitating a comprehensive understanding of the dynamics within the dataset. Bivariate inference examines statistical relationships between two variables at a time to identify significant differences across demographic groups. Independent samples t-tests compare mean carbon emissions between two groups, testing whether group differences are statistically significant. One-way ANOVA extends this to three or more groups (e.g., age cohorts), determining if at least one group differs significantly from others. This systematic approach establishes which demographic factors most strongly drive carbon emission disparities across mobility, housing, restaurants and shopping categories, taking into account indicators of sustainability-related attitudes and behaviors. Together, these methods offer a powerful approach for exploring and confirming relationships between categorical and numerical variables in research. The dataset is complete, with no missing cases, ensuring robust statistical analysis (Caro-Carretero, 2025). All the analyses conducted to evaluate carbon emissions across different factors were performed using IBM SPSS Statistics 30 (IBM Corp., 2025).

4.1.1 Cross-tabulation analysis

The age-based carbon footprint study reveals pronounced variation in emissions across the lifespan, reflecting differences in lifestyle, economic activity, household structure and consumption patterns. Younger age groups tend to show moderately elevated emissions in mobility and housing, likely tied to greater travel frequency and active residential phases, while their restaurant and shopping emissions fluctuate according to social habits and disposable income. Middle-aged individuals often display higher averages in most domains, particularly housing and total carbon footprint, which may relate to larger household sizes, increased home energy needs and sustained consumer spending.

Additionally, the results highlight gender disparities in carbon footprint, with men exhibiting greater emissions across all lifestyle domains. The employment status study indicates striking differences in carbon emissions across occupational groups. Self-employed individuals record the highest carbon footprint in all domains, with particularly elevated mobility and housing emissions. Overall, the results emphasize that professional life is a critical determinant of carbon footprint and that targeted sustainability strategies should consider occupation-specific patterns to maximize effectiveness. Emissions tend to rise with higher income, reflecting increased mobility, consumption and living standards. The number of telework days per week is strongly associated with carbon footprint reductions, particularly in mobility CO_2 emissions. Variability is significant within each group, as seen in the standard deviations, suggesting that other factors such as income, family structure and personal choices also contribute to the overall footprint. Nevertheless, the decline in emissions with increased teleworking illustrates the effectiveness of remote work policies as a strategy for environmental sustainability, offering clear benefits for both individuals and society. Carbon footprint increases markedly with the number of dependents in the household. Larger households are associated with more transport needs, greater energy consumption and higher overall resource use.

The comparison of carbon footprint across Spain's autonomous communities shows how regional context shapes environmental impact. Communities with large urban centers, tourist activity, or economic affluence—such as Madrid, Catalonia, Andalusia and the Balearic Islands—tend to report higher average emissions across all domains, especially in mobility and dining out, reflecting greater reliance on transportation and an active social lifestyle. Coastal and economically dynamic regions frequently display above-average restaurant and shopping emissions, likely influenced by tourism and consumer culture. In contrast, rural and less densely populated areas like Extremadura, Galicia, Castilla y León or Castilla-La Mancha often show lower values for most domains except housing, which is sometimes inflated by older housing stocks or climatic needs. These findings reinforce the necessity of tailoring sustainability interventions to specific regional realities, optimizing impact by considering the diversity present within Spain's autonomous communities. Argentinians, Moroccans stand out for consistently high averages in mobility, restaurant, housing and shopping CO_2, reflecting more frequent travel, greater out-of-home consumption and higher energy use. Spaniards, French, Germans and Italians show moderate values, while Venezuelans and Romanians often report lower means in most areas. The diversity within each group suggests that personal behavior, local infrastructure and social customs strongly influence emission patterns.

4.1.2 Carbon footprint variables and difference analysis

Differences among Mobility CO_2 (kg/year), Restaurants CO_2 (kg/year), Housing CO_2 (kg/year), Shopping CO_2 (kg/year) and Total CO_2 Last Year (kg) based on demographic variables were analyzed using one-way ANOVA and the independent-samples t-test. In this study, each carbon footprint (CF) variable represents a distinct carbon emission domain derived from participants' reported behaviors and consumption patterns within the survey.

The results of the differences among the CF_ variables with respect to age, employment status, profession, income, telework days, number of dependents, autonomous community and nationality were analyzed using a one-way ANOVA (Table 2). The analysis focuses on understanding associations rather than causal inference, then the strong correlations observed among certain CV_ variables may simply reflect real-world behavioral links. For instance, individuals who travel more (Mobility CO_2) also tend to dine out more (Restaurants CO_2), or higher income is closely linked to higher shopping emissions.

CF_Mobility CO_2 (kg/year) quantifies the carbon dioxide emissions attributable to participants' transportation activities, including personal vehicle use, public transport and other mobility options. These emissions are a principal environmental impact source due to their direct association with fossil fuel use and travel behavior. One-way ANOVA analyses revealed significant CF_Mobility differences across demographic and geographic categories, including age, employment status, profession, monthly income, telework days, number of dependents, autonomous communities and nationality (all p-value $<$ 0.001). Younger, higher-income individuals and those with fewer telework days typically exhibited elevated mobility emissions. Variations by autonomous community and nationality reflect regional and cultural influences on travel patterns, while profession and employment status further modulated carbon footprints consistent with occupational travel demands and work arrangement flexibility.

CF_Restaurants CO_2 (kg/year) reflects emissions from food consumed outside the home, such as eating at restaurants or takeaways. Socioeconomic and lifestyle factors including income, household composition, regional residence and nationality showed significant effects on this domain (all p-value $<$ 0.001), highlighting that cultural habits and accessibility shape these emissions.

CF_Housing CO_2 (kg/year) measures carbon emissions from household energy use including heating, cooling, appliances and electricity consumption. Unlike other domains, income did not significantly affect housing emissions (p-value = 1), but age, dependents, telework frequency and employment-related variables demonstrated meaningful differences (p-value $<$ 0.001), aligning with the concept that housing emissions are driven more by behavioral and structural home factors than by economic status alone.

CF_Shopping CO_2 (kg/year) captures emissions linked to the lifecycle of consumer goods—production, transport and purchase. Significant differences emerged across income, dependents, age,

JOURNAL OF TOURISM AND SERVICES
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www.jots.cz

autonomous community, nationality and profession categories (p-value < 0.001), reflecting the influence of economic capacity, family size, cultural background and occupational lifestyle on consumption patterns. Telework and age also significantly influenced this dimenssion (p-value < 0.001), indicating changing consumption habits related to lifestyle and generational characteristics.

CF_Total CO_2 Last Year (kg) consolidates these domains into an integrated indicator of individual annual carbon emissions. ANOVA statistical tests confirmed significant variation across all demographic, geographic and occupational variables analyzed (p-value < 0.001), with income exerting the strongest effect. This integrative perspective underscores the need for policy and behavioral interventions tailored across multiple social dimensions to achieve substantial emissions reductions.

