“Emotion-based insights into pro-environmental video campaigns: A study on waste sorting behavior in Ukraine”

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EMOTION-BASED INSIGHTS INTO PRO-ENVIRONMENTAL VIDEO CAMPAIGNS: A STUDY ON WASTE SORTING BEHAVIOR IN UKRAINE

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Abstract

This study aims to examine how different types of pro-environmental video content (featuring humans versus AI-generated characters) influence household waste sorting attitudes and behaviors among Ukrainian residents. The research was conducted in two stages using a mixed-method approach. In the first stage, 102 individuals aged 18–45 watched two videos on waste sorting and completed an online questionnaire. Cluster and variance analyses were performed using Statistica software. In the second stage, 35 participants underwent a laboratory-based emotion analysis using iMotions software, heart rate monitors, and galvanic skin response sensors at the Behavioral Lab of Sumy State University (Ukraine) from May to July 2024. The results revealed that videos featuring real people were more effective in generating interest (average rating: 3.5 vs. 3.2) and emotional engagement, particularly joy and contempt, which were the most frequently expressed emotions. Cluster analysis identified four distinct respondent groups. Cluster 1 (39.2%) – primarily young women – responded positively to human-led videos but showed limited behavioral change. Cluster 2 (19.6%) – women aged 26–35 – reacted positively to both videos and were most willing to adopt waste sorting behavior. Cluster 3 (23.5%) – primarily men – showed moderate engagement and sorted waste occasionally. Cluster 4 (17.6%) – highly educated women – exhibited the least positive responses and were least likely to change their behavior. The emotion analysis confirmed that videos featuring real people elicited stronger emotional responses across all categories, whereas AI-generated videos prompted higher levels of anger but generally weaker engagement.

Keywords attitude, survey, artificial intelligence, neuroscience, stimuli, sustainability, waste, promotion, communications

JEL Classification Q56, M31, D91, C91, D83

INTRODUCTION

The issue of household waste has become increasingly urgent due to its environmental and economic implications worldwide. In recent years, food and household waste volume has reached alarming levels, with private households contributing the largest share. The global community generated approximately one billion metric tons of food waste in 2022, approximately 17% of the total food produced and 60% of household waste (Alves, 2025). In the European Union, over half of the 58 million tons of food waste produced in 2021 originated from households, 54% of this was from private households (generating over 31 million tons of "fresh mass"), 21% from food and beverage manufacturers (5 million tons), 9% from restaurants and catering, and 7% from retail and other food distributors (Fleck, 2024). Similarly, Ukraine faces a significant waste management challenge, generating over 400 million tons of waste annually, with only a fraction adequately disposed

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of or recycled (Rui et al., 2019). Only 100 million tons of waste are disposed of, and 1 million tons are burned (Alves, 2025). This situation places a substantial financial burden on municipal governments and contributes to environmental degradation.

Despite the widespread availability of waste collection systems, improper sorting and disposal remain persistent problems. One of the key factors influencing this behavior is the public's awareness and motivation to engage in sustainable practices. International experience, particularly in countries such as Sweden, Croatia, and Slovenia, suggests that well-structured, long-term communication campaigns can effectively encourage more responsible waste behavior. Evidence shows that information-driven initiatives have the potential to reduce household waste by notable margins (Fleck, 2024). Countries where active and long-term advertising campaigns are carried out often experience an increase in the level of waste sorting and recycling. For example, information campaigns have been shown to be effective in reducing food waste by up to 28% (Reynolds et al., 2019).

However, while numerous awareness campaigns exist, there is limited empirical evidence on how the form and emotional appeal of these messages affect individual behavior, particularly among younger populations. This gap is especially relevant as new technologies, such as artificial intelligence, increasingly shape public communication strategies.

1. LITERATURE REVIEW

Effective household waste management remains a core challenge in achieving environmental sustainability, particularly in the context of increasing urbanization, consumerism, and ecological degradation. While technical waste management systems exist in many regions, individual behavior concerning sorting, disposal, and recycling continues to vary significantly, undermining the effectiveness of these systems and contributing to pollution and resource depletion.

Recent scholarship has concentrated on the broader transition to a green economy, which emphasizes sustainable energy consumption, green finance, and environmentally responsible consumer behavior (Birzhanova et al., 2024; Pekarskiene et al., 2023; Rozkwitalska & Lis, 2022; Štreimikienė et al., 2022; Vasilyeva et al., 2023). A central concept in this transition is the circular economy, which promotes waste prevention, material reuse, and efficient resource management. Scholars have increasingly explored this framework as a pathway to sustainable development (Amin & Oláh, 2024; Bliumska-Danko et al., 2022; Jakubelskas & Skvarciany, 2023; Potkány et al., 2024; Georgescu et al., 2022).

Jakubelskas and Skvarciany (2023) offered to assess the efficiency of implementing a circular economy in EU countries by developing renewable energy sources instead of reducing the use of raw materials. They proposed facilitating the reuse and processing of resources in all production cycles, from a project to utilization after use.

Potkány et al. (2024) compared the efficiency of the cyclic economy within the waste management system in individual European countries. GDP per capita negatively affected the efficiency of handling hazardous waste due to increased waste production intensity with economic growth. However, the impact of non-hazardous waste is positive, likely due to government expenditures in this area. Employment in the circular economy also positively influences waste management efficiency, indicating the development and support of the waste processing industry. Patents in the circular economy demonstrate a positive impact on efficiency, suggesting innovations in waste management practices.

Georgescu et al. (2022) confirmed that the recycling rate of municipal waste has a positive effect on economic development. Conversely, research and development expenditure has a positive effect on the recycling rate of municipal waste as well as on economic development. Generation of municipal waste per capita positively affects the recycling rate of municipal waste. Finally, the generation of municipal waste per capita has a positive effect on economic development. The efficiency of waste collection and management should be assessed by means of data envelopment analysis among the policies used by governmental agencies. Technology development, by a decreasing life of products, leads to an increase in waste generation.

Fu and Chang (2024) argue that realizing the circular economy requires a paradigmatic shift from traditional waste disposal practices to integrated, multi-sectoral strategies supported by policy, technology, and regulation. This argument is echoed by Dobrovolska et al. (2024), Halynskyi et al. (2024), Hornungová and Petrová (2023), and Lentner et al. (2024), who highlight the necessity of coordinated fiscal and governance measures. The successful adoption of circular economy principles relies on a combination of economic tools, public awareness campaigns, infrastructure improvements, and behavioral incentives (Jurkowska-Gomułka et al., 2021; Yurchyk et al., 2023; Yang et al., 2024; Onopriienko et al., 2023).

Equally important are non-technological levers such as public engagement, educational campaigns, and behavioral incentives. Environmental education and habit formation significantly enhance pro-environmental behavior (Zhghenti & Kapanadze, 2024; Małys, 2023). The COVID-19 pandemic, as shown by Firstová and Vysochyna (2024), even acted as a behavioral catalyst, prompting greater awareness and sustainable consumption patterns. Other researchers have identified key behavioral determinants, including environmental knowledge, perceived convenience, social norms, and transparency in communication (Zhidebekkyzy et al., 2022; Imashev et al., 2024; Skrynnyk & Vasylieva, 2020).

Zhidebekkyzy et al. (2023) found that the amount of household waste is influenced by waste processing awareness, the choice of green products and packaging, the circular economy awareness, acquaintance with the principles of circularity, such as reuse, processing, reduction of consumption, etc. The development of a circular economy begins with the formation of population pro-circular behavior. Population pro-circular behavior influences their attitude to joint consumption/use of services in the following positions: rental real estate (housing, apartments), vehicles, bicycles, workplace for a certain time, freelance work, food, book exchange, etc. Liu et al. (2022) demonstrated that attitudes and subjective standards have a significant positive impact on the intention to sort household waste, and the perceived policy efficiency has a positive and significant impact on the attitude and intention to sort waste. The desire (intention) to sort waste has a positive and significant impact on the behavior of waste sorting. In addition, individual characteristics, including gender, income level, and age, have a significant impact on the behavior of garbage sorting.

The role of communication and advertising in waste management has also received considerable scholarly attention. Chygryn et al. (2021), Makarenko et al. (2024), and Heinzova et al. (2024) emphasize the synergy between manufacturers and recyclers through coordinated advertising, which can bolster both environmental and economic outcomes. However, balancing ecological goals and commercial objectives is not always straightforward. Mwanaumo et al. (2024) determined that cooperative advertising does not always lead to optimal emissions outcomes, necessitating more strategic approaches. Poli et al. (2023) proposed evolutionary game-theoretic models to understand how advertising and policy interventions influence behavior in dynamic waste systems.

In operational terms, waste management policies must be built upon a nuanced understanding of systemic and behavioral drivers (Tielietov & Letunovska, 2014; Alfarizi et al., 2023; Pan & Liu, 2024).

Alfarizi et al. (2023) established a relationship between behavior, knowledge, and attitude behavior. The knowledge of the company's owners is strongly influenced by the knowledge of waste management (93.6%). The attitude of the owners is influenced by the knowledge of waste management and the knowledge of the company owner (92.5%). The behavior of waste management is influenced by the knowledge and attitude of business owners (97.8%). Entrepreneurs' better attitude and awareness about the potential of waste encourages them to better handle them through sorting procedures to convert waste into alternative energy.

Pan and Liu (2024) found that there are differences in the behavior of waste separation between children (aged 9 to 12 years) and adults (ages 18 to

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66). Adult attitudes, subjective norms, perceived behavior, and knowledge are largely positively related to their intention to share waste. Moreover, the perceived behavioral control and intention are positively related to the behavior of adults. However, for children, only perceived behavioral control and awareness are positively related to the intention, and perceived behavioral control is positively related to behavior.

Zhang et al. (2024) found that personal standards are key factors that affect the sorting of urban waste and the attitudes of rural residents. At the same time, drivers for urban residents are economic incentives, and rural residents face policy restrictions.

In Ukraine, targeted waste-sorting promotion remains underdeveloped despite its necessity for advancing recycling and processing infrastructure (Khomenko et al., 2021). While recycling initiatives often require significant upfront investment, studies affirm their long-term economic and environmental returns (Liubchak et al., 2021; Tvaronavičienė et al., 2021). A range of policy tools – such as ecological taxation, incentives, and public infrastructure – have proven effective in increasing the proportion of sorted waste and reducing landfill dependency (Hermann & Puntoni, 2024).

Recent developments in artificial intelligence have introduced a new dimension to sustainable communication strategies. AI-driven tools have gained traction for their ability to personalize content and enhance message targeting (Bian & Wang, 2024; Androniceanu, 2024). Studies show that such digital transformations can strengthen engagement with sustainability campaigns, especially when paired with behaviorally informed communication (Oualid et al., 2024; Abid et al., 2024; Yarovenko et al., 2024). These technologies empower public agencies and private firms to craft tailored messages that align with psychological triggers (Dobrovolska & Kolomiiets, 2024; Omarova et al., 2024; Kolupaieva & Tiesheva, 2023; Benchea & Ilie, 2023). Still, understanding public perception of AI-generated content and the psychological underpinnings of pro-environmental behavior remains a vital research priority (Szigeti & Jozsa, 2023; Zamir & Kim, 2022). Survey-based studies have helped identify the drivers and barriers of waste sorting behavior, offering critical data for evidence-based intervention design (Boutaleb, 2024; Oe & Yamaoka, 2024).