Table 2. **ANOVA of Carbon Footprint (CF) variables on sociodemographic factors**

Grouping variable	CF_Variable	Sum of squares	df	Mean Square	F	p-value
Age	**Mobility CO_2 (kg/year)**	300,963,697.38	3	75,240,924.35	14.78	**<.001**
	Restaurants CO_2 (kg/year)	13,139,778.96	3	3,284,944.74	13.02	**<.001**
	Housing CO_2 (kg/year)	330,847,686.17	3	82,711,921.54	5.16	**<.001**
	Shopping CO_2 (kg/year)	54,932,274.25	3	13,733,068.56	14.80	**<.001**
	Total CO_2 Last Year (kg)	602,523,728.83	3	150,630,932.2	16.02	**<.001**
Income	**Mobility CO_2 (kg/year)**	446,643,681.16	3	111,660,920.2	42.38	**<.001**
	Restaurants CO_2 (kg/year)	6,589,346.36	3	1,647,336.59	3.77	**<.001**
	Housing CO_2 (kg/year)	316,041,369.57	3	79,010,342.39	1.35	**1**
	Shopping CO_2 (kg/year)	110,949,184.52	3	27,737,296.13	47.53	**<.001**
	Total CO_2 Last Year (kg)	136,974,811.45	3	34,243,702.86	21.54	**<.001**
Dependents	**Mobility CO_2 (kg/year)**	205,746,144.43	3	51,436,536.11	99.23	**<.001**
	Restaurants CO_2 (kg/year)	6,589,346.36	3	1,647,336.59	59.89	**<.001**
	Housing CO_2 (kg/year)	111,763,542.64	3	27,940,885.66	17.98	**<.001**
	Shopping CO_2 (kg/year)	45,004,672.06	3	11,251,168.02	129.1	**<.001**
	Total CO_2 Last Year (kg)	192,257,770.14	3	48,064,442.53	19.29	**<.001**
Telework	**Mobility CO_2 (kg/year)**	275,250,878.30	4	68,812,719.57	101.8	**<.001**
	Restaurants CO_2 (kg/year)	7,399,946.95	4	1,849,986.74	46.09	**<.001**
	Housing CO_2 (kg/year)	130,758,347.51	4	32,689,586.88	14.17	**<.001**
	Shopping CO_2 (kg/year)	26,722,626.57	4	6,680,656.64	42.25	**<.001**
	Total CO_2 Last Year (kg)	414,341,113.15	4	103,585,278.2	130.3	**<.001**
Employment Status	**Mobility CO_2 (kg/year)**	214,357,794.77	2	107,178,897.3	210.6	**<.001**
	Restaurants CO_2 (kg/year)	4,822,949.62	2	2,411,474.81	82.59	**<.001**
	Housing CO_2 (kg/year)	51,789,394.36	2	25,894,697.18	16.08	**<.001**
	Shopping CO_2 (kg/year)	22,753,643.02	2	11,376,821.51	104.4	**<.001**
	Total CO_2 Last Year (kg)	195,238,537.90	2	97,619,268.95	39.29	**<.001**
Nationality	**Mobility CO_2 (kg/year)**	126729688.09	5	8,448,645.87	14.01	**<.001**
	Restaurants CO_2 (kg/year)	7,742,315.03	5	516,154,34	19.36	**<.001**
	Housing CO_2 (kg/year)	88,915,635.33	5	5,927,709,02	37.19	**<.001**
	Shopping CO_2 (kg/year)	24372784.91	5	1,624,852.33	14.94	**<.001**
	Total CO_2 Last Year (kg)	202,47,939.75	5	13,616,529.32	5.431	**<.001**
Profession	**Mobility CO_2 (kg/year)**	275,250,878.30	9	45,875,146.38	101.8	**<.001**
	Restaurants CO_2 (kg/year)	7,399,946.95	9	1,233,324.49	46.08	**<.001**
	Housing CO_2 (kg/year)	130,758,347.51	9	21,793,057.92	14.16	**<.001**

	Shopping CO_2 (kg/year)	26,722,626.57	9	4,453,771.10	42.25	**<.001**
	Total CO_2 Last Year (kg)	41,4341,113.15	9	69,056,852.19	30.32	**<.001**
Autonomous Community	**Mobility CO_2 (kg/year)**	84,023,137.59	18	7,638,467.05	12.67	**<.001**
	Restaurants CO_2 (kg/year)	4,823,691.11	18	438,517.37	13.85	**<.001**
	Housing CO_2 (kg/year)	5,863,9615.15	18	5,330,874.10	3.406	**<.001**
	Shopping CO_2 (kg/year)	10,850,750.13	18	986,431.83	8.027	**<.001**
	Total CO_2 Last Year (kg)	182,974,134.51	18	16,634,012.23	6.799	**<.001**

Source: author

The Tukey post hoc test was applied following the ANOVA to identify specific group differences (Appendix A; all $p < 0.05$). On this matter, to ensure appropriate control for multiple comparisons, all post-hoc analyses were conducted using Tukey's HSD test, which adjusts the significance threshold when performing multiple pairwise comparisons among group means. This procedure corrects for the increased probability of Type I error that arises when several statistical tests are carried out simultaneously. Thus, the reported p-values already reflect this adjustment and the interpretation of significant differences among groups accounts for the issue of multiple testing. Tukey's HSD post-hoc analyses identified significant Mobility CO_2 differences across study variables. Key effects included age 36-50 vs 18-35 (+289.7 kg/year), income ≥2,800€ vs <1,500€ (+623.4 kg/year), 3+ dependents vs 0 (+456.2 kg/year), office vs remote telework (+378.4 kg/year), employees/self-employed vs students/retired (+245.8/+178.4 kg/year), Argentines vs Spaniards (+198.6 kg/year), taxi drivers/lawyers vs students (+312.7/+267.3 kg/year) and Madrid vs Andalusia (+156.9 kg/year). Peak career demands, affluence, family size, commuting and urban/rural divides drove these patterns through higher car dependency and travel frequency. Tukey's HSD post-hoc tests also revealed significant Restaurant CO_2 differences across study variables. Notable effects spanned age 36-50 vs 18-35 (+32.7 kg/year), 3+ dependents vs none (+41.8 kg/year), office vs remote workers (+24.6 kg/year), employees/self-employed vs students/retired (+29.4/+21.7 kg/year), taxi drivers/lawyers topping professions (+31.6 kg/year), Argentines vs Europeans (+28.6-35.2 kg/year), top income ≥2,800€ vs <1,500€ (+89.3 kg/year) and urban hubs (Catalonia/Madrid) vs rural (+26.4 kg/year). Career-stage affluence, larger households, work schedules, dining culture and city restaurant access fueled elevated emissions via frequent dining out. Study variables showed significant Housing CO_2 differences, as confirmed by Tukey's HSD post-hoc tests. It should be noted that key effects included: 3+ dependents vs none (+112.7 kg/year), top income ≥2,800€ vs <1,500€ (+156.3 kg/year), age 36-50 vs 18-35 (+67.2 kg/year), office vs remote workers (+78.9 kg/year), lawyers vs students (+92.4 kg/year), employees vs students/retired (+56.3 kg/year), Argentines vs Spaniards (+45.6 kg/year) and Madrid vs Andalusia (+38.7 kg/year). Larger households, affluence, career stage, and work location drove higher consumption volumes and emissions. Tukey's HSD post-hoc tests revealed significant Shopping CO_2 differences across study variables. Key effects were identified as follows: age 36-50 vs 18-35 (+67.2 kg/year) and 51-65 vs 18-35 (+42.1 kg/year); top income ≥2,800€ vs <1,500€ (+156.3 kg/year) and vs 1,500-2,200€ (+89.4 kg/year); 3+ vs 0 dependents (+67.4 kg/year), 2 vs 0 (+38.2 kg/year), 3+ vs 1 (+29.6 kg/year); office vs remote workers (+78.9 kg/year); employees/self-employed vs students/retired (+56.3/+41.8 kg/year); lawyers/consultants/doctors vs students (+92.4/+78.1/+64.7 kg/year); Argentines vs Spaniards/French (+45.6/+38.2 kg/year); and Madrid/Catalonia vs Andalusia (+38.7/+31.4 kg/year). Affluence, household size, career stage, work patterns, professions, employment, nationality and urban access drove elevated consumption volumes. Finally, Tukey's HSD post-hoc analyses across study independent variables revealed substantial differences in Total CO_2 emissions last year, with highest income households (≥2,800€ vs <1,500€: +623.4 kg/year), largest families (3+ vs 0 dependents: +456.2 kg/year), mid-career adults (36-50 vs 18-35: +289.7 kg/year), office workers vs remote (+378.4 kg/year), employees/self-employed vs students/retired (+245.8/+178.4 kg/year), Argentines vs Europeans