Moreover, emotional and cultural dimensions play a substantial role in shaping attitudes toward sustainability. Empathy, joy, or even disgust can amplify the impact of environmental messages, while cultural narratives may reinforce or obstruct behavioral change (Oe & Yamaoka, 2023; Saleh Al-Omoush et al., 2023). Despite this, little is known about how emotionally charged content – mainly when delivered by AI-generated versus real human characters – influences actual behavior in the context of household waste management (Nguyen et al., 2024).

While previous research has examined communication channels and general content strategies for promoting household waste sorting (Amrani et al., 2022), limited attention has been given to message design's emotional and psychological dimensions. In particular, there is a notable gap in empirical studies that directly link emotional responses to behavioral change, primarily through experimental comparisons of AI-generated versus real-person content. This study seeks to address this gap by examining how different types of pro-environmental video content (featuring real people versus AI-generated characters) influence household waste sorting attitudes and behaviors among Ukrainian residents. The secondary research objectives are to determine which video format most effectively promotes environmentally responsible behavior among Ukrainian youth, to classify the population into behaviorally distinct clusters, and to analyze the emotional responses elicited by various forms of visual communication technology.

2. METHODOLOGY

This study was conducted in two stages and employed both survey-based and experimental research methods to examine the emotional and behavioral responses to pro-environmental video content related to household waste sorting.

In the first stage, two thematic videos were created to convey the importance of waste sorting. These videos were specially designed and produced by the authors to investigate emotional responses and behavioral intentions toward waste sorting. Specifically, two short pro-environmental videos were created, each approximately equal in length and content, emphasizing the importance of household waste sorting. One video featured real human actors to provide authentic, relatable communication, while the other utilized AI-generated characters to test the effectiveness of novel digital technologies in environmental communication. Both videos employed similar narrative structures and informational content to ensure comparability, differing primarily in the presence and authenticity of the actors portrayed. The videos used in the research can be accessed via Lyeonov et al. (2025). The target population was Ukrainian residents aged 18-45, a demographic selected due to its higher receptivity to digital technologies and active environmental engagement. These characteristics were critical for assessing AI-generated content perceptions and responsiveness to environmental messaging.

A structured online survey was administered using Google Forms and distributed via internet platforms. The questionnaire contained 25 items (Appendix A), focusing on respondents' waste management behavior and reactions to the two video formats. A total of 102 valid responses were collected. This sample size meets the requirements for statistical representativeness in social research, as supported by methodological guidelines related to population size, confidence intervals, and margin of error (Samborskyi, 2017). Demographic characteristics of the sample included 70% female and 30% male participants, with 64.7% aged 18-25, 20.6% aged 26-35, and 14.7% aged 36-45. Educational attainment ranged from secondary education to postgraduate degrees.

Quantitative data were analyzed using the STATISTICA 10 software. Cluster analysis was conducted using the k-means method, with initial cluster centers sorted by distance and regular observation assignment. Variance analysis was applied to identify significant parameters (12 of 21) using a significance level of $p < 0.05$. The analysis explored two to ten clusters, and average values within clusters were examined to develop targeted recommendations for improving waste sorting practices (Kong et al., 2023).

The second stage of the study involved an experimental procedure focusing on physiological and emotional responses to the same video content. A total of 35 participants (alternative treatment group) were recruited based on geographic accessibility (Sumy, Ukraine). This sample size aligns

Source: Screenshot made in iMotions program.

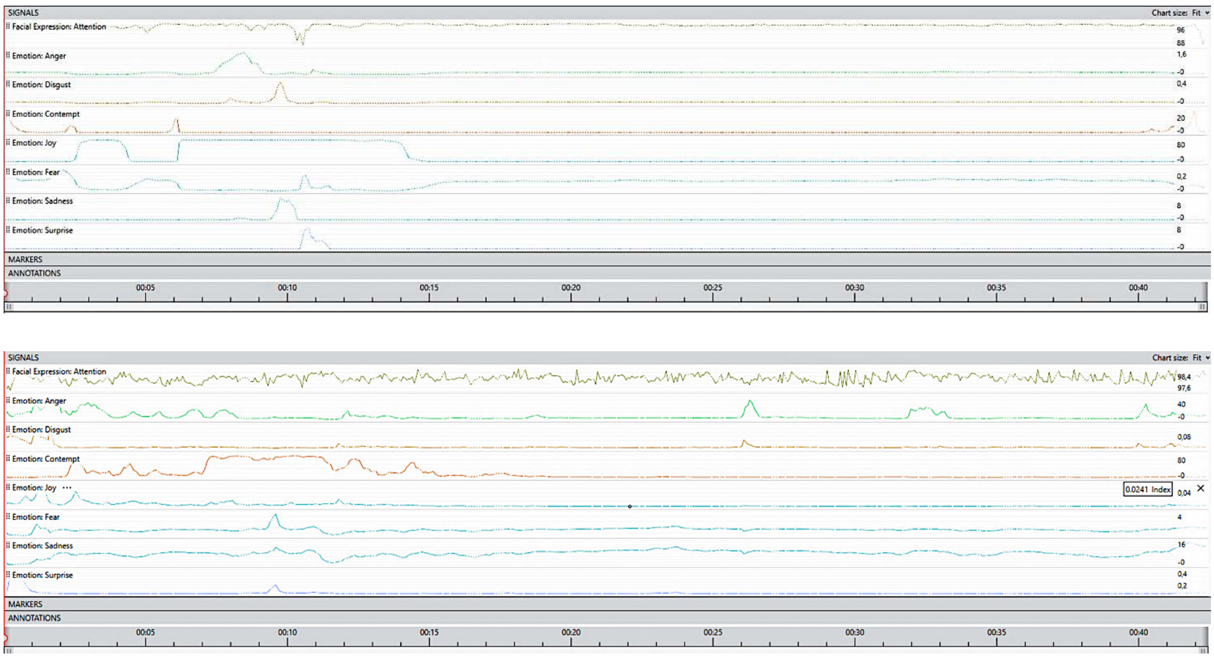

Figure 1. Real-time graph: Frame-by-frame analysis of emotional responses

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with established recommendations for neuropsychological and experimental research, where 30–50 participants are generally sufficient to ensure statistical power and feasibility (Baker et al., 2021; Luck, 2014; Szucs & Ioannidis, 2020; Goodwin et al., 2015; Kringelbach & Berridge, 2010).

Participants were equipped with Shimmer sensors to capture heart rate and galvanic skin response (GSR). The GSR sensors were affixed to the index and middle fingers, while the heart rate sensor was placed on the ring finger using Velcro straps. Facial expressions were recorded via webcam as participants viewed both video stimuli. Before the session, participants provided written informed consent and received detailed instructions regarding the procedure.

Emotion recognition and biometric data were analyzed using the iMotions software platform. Upon completion of the recordings, raw data were exported to Excel for further processing. Frame-by-frame analyses were conducted to identify emotional fluctuations and create graphical representations of average emotional response times across all participants. Graphs showing the emotions and feelings of each respondent were made. Examples of a frame-by-frame analysis of some emotional responses are presented in Figure 1. Graphs showing the average fraction of the emotion time for all the respondents were made. Similarly, a graph with the average emotion time by percent for all the respondents was also created.

2.1. Ethical considerations

For respondents, consent was obtained directly, with clear information provided about the study's purpose and confidentiality assurances. This study followed strict ethical standards for research involving human participants, per the Declaration of Helsinki and the Belmont Report. All participants provided informed consent and were made aware of their right to withdraw from the study at any time without repercussions. Confidentiality and anonymity of the data were upheld throughout the study. This included maintaining the anonymity of participants, securing data storage, and ensuring that the findings would be reported in an aggregated manner to prevent any potential identification of individual respondents.

3. RESULTS

The generalized results of gathering answers from respondents in Google Forms are presented in Table 1.

Table 1. Generalized survey results about the respondents' attitude to the proposed videos about waste management approaches

Question	Answer options	Video 1 (with real people)	Video 2 (with characters developed using AI technologies)
Rate how much you were interested in the video	From 1 to 5, where one is not attractive at all, five is very interesting	3.5 points	3.2 points
Is the main idea of this video clear to you?	Of course	85.3%	64.7%
	Somewhat clear	5.9%	9.8%
	Neutral	8.8%	25.5%
Do you desire to change your behavior after watching the video?	Yes, definitely	20.6%	18.6%
	Maybe	40.2%	29.4%
	Not sure	18.6%	20.6%
	Unlikely	14.7%	21.6%
	No, not at all	5.9%	9.8%
Should this and similar videos on the given topic be shown to a broader audience?	Yes, of course	52.0%	27.4%
	Yes, maybe	35.3%	26.5%
	Neutral	9.8%	21.6%
	Unlikely	2.9%	14.7%
	Not worth it at all	0%	9.8%
Has your attitude to the topic changed after watching the video?	Yes, much improved	15.7%	18.6%
	Yes, it has improved a bit	40.2%	26.5%
	Nothing has changed	44.1%	54.9%

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The survey results indicate that respondents found the video featuring real people slightly more engaging, with an average rating of 3.5 compared to 3.2 for the AI-generated video. Additionally, a more significant proportion of viewers clearly understood the video's main message with real individuals (85.3%) compared to the AI-generated one (64.7%), suggesting that the human-led video was more effective in delivering a comprehensible message. Regarding behavioral influence, the video with real people showed a higher willingness to change behavior, as approximately 60.8% of respondents indicated at least some intention to alter their habits following the viewing. In contrast, fewer respondents (48%) indicated similar intentions after viewing the AI-generated video, highlighting its comparatively lower effectiveness in influencing viewers' behavioral intentions.

Participants also strongly favored broader dissemination of the real-person video, with 87.3% supporting its wider distribution. In contrast, support for the AI-generated video's broader dissemination was substantially lower at 53.9%, with a notable portion expressing neutrality or opposition. Regarding attitudinal change, the video featuring real people prompted positive changes in attitudes toward waste management for 55.9% of respondents. In contrast, the AI-generated video influenced fewer respondents positively (45.1%), leaving the majority unaffected. These findings consistently indicate that videos featuring real individuals are more effective than AI-generated alternatives in engaging viewers, clearly communicating pro-environmental messages, motivating behavioral change, and positively influencing attitudes toward sustainable waste management practices.