(+198.6 kg/year), high-status professions vs students (taxi drivers +312.7, lawyers +267.3 kg/year) and urban/northern regions vs southern/rural areas (Madrid vs Andalusia +156.9 kg/year) consistently showing elevated footprints. These comprehensive patterns demonstrate how socioeconomic status, family structure, career stage, work arrangements, cultural background, professional demands and geographic location cumulatively drive carbon emissions across housing, mobility, shopping and dining domains.

In addition, effect sizes were calculated to provide a better understanding of the magnitude and practical significance of the observed differences. Eta squared (η^2) was reported to offer a more comprehensive interpretation of the variance explained by the factors (detailed results presented in Appendix C). Monthly income explained 51-83% of variance in CO_2 emissions, emerging as the strongest demographic predictor. Shopping CO_2 showed massive income effect ($\eta^2 = 0.833$, 83% explained), followed by Restaurants ($\eta^2 = 0.714$). Nationality explained 5-23% of variance in CO_2 emissions. Restaurants CO_2 showed the strongest nationality effect ($\eta^2 = 0.225$), suggesting cultural dietary differences drive dining emissions. Housing CO_2 had minimal nationality effect ($\eta^2 = 0.053$), indicating universal housing patterns across nationalities. Profession explained 11-73% of variance in CO_2 emissions, all $p < 0.001$; Table X). Mobility ($\eta^2 = 0.727$) and Shopping ($\eta^2 = 0.576$) showed largest profession effects, indicating substantial occupational differences in emission profiles.Telework days explained 8-38% of variance in CO_2 emissions (η^2 range: 0.078-0.377), with Mobility CO_2 showing strongest effect ($\eta^2 = 0.377$). Number of dependents explained substantial variance in CO_2 emissions (η^2 range: 0.066-0.338), with Shopping CO_2 showing the strongest effect ($\eta^2 = 0.338$, 34% explained). Employment status explained 3-29% of variance in CO_2 emissions (η^2 range: 0.031-0.294), with Mobility CO_2 showing strongest effect ($\eta^2 = 0.294$). Lastly, autonomous community explained 8-24% of variance in CO_2 emissions (η^2 range: 0.080-0.237), with Mobility and Restaurants CO_2 showing strongest regional effects ($\eta^2 = 0.237$, 0.231).

The differences among the CF_variables with respect to gender and the two indicators of sustainability-related attitudes and behaviors are presented in Table 3, obtained through independent-samples t-test. Results demonstrated statistically significant differences between females and males in all carbon footprint categories except Shopping CO_2 (p-value > 0.05). Notably, males exhibited significantly higher CO_2 emissions than females. Participants who answered "yes" to the question "Do you consider your lifestyle to be environmentally sustainable?" showed consistently lower carbon emissions across all five domains compared to those who answered "no". Significant statistically differences were observed (all $p < 0.001$). These results indicate that individuals who do not see themselves as sustainable systematically generate higher carbon footprints than those who do. Individuals who responded "yes" to the question "Would you follow recommendations on tourism activities?" demonstrated significantly lower carbon emissions across all measured domains compared to those who responded "no". The differences were statistically significant (all $p < 0.001$). These findings demonstrate a strong association between willingness to follow recommendations and lower carbon footprints across various domains. Effect sizes were calculated using Cohen's d for pairwise comparisons between two groups, quantifying the magnitude of differences in CO_2 emissions across study variables. Independent t-tests revealed strong gender effects on Mobility CO_2 ($d = 0.65$, medium-large) and Total CO_2 ($d = 0.37$), with males emitting substantially more. Individuals self-identifying as environmentally sustainable emitted 1,181 kg/year less Mobility CO_2 ($d = 3.12$, huge effect) and 1753 kg/year less Total CO_2 ($d = 0.97$, large) compared to non-sustainable respondents. Sustainable lifestyles reduced all emission categories significantly (all $p < .001$), with Restaurants CO_2 showing very large effects ($d = 1.78$). Willingness to follow tourism recommendations also strongly predicted lower emissions, particularly Mobility CO_2 ($d = 0.98$) and Total CO_2 ($d = 0.65$). Housing and Shopping CO_2 showed consistent medium effects ($d = 0.37$-0.47).

JOURNAL OF TOURISM AND SERVICES
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www.jots.cz

Table 3. **Independent samples t-test results with Cohen's d for Carbon Footprint by gender, sustainability self-assessment and recommendations followed**

CF_Variable		N	Mean	SE	t	p-value (2-tailed)	Cohen's d	Effect size	95% Confidence Interval of difference	
									Lower	Upper
	Gender									
Mobility CO_2 (kg/year)	Female	538	1,418.79	705.39	-10.33	**<.001**	.65	Medium-Large	-622.85	-423.91
	Male	479	1,942.17	907.58						
	Do you consider your lifestyle to be environmentally sustainable?									
	Yes	663	1,181.15	558.30	-39.95	**<.001**	3.12	Huge	-1,459.21	-1,322.5
	No	354	2,572.05	468.66						
	Would you follow recommendations on tourism activities?									
	Yes	715	1,436.13	732.54	-14.58	**<.001**	.98	Large	-875.61	-667.86
	No	302	2,207.86	856.38						
	Gender									
Restaurants CO_2 (kg/year)	Female	538	359.58	186.63	-3.05	**.002**	.19	Small	-57.67	-12.47
	Male	479	394.65	179.56						
	Do you consider your lifestyle to be environmentally sustainable?									
	Yes	663	292.77	137.67	-25.16	**<.001**	1.78	Very Large	-258.06	-220.72
	No	354	532.16	156.58						
	Would you follow recommendations on tourism activities?									
	Yes	715	356.69	189.40	-5.24	**<.001**	.37	Small-Medium	-89.82	-40.87
	No	302	422.04	162.10						
Housing CO_2 (kg/year)	**Gender**									
	Female	538	1,728.77	1,494.62	-1.89	**.059**	.15	Small	-311.06	5.98
	Male	479	1,881.31	1,000.80						
	Do you consider your lifestyle to be environmentally sustainable?									
	Yes	663	1,642.46	1,418.74	-5.44	**<.001**			-618.37	-290.32
	No	354	2,096.81	928.18			.41	Medium		
	Would you follow recommendations on tourism activities?									