Waste sorting practices typically involve categorization into twelve distinct groups, specifically paper and cardboard, glass, metal, and synthetic materials (including plastics), organic waste (food and garden residues), electronic waste (batteries, accumulators), textiles and clothing, wood and furniture, hazardous waste (chemicals, paints), medical waste, construction materials, waste electrical equipment, and mixed waste, which comprises items that do not fit into other categories. Respondents in this study indicated an average preference for sorting waste into approximately seven groups. The detailed outcomes of the variance analysis are presented in Table 2.

Cluster 1 included 40 respondents, representing 39.2% of the total sample, predominantly comprising young adults aged 18–25 (67.5%), with females accounting for 72.5% and males for 17.5%. 37.5% had completed higher education, and 40% held pre-higher educational qualifications. Videos featuring real people achieved an average interest rating of 3.45 on a five-point scale within this cluster. Notably, 72.5% expressed intentions to modify their waste sorting behavior after viewing the real-person video, and 97.5% supported the dissemination of similar content. However, 62.5% reported no significant attitudinal change following the viewing. Conversely, the AI-generated video garnered a lower average interest rating of 2.55 points. After watching the AI-generated video, 47.5% indicated a willingness to alter their behavior, yet 70% either opposed or remained neutral regarding broader exposure to similar AI-generated content. A considerable majority (92.5%) noted no change in their attitudes toward waste sorting after exposure to this video. Approximately 67.5% of respondents from Cluster 1 reported frequently or regularly engaging in waste sorting, advocating for sorting waste into four to seven categories. On average, respondents identified between six to eight, or up to twelve, distinct factors influencing their decisions regarding waste sorting behaviors.

Based on the average distances, the characteristics of each of the clusters are determined.

Cluster 2 comprises 20 respondents, accounting for 19.6% of the sample. All members of this cluster are female, with half falling within the age range of 26–35 years. Educationally, 50% possess higher education qualifications, while 20% have attained pre-higher education levels. The video featuring real individuals achieved a high average interest score of 4.6 on a five-point scale, with unanimous agreement (100%) among respondents regarding their intention to alter their waste-sorting behaviors following exposure. Additionally, all participants supported broader dissemination of similar content featuring real people. However, despite strong intentions to change behavior, 95% indicated no significant attitudinal shift post-viewing. Conversely, the AI-generated video was

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Table 2. Analysis of variance for 12 parameters

Source: Calculations in Statistica.

Indicators	Between SS	df	Within SS	df	F	p-value
Interest in watching Video 1	43.79927	3	57.20073	98	25.01325	0.000000
Desire to change behavior after watching Video 1	41.00227	3	59.99773	98	22.32430	0.000000
The feasibility of showing Video 1 with real people to a broader audience	39.20148	3	61.79852	98	20.72189	0.000000
Change of attitude to the topic after watching Video 1	37.39027	3	63.60973	98	19.20171	0.000000
Interest in watching Video 2	47.86959	3	53.13041	98	29.43211	0.000000
Desire to change behavior after watching Video 2	54.69872	3	46.30128	98	38.59127	0.000000
The feasibility of showing Video 2 with real people to a broader audience	36.60759	3	64.39241	98	18.57126	0.000000
Change of attitude to the topic after watching Video 2	62.84748	3	38.15252	98	53.81080	0.000000
Frequency of waste sorting	13.13484	3	87.86517	98	4.88329	0.003310
Number of types of waste that need to be sorted for efficient removal, processing, and disposal	27.60034	3	73.39967	98	12.28358	0.000001
The number of factors that most influence people's behavior when making decisions about waste sorting	42.76104	3	58.23896	98	23.98499	0.000000
Gender	20.44168	3	80.55833	98	8.28917	0.000057

rated marginally lower, at an average of 4.5 points. At the same time, 90% expressed a willingness to change behavior following the AI-generated video, and 95% opposed or were neutral toward its broader public dissemination. Interestingly, this video resulted in attitudinal shifts toward waste sorting in 95% of respondents. Approximately 60% of this cluster regularly engage in waste sorting, while the remaining 40% do so occasionally. Most respondents (55%) recommended dividing waste into 5–6 distinct categories and identified between ten and twelve influential factors affecting waste sorting decisions.

Cluster 3 comprises 24 respondents, representing 23.5% of the total sample. The majority (70.8%) are aged between 18–25 years, while 20.8% are aged between 26 and 35. This cluster predominantly comprises males (62.5%), with females constituting 37.5%. Educational attainment within this group is high, with 79.2% having either higher or professional pre-higher education. Videos featuring real individuals received an average rating of 3.7 on a five-point scale, with 79.2% expressing intentions to change their behavior and 87.5% supporting broader exposure of similar videos. Notably, 75% reported an attitudinal shift toward waste sorting following viewing. The AI-generated video received a comparable average rating of 3.8, yet 87.5% indicated no intention to alter their behavior, and a similar percentage (87.5%) reported no attitudinal change post-viewing. Nevertheless, 79.2% supported broader dissemination of AI-generated content. Approximately half of the cluster (50%) engages occasionally in waste sorting, and 29.1% do so frequently. A significant proportion (75%) advocated sorting waste into fewer categories, primarily one to three, and identified an average of three to five influential factors affecting sorting decisions.