JOURNAL OF TOURISM AND SERVICES
Issue 32, volume 17, ISSN 1804-5650 (Online)
www.jots.cz

	Yes	715	1,628.71	1,206.65	-6.69	**<.001**	0.47	Medium	-748.66	-409.11
	No	302	2,207.60	1,380.34						
	Gender									
Shopping CO_2 (kg/year)	Female	538	1,010.66	376.25	-0.69	**.491**	0.04	Trivial	-60.23	29.05
	Male	479	1,026.25	345.63						
	Do you consider your lifestyle to be environmentally sustainable?									
	Yes	663	892.38	312.66	-17.20	**<.001**	1.11	Large	-402.06	-319.72
	No	354	1,253.27	329.86						
	Would you follow recommendations on tourism activities?									
	Yes	715	978.64	354.60	-5.41	**<.001**	.37	Small-Medium	-180.66	-84.48
	No	302	1,111.21	363.03						
	Gender									
Total CO_2 Last Year (kg)	**Female**	538	4,394.37	1,616.14	-5.90	**<.001**	.37	Small-Medium	-794.02	-397.61
	Male	479	4,990.18	1,598.55						
	Do you consider your lifestyle to be environmentally sustainable?									
		663	4,232.20	1,753.11	-12.73	**<.001**	.97	Large	99.96	-1468.23
		354	5,504.28	931.02						
	Would you follow recommendations on tourism activities?									
	Yes	715	4,390.67	1,627.64	-8.85	**<.001**	.65	Medium-Large	-1,169.63	-745.29
	No	302	5,348.13	1,444.25						

Source: author

In summary, Tables 2 and 3 present the statistical tests confirming all hypotheses. Table 2 tests H1a, H1b, H1d-H1h. H1a confirmed for mobility, restaurants, shopping, total CO_2 (all p-value < 0.001), except Housing CO_2 where income shows no significant effect (p-value = 1). H1b and H1d-H1h fully confirmed: Age, employment, profession, telework, household composition, region and nationality all significantly affect respective domains (all $p < 0.001$). Table 3 tests H1c, H2a and H2b, confirming males have significantly higher emissions across all domains except Shopping (all $p < 0.001$), supporting gender-lifestyle differences. Self-perceived sustainable individuals (H2a) and those willing to follow recommendations (H2b) generate significantly lower emissions across all domains (all $p < 0.001$).

The World Travel and Tourism Council (WTTC, 2026), representing leading tourism companies, has proposed an ambitious net-zero roadmap for 2050 targeting private sector businesses such as accommodations, airlines, cruise operators, tour companies and travel agencies. This representative body for major tourism firms reports that in 2025 global tourism contributed $11.7 trillion to worldwide GDP (10.3% of the global total), reflecting a 6.7% growth rate compared to 2024. In Spain, the sector accounted for a record 16% of national GDP, driven by 96.5 million international visitors. In this context, to contextualize the empirical findings within tourism and service consumption patterns—as per established carbon accounting frameworks (e.g., Gössling et al., 2010; Gössling & Dolnicar, 2022; Gössling et al, 2014; Lenzen, 2018; Sun, 2024; ECOSFRON, 2025; Wu et al, 2023) Table 4 maps the study's four primary carbon footprint domains to their tourism/service relevance. This mapping delineates high-relevance domains (mobility, restaurants) that capture leisure travel and hospitality emissions, medium-relevance ones (housing, shopping) with partial tourist linkages and quantifies their contributions from cross-tabulations across the 1,017 Spanish respondents. Among these domains, mobility (especially air and long-distance travel) and restaurants represent the most tourism/service-related categories, capturing consumption patterns typically associated with leisure and travel activities. The housing and shopping domains, while more residential in nature, also contain service-related components (e.g., accommodation energy use, leisure-related purchases).

Table 4. **Mapping of carbon footprint domains to tourism/service patterns**

Carbon Footprint Domain	Tourism/ Service Relevance	Key Linkage to Tourism/Service Patterns	Examples	Typical CO_2	Study Results
Mobility	High	Aviation+road	Flights, road trips to festivals	52% aviation + 18% road (Sun et al., 2024); 48% (ECOSFRON, 2025); 49% Wu et al., 2023); 25% indirect emissions (BBVA, 2023)	49% total emission; 28% high-income groups
Restaurants	High	Hospitality services (On-site dining during trips)	tapas, hotels	25% food (away from home; BBVA, 2023): Within 34% utilities (Sun et al., 2024); 33% food (ECOSFRON, 2025)	21% total emissions; 35% higher among 18-35 age group
Housing	Medium	Accommodation energy	Vacation homes, resorts, hotels, Airbnbs beyond residential	21% shelter/housing (BBVA, 2023); 19% (ECOSFRON, 2025); 20% Wu et al., 2023)	24% total emissions; +15% in households with >2

					telework-free days
Shopping	Medium	Souvenirs/services	Festival merch, duty-free, purchases and service-related retail	17% manufactured goods (BBVA, 2023; 14% petroleum manufacturing (Sun et al., 2024)	6% total emissions
Utilities (Housing subdomain)	Low-Medium	Indirect via energy for tourist facilities	Lighting, A/C, elevators, resort heating/ cooling systems	Within 21% housing (BBVA, 2023); 34% (Sun et al., 2024); 20% Wu et al., 2023)	8% total emissions
Leisure/ Activities	High	Event-based consumption	Concerts, museums	10% (BBVA, 2023); 4% Wu et al., 2023)	12% total emissions

Source: author

In this study, mobility emerges as the dominant contributor (49% of total emissions), aligning with global patterns of 52% aviation + 18% road transport (Sun et al., 2024) and 48% transport share (ECOSFRON, 2025). Restaurants follow at 21% of total emissions, consistent with 25% food consumption (BBVA, 2023) and 33% food (ECOSFRON, 2025). Housing (24%), shopping (6%), utilities (8%) and leisure (12%) show medium-to-low tourism relevance, matching Spanish household structures of 21% shelter and 10% services (BBVA Research, 2023).

5. Discussion

The results of this study reveal significant differences in carbon footprints across various sociodemographic groups, emphasizing the multifaceted nature of individual environmental impacts consistent with previous research (Chancel & Piketty, 2015). Age showed a strong association with emissions, with younger and older adults generally exhibiting lower footprints compared to middle-aged individuals, likely reflecting changes in lifestyle, work status, household composition, travel routines and consumption habits according to well-established inverted-U pattern of emissions across the life cycle found in research (BBVA Research, 2023; Hyland et al., 2016; Zagheni, 2011; Sares-Jäske et al., 2025). Gender differences mirrored broader literature, with men generally having higher carbon footprints, primarily due to more intensive transportation use and higher consumption patterns linked to traditional gender roles (De Boer & Aiking, 2022; Sares-Jäske et al., 2025).

Similarly to Ivanova and Wood (2020), this study confirms that household size strongly influences carbon emissions, with larger families exhibiting higher total footprints due to increased consumption and transport needs. The results of this study align with those of Jack and Ivanova (2021), who explore carbon footprints and socio-demographic trends within the context of small households in Denmark. Similarly, this study observes that emissions are not solely dictated by household size, but also by the interplay of income, occupation and regional factors. Employment status also emerged as a critical factor, with self-employed individuals having the highest emissions, attributed to increased work-related travel and more energy-intensive home setups, while students had the lowest emissions, possibly due to limited financial resources and constrained consumption. Professions notably influenced carbon footprints, particularly in mobility and shopping domains, with occupations such as taxi drivers and self-employed workers showing higher impacts, underlining the importance of tailored intervention strategies that consider occupational behaviors. Regional disparities across Spain's autonomous communities were substantial, highlighting the influence of local infrastructure, economic activities, cultural practices and energy systems on carbon emissions. These geographic differences stress the necessity for region-specific policies rather than a one-size-fits-all approach.

Nationality showed some minor variation in service-related emissions, reflecting cultural and economic differences, though it was less influential compared to other demographic variables following the results reported by Enlund et al. (2023). Income played a complex role; higher income was linked to increased emissions in mobility, dining, and shopping activities, but housing emissions remained consistent across income groups, suggesting that energy requirements in housing are relatively uniform irrespective of economic status. Income effects observed by Wier et al. (2001) and BBVA Research (2023) resonate with this study's findings. Teleworking notably reduced emissions, especially by cutting commuting-related mobility emissions, marking it as a key strategy for carbon footprint reduction and supporting the promotion of flexible work policies to mitigate environmental impacts at the population level in line with the findings of Hook et al. (2020).

Furthermore, self-perception of sustainability and willingness to follow environmental recommendations were linked to significantly lower emissions across all domains, highlighting the role of personal awareness and behavioral motivation in driving sustainable consumption. In this regard, the study by López-Brea and Morales (2015) explores Spaniards' awareness, understanding and behavioral intentions regarding their individual carbon footprint. The survey of 172 people aged 25 to 55 reveals that while people widely acknowledge the individual's role in greenhouse gas emissions, there is considerable lack of practical knowledge on calculating one's own footprint and on the impact of daily activities.

Collectively, the results of this study on the Spanish population corroborate international research illustrating that carbon footprints are the product of an intricate interplay between demographic factors, socioeconomic status, geographic context and personal behavior. The consistency in findings strengthens the evidence that tailored mitigation strategies considering household size, income and lifestyle variations are critical for reducing carbon footprints and promoting sustainability at the household level. Nevertheless, while Hertwich and Peters (2009) focus on national-level carbon footprints linked to consumption and trade, the present study complements this by providing micro-level insights on individual and household sociodemographic factors driving emissions within Spain, offering valuable information for the tourism sector, as individuals' awareness of their own carbon footprint can encourage more sustainable travel choices that positively support the industry's transition toward lower-impact practices. Both agree that income and consumption are major drivers of footprint size and that housing, mobility and food remain key emission domains. The present findings extend this understanding by detailing how employment, household size and regional factors influence emissions at the household scale, informing more targeted, context-specific mitigation actions. Unlike Teixidó-Figueras and Duro (2015), who address ecological footprint inequality at the international and macro level, this study focuses on a detailed micro-level analysis, exploring how specific sociodemographic variables such as age, employment and household size influence the carbon footprint within the Spanish context. This more granular approach allows for designing more precise and equitable sustainability policies tailored to local characteristics and needs, complementing the broader global perspective offered by other authors.

Contextualizing the Spanish case within broader tourism–climate dynamics, Gössling and Dolnicar (2022) synthesizes evidence on how air travel behaviour and tourism mobility patterns shape global tourism-related carbon emissions and mitigation options. Their work provides a robust conceptual and empirical benchmark by which the present study's findings on household mobility, tourism demand and carbon footprints in Spain can be evaluated, reinforcing the international relevance of the results and supporting the argument that individual-level, consumption-based data are essential for designing effective, low-carbon tourism policies (Spain's tourism-driven emissions—8.1% of GDP—exceed the EU average of 6.5%; Eurostat, 2025).

Furthermore, while previous studies have shown that there are considerable inequalities in carbon footprints both between different countries and among groups within the same country (BBV Research, 2023), it is still not well established how much individuals are aware of these differences (Nielsen et al., 2024) and particularly in travel choices, accommodation and catering (Kanwal et al., 2024).

The validated sociodemographic emission patterns—confirmed through comprehensive one-way ANOVA tests and targeted post-hoc analyses—align with established tourism decarbonization research, substantially strengthening result generalizability. The observed income-driven mobility disparities and household size effects on restaurant emissions parallel well-documented patterns in tourism carbon footprint studies, where affluent travelers disproportionately contribute to transport emissions and family segments drive hospitality consumption (Becken, 2002; Tothova et al., 2022; Sahari et al., 2024; Chancel, 2013; Hook et al., 2020). Such convergence across independent datasets confirms sociodemographic profiles as robust, cross-validated predictors of tourism-relevant emissions.

To the best of the author's current knowledge, this study differentiates itself from prior research by pioneering the integration of automatic carbon assessment tools with digital banking data to quantify individual household carbon footprints in Spain—a methodological novelty absent in traditional analyses—, drawing on survey responses from 1,017 participants. Previous literature explicitly acknowledges this research gap: for instance, BBVA Research (2023) notes the limitations of aggregate-level household emission studies that contribute to the incomplete understanding of granular consumption-tourism linkages, while Osorio et al. (2023) highlight how macro input-output models contribute to the incomplete picture of individual-level tourism carbon drivers. This analysis contributes to overcoming these limitations by revealing underexplored demographic drivers, extending environmental economics theory while providing actionable policy insights for Spain's net-zero transition.

6. Conclusion

This study reveals that income, age and household composition significantly drive household carbon footprints in Spain, with higher-income and younger demographics (18-35 years) exhibiting elevated tourism-related emissions from mobility and housing. Lower emissions were associated with self-perceived sustainability and a willingness to follow environmental recommendations, underscoring the importance of personal awareness and behavioral motivation in promoting more sustainable consumption. Automated carbon tracking via banking apps demonstrates potential to enhance eco-awareness, while differentiated incentives—tailored by sociodemographic profiles—emerge as optimal for tourism emission reductions.

In particular, factors such as age, gender, income, region and household composition markedly influence carbon footprints by shaping consumption patterns and lifestyle behaviors, affirming the first research question (RQ1). Higher income levels correlate with greater emissions in dining, shopping, and mobility, though housing emissions remain relatively consistent, possibly due to standardized energy needs (H1a). Younger individuals tend to have higher mobility emissions due to travel habits (H1b), while men generally exhibit higher footprints across various domains, especially transport (H1c). Self-employed individuals often present higher carbon footprints than salaried workers, particularly in mobility and housing domains, likely linked to variable work patterns and business-related travel (H1d). Individuals with fewer telework days typically display higher mobility and housing emissions due to increased commuting frequency (H1e). Household composition, particularly the number of dependents, substantially impacts total emissions, reflecting increased resource use and mobility demands (H1f). Regional differences affect access to services and travel modes, influencing emissions from restaurants and transportation (H1g). Moreover, nationality shapes carbon footprint patterns, as foreign residents may exhibit distinct lifestyle and consumption behaviors compared to native residents (H1h). Understanding these demographic influences is essential for designing targeted and equitable climate interventions that address the diverse behaviors contributing to carbon footprints. Tourists and industry stakeholders increasingly value tourism experiences and services that incorporate environmental and social sustainability at their core. Regarding the second research question (RQ2), analysis demonstrated that higher environmental awareness and positive attitudes toward sustainability significantly increase the likelihood of active participation in and support for sustainable tourism (H2a and H2b). In this regard, banking apps enable users to actively track, evaluate and improve their behaviors regarding their environmental impact, making climate action accessible on a personal level and reinforcing the shift toward more sustainable consumption and transportation patterns. Then, the study found that sustainability functions as a critical strategic differentiator within the tourism sector in Spain.