Cluster 4 includes 18 respondents, constituting 17.6% of the total sample. This cluster predominantly consists of younger individuals, with 61.1% aged between 18–25 years, 16.7% between 26–35 years, and an additional 16.7% between 36–45 years. Females represent 72.2% of this cluster, with males accounting for the remaining 27.8%. Most (55.6%) have attained higher education, 22.2% hold scientific degrees, and 16.7% have pre-higher educational qualifications. The video featuring real individuals was less appealing to this cluster, receiving an average rating of 2.4. Behavioral intentions following exposure were evenly divided, with half indicating a willingness to change and half remaining unchanged. Only half of the respondents supported broader dissemination of similar real-person content, with an additional 33.3% expressing neutrality. Furthermore, 72.2% reported no attitudinal shift post-viewing. The AI-generated video elicited slightly higher average interest (2.5 points), yet 55.6% indicated no desire to alter behavior afterward. Similarly, 72.2% opposed or were neutral toward broader dissemination of AI-generated content, with 83.3% experiencing no attitudinal change. Despite lower

Table 3. Average percent of each emotion time for two videos for all respondents

Source: Formed using the iMotions software.

Video type	Average emotion time for each emotion, %						
	Anger	Disgust	Contempt	Joy	Fear	Distress	Surprise
Video 1 (with real people)	3.91	2.5	15.03	11.89	1.59	5.37	3.49
Video 2 (with characters developed using AI)	4.39	2.38	11.23	10.33	0.95	3.85	0.48

video engagement, approximately 94.5% regularly or frequently engage in waste sorting, typically preferring sorting into one to four categories. Respondents in this cluster identified between two and four influential factors shaping their decisions related to waste sorting. Multiple clustering methods – precisely squared Euclidean distances, Manhattan distance, Chebyshev distance, and 1-r Pearson distance – were utilized to verify model adequacy, confirming the robustness of the cluster model employed.

During the experimental phase, which utilized iMotions software, respondents' emotional reactions were assessed while viewing the two distinct videos, focusing on seven primary emotions: anger, disgust, contempt, joy, fear, distress, and surprise. The average duration percentages for each emotion experienced by respondents for both videos are detailed in Table 3.

Analysis indicates that contempt (15.03% for the real-person video and 11.23% for the AI-generated video) and joy (11.89% and 10.33%, respectively) were the most prominently expressed emotions. Negative emotions such as anger (3.91% and 4.39%) and distress (5.37% and 3.85%) were moderately expressed, while disgust, fear, and surprise were minimally observed, ranging between 0.95% and 3.49%.

Notably, distress was more prevalent among viewers of the video featuring real individuals (5.37%), whereas anger was more frequently elicited by the AI-generated video (4.39%). These findings suggest that the nature of the video production technology might differentially trigger specific emotional reactions, potentially offering valuable insights for optimizing video content.

The video with real people generated stronger emotional responses than its AI-generated counterpart. The exception was anger, which was more pronounced in response to the AI-generated video. Figures 2 and 3 illustrate the average percentage duration for the four most significantly expressed emotions (contempt, joy, distress, and anger).

Figure 2a illustrates the percentage of time each respondent expressed the emotion of contempt while viewing each of the two videos. Observing the bars, it becomes clear that contempt was not uniformly distributed among respondents. Some respondents expressed a notably higher level of contempt toward Video 1, whereas others had stronger emotional responses of contempt toward Video 2. Specifically, respondents such as R08, R12, R21, R24, R25, R27, and R32 showed elevated levels of contempt (> 40%), suggesting strong negative emotional responses that varied significantly depending on the video format. The differences in responses indicate that emotional engagement and negativity toward content vary considerably between individuals and video formats. Figure 2b represents the proportion of viewing time during which respondents experienced joy. Like the first figure, emotional responses varied significantly among individuals and between video formats. Notably, respondents such as R18, R19, R20, R21, and R26 expressed high levels of joy (> 60%) predominantly during Video 1 (with real people), signifying a strong positive emotional engagement with human-led content. In contrast, respondents such as R01, R06, and R17 showed higher joy levels during Video 2 (AI-generated). However, these instances are relatively less frequent, suggesting that AI-generated videos generally elicited lower positive emotional engagement across most respondents.

Figure 3a illustrates the proportion of viewing time during which respondents experienced distress while watching each of the two videos. Overall, distress was relatively infrequent and exhibited considerable variation among respondents. A few individuals demonstrated notably higher levels of distress. For instance, Respondent R22 exhibited a substantially higher level of distress (approximately 40%) during Video 1, indicating a strong adverse emotional reaction. Respondent

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Source: Formed using the iMotions software.