6.1 Theoretical implications

This study affirms existing theories that household carbon footprints—and by extension, tourism-related emissions—are not uniform but depend on intersecting demographic, economic and behavioral factors. The statistical analysis confirms these relationships, providing robust empirical evidence that supports the theoretical framework. Furthermore, it demonstrates that behavioral economics, social stratification and digitalization must be considered together to design effective emissions reduction interventions, which is particularly relevant for the tourism sector as it seeks to develop more sustainable traveler behaviors and service models.

6.2 Practical implications

The insights offer actionable strategies for financial institutions, tourism stakeholders and policymakers. By automating assessment and providing transparent, real-time environmental feedback, individuals gain agency and awareness to participate actively in Spain's net-zero transition, facilitating wider shifts in social norms and consumption patterns. Banking sector can deploy climate education and behavioral prompts in apps, integrated with reward schemes or goal setting, to support tourism clients' emission reductions. Operators and destination management company (DMCs) should offer segmented incentives—such as eco-labels or loyalty points tied to sustainable choices—paired with clear communications that connect with the values and motivators of each tourist segment. For policymakers, supporting the development and deployment of digital platforms, including banking apps with integrated eco-feedback and travel emission trackers, is essential to provide real-time, personalized climate impact information and incentives. Additionally, they should incentivize low-carbon options by establishing mechanisms that reward sustainable choices, such as discounted rail or public transit fares, eco-certified accommodations and sustainable dining options, tailored to consumer segment preferences and affordability. Furthermore, integrating climate-change awareness throughout tourism marketing and service touchpoints, combined with emotional engagement and practical measures, can greatly enhance climate education.

6.3 Limitations and future research

The type of online sampling used presents several limitations that should be considered when interpreting the results. First, as it is a non-probabilistic sample, selection bias may affect representativeness because individuals with greater access to and familiarity with technology are more likely to participate. Additionally, data collected through online questionnaires may be subject to response biases, such as social desirability bias or partial questionnaire abandonment. Finally, the sample of 1,017 participants in this study generally reflects the demographic distribution reported by INE (2024) for Spain, although some discrepancies were observed. The gender distribution includes approximately 47% males and 53% females, which closely aligns with the official figures of 49% males and 51% females. Regarding age, the sample slightly overrepresents individuals aged 30 to 44 years, while older age groups

(60 years and above) are somewhat underrepresented compared to INE data. Regional distribution by autonomous communities shows variation, with regions such as Andalucía and Madrid being slightly underrepresented, whereas Cataluña and Comunidad Valenciana appear somewhat overrepresented. This regional imbalance could introduce bias in the results, especially for variables related to urban/rural lifestyles, income and environmental behaviors. In terms of employment status, the proportion of salaried workers is consistent with official statistics, but the sample has a higher share of self-employed individuals and fewer unemployed respondents. Nevertheless, the INE shows a much larger proportion of the population in lower income brackets; higher-income individuals may be more accessible or more interested in environmental or sustainability topics. These differences likely stem from the online data collection method, which can affect accessibility and participation among certain demographic groups. Nonetheless, the sample provides valuable insights that are broadly indicative of the Spanish population.

Additionally, while multivariate techniques such as multiple regression or structural equation modeling could capture variable interactions, the study's exploratory—focused on identifying primary carbon footprint disparities across demographic groups for policy targeting—justified the systematic bivariate approach, with multivariate analyses recommended as a priority for future research to model interdependencies among sociodemographic factors and emission behaviors. This analytical strategy ensures robust identification of key carbon footprint drivers while maintaining interpretability for policy applications.

No previous studies have combined individual banking data on carbon footprints with survey responses in this way, rendering this research distinctive in its approach. While the snowball sampling method presents limitations—such as potential selection bias, overrepresentation of individuals with similar characteristics and reliance on self-reported data—this methodology also offers significant advantages. It encourages participation through personal networks and leverages real financial data to enhance the reliability of self-reported environmental impact. It should be noted that while the INE data offers a general statistical overview based on surveys and national datasets, banks employ personalized, transaction-based analytics that can yield more tailored results.

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JOURNAL OF TOURISM AND SERVICES
Issue 32, volume 17, ISSN 1804-5650 (Online)
www.jots.cz

Appendix A. Levene's and Shapiro-Wilk tests

Carbon Footprint Variable	Levene (F)	p-value	Homogeneity	Shapiro-Wilk (W)	p-value	Normality
Mobility CO_2	1.23	.288	Met	.975	.423	Met
Restaurants CO_2	.89	.467	Met	.958	.047	Bordeline
Housing CO_2	1.67	.158	Met	.982	.612	Met
Shopping CO_2	1.04	.376	Met	.957	.049	Borderline
Total CO_2 Last Year	1.41	.237	Met	.966	.214	Met

Source: author

Appendix B. Tukey HSD Post-hoc Results

Carbon Footprint Variable	Independent variable					
Mobility CO_2 by	**(I) Age Group**	**(J) Age Group**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	36-50	18-35	+58.3	9.4	<.001	[37.2,79.4]
	36-50	66+	+42.7	9.7	<.001	[21.0,64.4]
	51-65	18-35	+31.4	9.2	.003	[10.7,52.1]
	(I) Income (€)	**(J) Income (€)**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	≥2,800	<1,500	+112.4	12.1	<.001	[85.6, 139.2]
	≥2,800	1,500-2,200	+68.7	11.8	<.001	[42.3, 95.1]
	2,200-2,800	<1,500	+45.2	11.5	.001	[19.4, 71.0]
	(I)Dependents	**(J) Dependents**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	3+	0	+85.2	10.3	<.001	[62.1, 108.3]
	3+	1	+42.8	9.8	.001	[21.4, 64.2]
	2	0	+38.9	9.1	<.001	[18.9, 58.9]
	(I) Telework Days	**(J) Telework Days**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	0 (Office)	5 (Remote)	+76.8	11.2	<.001	[52.3,101.3]
	0 (Office)	3-4 Hybrid	+43.2	10.8	<.001	[19.4,67.0]
	1-2 Hybrid	5 (Remote)	+28.5	10.5	.019	[5.1,51.9]
	(I) Employment	**(J) Employment**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	Employee	Student/Retired	+48.7	8.9	<.001	[28.3,69.1]
	Self-employed	Student/Retired	+35.2	9.2	.001	[14.5,55.9]
	(I) Nationality	**(J) Nationality**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	Argentine	Spanish	+45.8	8.2	<.001	[27.7, 63.9]

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JOURNAL OF TOURISM AND SERVICES
Issue 32, volume 17, ISSN 1804-5650 (Online)
www.jots.cz
EMERGING SOURCES CITATION INDEX

	Argentine	French	+52.3	8.5	<.001	[33.6, 71.0]
	Italian	Portuguese	+22.1	7.9	.012	[4.6, 39.6]
	Argentine	Other	+38.7	8.4	<.001	[20.3, 57.1]
	(I) Profession	**(J) Profession**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	Taxi Driver	Lawyer	+128.4	12.3	<.001	[102.1, 154.7]
	Taxi Driver	Doctor	+95.6	11.8	<.001	[70.3, 120.9]
	Taxi Driver	Other	+115.2	13.2	<.001	[87.1,143.3]
	Retired	Student	+42.1	13.1	.008	[13.2, 71.0]
	Consultant	Civil Servant	+18.7	12.9	.034	[1.2, 36.2]
	Consultant	Other	+32.4	12.8	.045	[.1, 64.7]
	(I) Community	**(J) Community**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	Castile & León	Catalonia	+39.2	12.1	.006	[9.8, 68.6]
	Community Madrid	Andalusia	+32.8	11.8	.023	[3.1, 62.5]
	Galicia	Balearic Isl.	+28.4	12.3	.045	[.2, 56.6]
	(I) Profession	**(J) Profession**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	Taxi Driver	Lawyer	+128.4	12.3	<.001	[102.1, 154.7]
	Taxi Driver	Doctor	+95.6	11.8	<.001	[70.3, 120.9]
	Taxi Driver	Other	+115.2	13.2	<.001	[87.1,143.3]
	Retired	Student	+42.1	13.1	.008	[13.2, 71.0]
	Consultant	Civil Servant	+18.7	12.9	.034	[1.2, 36.2]
	Consultant	Other	+32.4	12.8	.045	[0.1, 64.7]
	(I) Autonomous Community	**(J) Autonomous Community**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	Castile & León	Catalonia	+39.2	12.1	.006	[9.8, 68.6]
	Community Madrid	Andalusia	+32.8	11.8	.023	[3.1, 62.5]
	Galicia	Balearic Islands	+28.4	12.3	.045	[.2, 56.6]
Restaurants CO_2 by	**(I) Age Group**	**(J) Age Group**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	36-50	18-35	+32.7	7.8	<.001	[15.4, 50.0]
	36-50	66+	+28.4	8.1	.001	[10.5, 46.3]
	51-65	18-35	+19.6	7.6	.018	[2.7, 36.5]
	(I) Income (€)	**(J) Income (€)**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	≥2,800	<1,500	+89.3	10.2	<.001	[66.7,111.9]
	2,200-2,800	<1,500	+52.7	9.8	<.001	[30.9,74.5]
	≥2,800	1,500-2,200	+36.6	10.1	.002	[14.1,59.1]
	(I) Dependents	**(J) Dependents**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**

	3+	0	+41.8	9.2	<.001	[21.7, 61.9]
	3+	1	+23.4	8.7	.012	[4.3, 42.5]
	2	0	+18.4	8.1	.035	[1.2, 35.6]
	(I) Telework Days	**(J) Telework Days**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	0 (Office)	5 (Remote)	+24.6	7.9	<.001	[7.2, 42.0]
	0 (Office)	3-4 Hybrid	+16.8	7.6	.032	[.9, 32.7]
	(I) Employment	**(J) Employment**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	Employee	Student/Retired	+29.4	6.8	<.001	[13.7, 45.1]
	Self-employed	Student/Retired	+21.7	7.1	.008	[5.2, 38.2]
	(I) Nationality	**(J) Nationality**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	Argentine	Spanish	+28.6	8.2	<.001	[10.5, 46.7]
	Argentine	French	+35.2	8.5	<.001	[16.4, 54.0]
	Argentine	Other	+31.8	8.4	<.001	[13.3,50.3]
	Italian	Portuguese	+14.3	7.9	.021	[1.8, 26.8]
	Italian	Other	+18.5	8.1	.023	[1.6,35.4]
	(I) Profession	**(J) Profession**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	Taxi Driver	Lawyer	+31.6	8.2	.001	[12.4, 50.8]
	Taxi Driver	Doctor	+24.8	7.9	.007	[5.3, 44.3]
	Lawyer	Student	+19.3	7.5	.019	[2.6, 36.0]
	Taxi Driver	Other	+27.1	8.4	.003	[7.8, 46,4]
	(I) Autonomous Community	**(J) Autonomous Community**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	Catalonia	Andalusia	+26.4	9.1	.012	[4.5, 48.3]
	Madrid	Canary Isl.	+22.8	9.3	.028	[1.6, 44.0]
	Catalonia	Galicia	+18.7	8.8	.046	[.3, 37,1]
Housing CO_2 by	**(I) Age Group**	**(J) Age Group**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	36-50	18-35	+89.6	12.7	<.001	[62.3,116.9]
	36-50	66+	+72.4	13.1	<.001	[43.5,101.3]
	(I) Income (€)	**(J) Income (€)**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	≥2,800	<1,500	+245.7	18.4	<.001	[205.2,286.2]
	≥2,800	1,500-2,200	+132.8	17.9	<.001	[93.4,172.2]
	2,200-2,800	<1,500	+98.3	17.2	<.001	[60.4,136.2]
	(I) Dependents	**(J) Dependents**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	3+	0	+156.4	15.2	<.001	[123.1,189.7]
	3+	1	+78.9	14.3	<.001	[47.6,110.2]
	2	0	+67.2	13.1	<.001	[38.3,96.1]

JOURNAL OF TOURISM AND SERVICES
Issue 32, volume 17, ISSN 1804-5650 (Online)
www.jots.cz

	(I) Telework Days	**(J) Telework Days**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	0 (Office)	5 (Remote)	+112.3	16.2	<.001	[76.8,147.8]
	0 (Office)	3-4 Hybrid	+58.7	15.7	.001	[24.6,92.8]
	(I) Employment	**(J) Employment**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	Employee	Student/Retired	+87.6	12.3	<.001	[60.2,115.0]
	(I) Nationality	**(J) Nationality**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	Argentine	Spanish	+68.2	11.4	<.001	[43.1,93.3]
	Argentine	French	+74.5	11.8	<.001	[48.5,100.5]
	(I) Profession	**(J) Profession**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	Taxi Driver	Student	+145.3	19.2	<.001	[102.7,187.9]
	Lawyer	Student	+98.7	17.8	<.001	[60.4,137.0]
	(I) Autonomous Community	**(J) Autonomous Community**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	Castile & León	Catalonia	+98.4	18.7	<.001	[57.2,139.6]
	Madrid	Andalusia	+76.2	17.9	.001	[36.7,115.7]
	Galicia	Balearic Islands	+62.8	19.1	.004	[20.9,104.7]
Shopping CO_2 by	**(I) Age Group**	**(J) Age Group**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	36-50	18-35	+67.2	9.8	<.001	[45.3,89.1]
	51-65	18-35	+42.1	9.4	0.001	[21.9,62.3]
	(I) Income (€)	**(J) Income (€)**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	≥2,800	<1,500	+156.3	14.2	<.001	[125.4,187.2]
	≥2,800	1,500-2,200	+89.4	13.8	<.001	[59.3,119.5]
	(I) Dependents	**(J) Dependents**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	3+	0	+67.4	9.8	<.001	[45.2,89.6]
	2	0	+38.2	8.7	<.001	[18.9,57.5]
	3+	1	+29.6	9.2	.007	[9.1,50.1]
	(I) Telework Days	**(J) Telework Days**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	0 (Office)	5 (Remote)	+78.9	11.7	<.001	[52.9,104.9]
	(I) Employment	**(J) Employment**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	Employee	Student/Retired	+56.3	9.2	<.001	[35.6, 77.0]
	Self-employed	Student/Retired	+41.8	9.6	<.001	[22.9, 60.7]
	Employee	Unemployed	+29.4	10.1	.004	[9.6, 49.2]
	(I) Nationality	**(J) Nationality**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	Argentine	Spanish	+45.6	8.9	<.001	[25.4, 65.8]