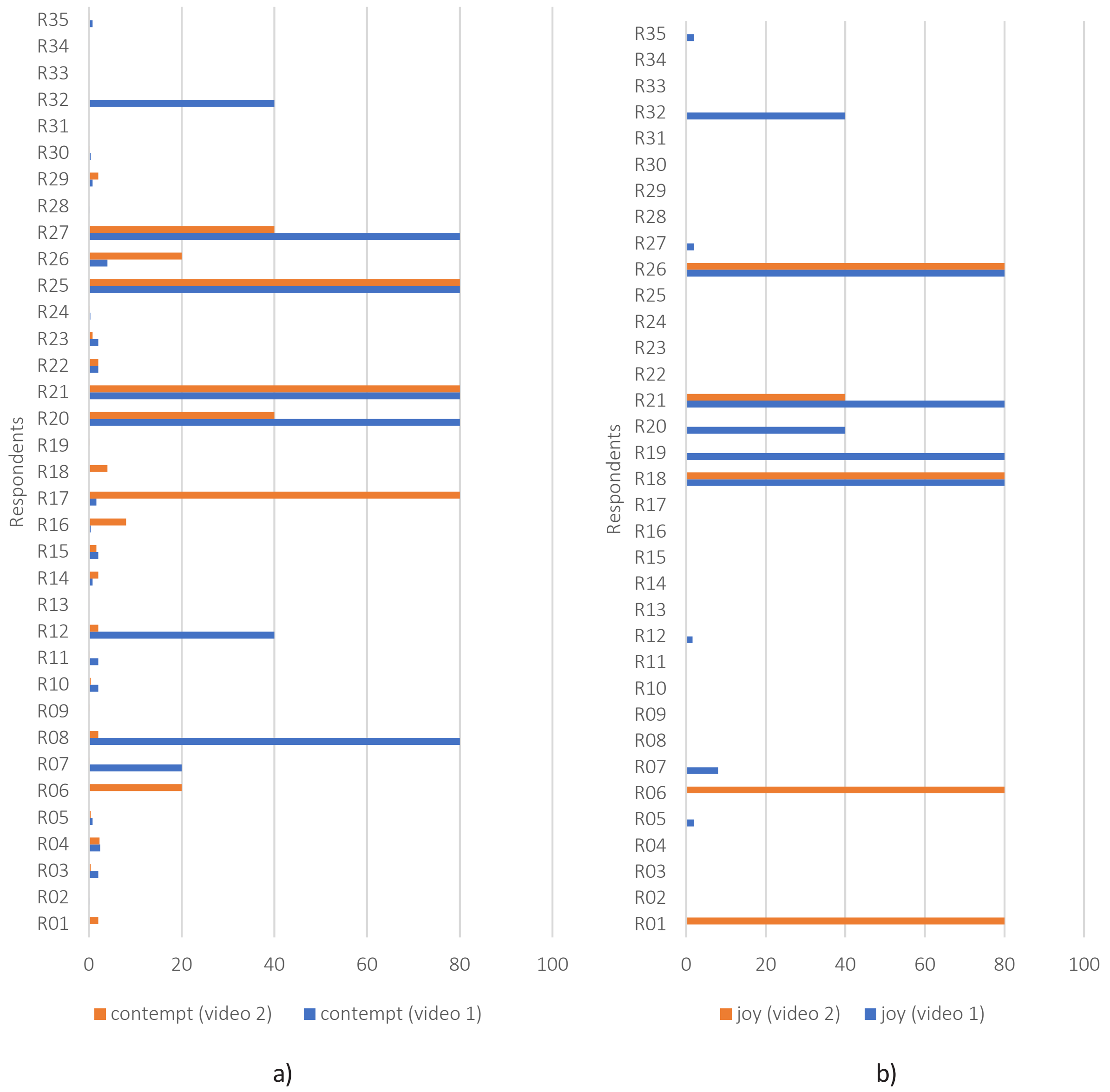

Figure 2. Average emotion time for all respondents (contempt and joy)

R02 showed considerable distress during Video 2 (around 35%), highlighting individual-specific responses to the AI-generated content. However, most respondents experienced relatively low distress levels (below 20%), indicating that both videos were generally not highly distressing to most viewers. Figure 3b compares the percentage of time respondents expressed anger during each video. Like distress, anger was predominantly low across respondents, although a few individuals showed significant levels. Notably, Respondent R22 displayed a remarkably high anger level during Video 1 (around 40%), whereas Respondent R08 exhibited considerable anger during Video 2 (around 40%). These variations underscore differences in emotional responses triggered by the distinct video formats. Nevertheless, most respondents' anger levels remained minimal (below 20%) across both videos, reflecting generally mild adverse reactions.

Despite the high average percentages for contempt and joy, fewer than 20% of participants exhibited contempt exceeding 40% of their viewing duration, indicating considerable variability in emotional intensity among individuals. Additionally, the analysis revealed that respondents' emotional reactions varied significantly between videos, with

Source: Formed using the iMotions software.