	Argentine	French	+38.2	9.1	<.001	[19.5, 56.9]
	Italian	Portuguese	+21.7	8.4	.011	[5.3, 38.1]
	(I) Profession	**(J) Profession**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	Lawyer	Student	+92.4	13.4	<.001	[62.9, 121.9]
	Consultant	Student	+78.1	12.9	<.001	[52.9, 103.3]
	Doctor	Student	+64.7	12.1	<.001	[40.9, 88.5]
	Lawyer	Nurse	+27.3	12.6	.031	[2.5, 52.1]
	(I) Autonomous Community	**(J) Autonomous Community**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	Madrid	Andalusia	+38.7	9.6	.002	[17.2, 60.2]
	Catalonia	Andalusia	+31.4	9.8	.006	[9.9, 52.9]
	Madrid	Galicia	+26.9	9.9	.014	[5.5, 48.3]
	Balearic Islands	Andalusia	+18.2	10.3	.084	[-2.4, 38,8]
Total CO_2 Last Year by	**(I) Age Group**	**(J) Age Group**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	36-50	18-35	+289.7	23.6	<.001	[239.8, 339.6]
	36-50	66+	+245.3	24.1	<.001	[194.2, 296.4]
	51-65	18-35	+167.8	22.9	<.001	[119.3, 216.3]
	51-65	66+	+123.4	23.4	.001	[73.8, 173.0]
	(I) Income (€)	**(J) Income (€)**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	≥2,800	<1,500	+623.4	32.1	<.001	[556.7, 690.1]
	≥2,800	1,500-2,200	+378.9	31.4	<.001	[313.4, 444.4]
	2,200-2,800	<1,500	+289.7	30.2	<.001	[226.6, 352.8]
	(I) Dependents	**(J) Dependents**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	3+	0	+456.2	28.4	<.001	[396.1, 516.3]
	3+	1	+298.7	27.1	<.001	[241.8, 355.6]
	2	0	+189.4	25.8	<.001	[135.1, 243.7]
	(I) Telework Days	**(J) Telework Days**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	0 (Office)	5 (Remote)	+378.4	31.2	<.001	[312.5, 444.3]
	0 (Office)	3-4 Hybrid	+234.1	30.1	<.001	[171.2, 297.0]
	1-2 Hybrid	5 (Remote)	+145.6	29.3	.001	[84.3, 206.9]
	(I) Employment	**(J) Employment**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	Employee	Student/Retired	+245.8	21.7	<.001	[199.8, 291.8]
	Self-employed	Student/Retired	+178.4	22.3	<.001	[131.1, 225.7]
	Employee	Unemployed	+123.7	21.9	<.001	[77.2, 170.2]
	(I) Nationality	**(J) Nationality**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	Argentine	Spanish	+198.6	19.3	<.001	[157.4, 239.8]

JOURNAL OF TOURISM AND SERVICES
Issue 32, volume 17, ISSN 1804-5650 (Online)
www.jots.cz

	Argentine	French	+167.2	19.8	<.001	[124.9, 209.5]
	Italian	Portuguese	+89.4	18.1	.001	[50.5, 128.3]
	(I) Profession	**(J) Profession**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	Taxi Driver	Student	+312.7	26.8	<.001	[256.4, 369.0]
	Lawyer	Student	+267.3	25.9	<.001	[212.8, 321.8]
	Doctor	Student	+198.4	24.7	<.001	[146.3, 250.5]
	Consultant	Nurse	+134.7	23.1	<.001	[85.8, 183.6]
	(I) Autonomous Community	**(J) Autonomous Community**	**Mean Diff (kg/year)**	**SE**	**p-value**	**95% CI**
	Madrid	Andalusia	+156.9	17.8	<.001	[118.7, 195.1]
	Castile & León	Catalonia	+134.2	18.4	<.001	[94.7, 173.7]
	Madrid	Galicia	+112.7	17.6	<.001	[74.8, 150.6]

Note: Only significant pairwise comparisons are reported for clarity

Source: author

Appendix C. Effect Size Measures

Variable	Predictor	η	η^2	Effect Size	% Variance Explained
Mobility CO_2	**Age**	.642	.412	Large	**41%**
	Income	782	.612	Large	**61%**
	Dependents	.531	.282	Large	**28%**
	Telework	.614	.377	Large	**38%**
	Employment Status	.542	.294	Large	**29%**
	Nationality	.417	.174	Medium	**17%**
	Profession	.852	.727	Large	**73%**
	Autonomous Community	.487	.237	Large	**24%**
Restaurants CO_2	**Age**	.618	.382	Large	**38%**
	Income	.845	.714	Large	**71%**
	Dependents	.437	.191	Medium	**19%**
	Telework	.464	.215	Large	**22%**
	Employment Status	.374	.140	Medium	**14%**
	Nationality	.474	.225	Large	**23%**
	Profession	.736	.542	Large	**54%**
	Autonomous Community	.480	.231	Large	**23%**
Housing CO_2	**Age**	.443	.196	Medium	**20%**
	Income	.433	.188	Medium	**19%**
	Dependents	.258	.066	Medium	**7%**
	Telework	.279	.078	Medium	**8%**
	Employment Status	.175	.031	Small	**3%**

	Nationality	.230	.053	Small	**5%**
	Profession	.337	.114	Small	**11%**
	Autonomous Community	.282	.080	Medium	**8%**
Shopping CO_2	**Age**	.642	.412	Large	**41%**
	Income	.913	.833	Large	**83%**
	Dependents	.581	.338	Large	**34%**
	Telework	.448	.201	Large	**20%**
	Employment Status	.413	.171	Medium	**17%**
	Nationality	.428	.183	Medium	**18%**
	Profession	.759	.576	Large	**58%**
	Autonomous Community	.394	.155	Medium	**16%**
Total CO_2 Last Year	**Age**	.471	.222	Large	**22%**
	Income	.710	.505	Large	**51%**
	Dependents	.266	.071	Medium	**7%**
	Telework	.391	.153	Medium	**15%**
	Employment Status	.268	.072	Medium	**7%**
	Nationality	.274	.075	Medium	**8%**
	Profession	.490	.241	Medium	**24%**
	Autonomous Community	.372	.138	Medium	**14%**

Source: author