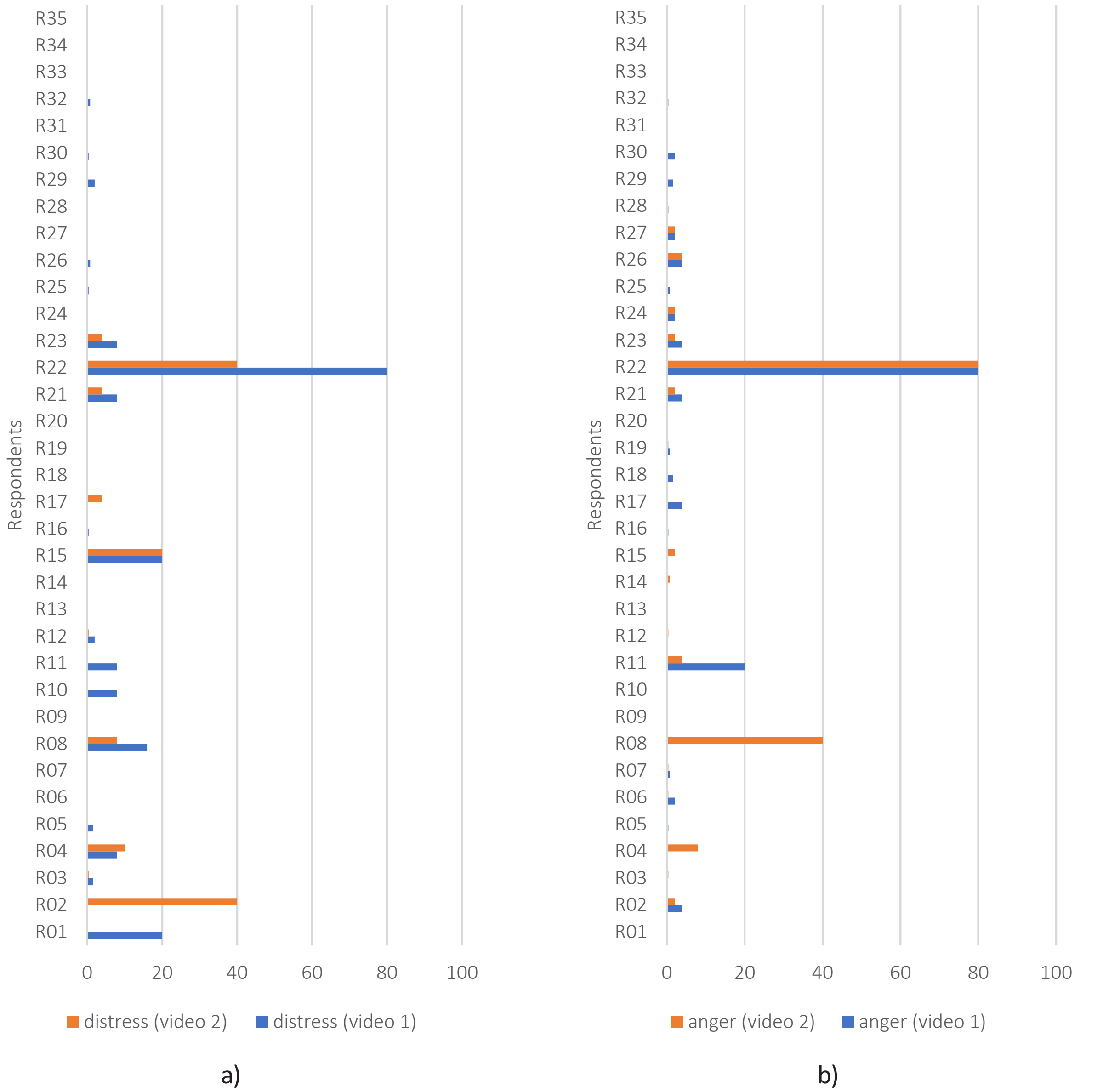

Figure 3. Average percent of emotion time for all respondents (distress and anger)

some respondents showing stronger emotional reactions to the real-person video. In contrast, others reacted more strongly to the AI-generated video. This variability highlights the dynamic and individual nature of emotional engagement throughout video viewing. The emotions of distress and anger were generally weakly expressed (below 20%) in both videos, suggesting limited emotional intensity in response to these stimuli.

Both videos successfully elicited a broad spectrum of emotions, encompassing both positive (joy) and negative (anger, contempt, distress) responses. Notably, the video featuring real people elicited higher emotional intensity overall, with more prominent expressions of contempt and joy among individual respondents. In contrast, negative emotions in the AI-generated video were less intense overall, though anger occurred more frequently and with greater intensity in specific cases. Detailed emotional response data for all participants are provided in Appendices B and C.

4. DISCUSSION

The findings of this study highlight the critical role of emotional engagement and personalization in promoting pro-environmental behavior, particu-

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larly in household waste sorting among Ukrainian residents. Results demonstrate that videos featuring real individuals significantly outperform AI-generated content in evoking emotional responses, such as joy and contempt, and in influencing behavioral intentions. These outcomes align with existing literature emphasizing the effectiveness of emotionally charged and personalized communication strategies in promoting sustainable behaviors.

The current research findings resonate with Liu et al. (2022), who emphasized the importance of subjective norms and individual characteristics as critical determinants of waste-sorting intentions. Specifically, this study confirms that intrinsic motivators and prior habits significantly outweigh the impact of external video stimuli, suggesting a strong alignment between personal normative beliefs and actual environmental behaviors.

Furthermore, these findings parallel those of Zhang et al. (2024), who identified significant demographic differences in responses to pro-environmental interventions. The cluster analysis conducted in this study reinforces this notion by demonstrating varying levels of engagement and behavioral intentions across distinct demographic groups, particularly highlighting differences based on age, gender, and educational attainment. This underscores the importance of targeted messaging tailored to specific audience segments to enhance intervention efficacy.

Interestingly, the role of emotional content, emphasized in this study, extends previous insights from Hermann and Puntoni (2024), who highlighted the psychological impacts of environmental advertising through visual contexts rather than emotional narratives. This study advances the conversation by demonstrating that human presence significantly amplifies emotional engagement, which may lead to stronger behavioral responses than AI-generated representations.

The study further contrasts with the approach taken by Hartmann and Apaolaza-Ibanez (2012), who focused on symbolic value and psychological benefits without explicitly examining emotional responses to human versus AI-generated content. This paper fills a gap by directly linking emotional responses to behavioral intentions, suggesting that the authenticity and relatability of human characters in promotional content significantly enhance engagement and potential behavior change.

This study diverges from Chan (2004) and Wenting et al. (2022), who explored consumer preferences for print versus broadcast environmental advertisements and the impact of advertising color, respectively. Unlike these studies, the current analysis specifically evaluates the dynamic emotional impact of video content and the critical importance of real human engagement versus artificial characters, thereby providing unique insights into the efficacy of video as a persuasive medium for environmental communication.

Finally, while S. Liu and X. Liu (2020) highlighted cultural and social factors affecting consumer preferences in advertising campaigns, the present investigation indicates that universal psychological responses – particularly emotional engagement with real people – are powerful drivers of pro-environmental behavior, regardless of cultural nuances. This suggests that employing real human actors may universally enhance the effectiveness of environmental campaigns across diverse cultural contexts.

This study contributes valuable insights into the psychological dimensions of pro-environmental communications, emphasizing the importance of emotional engagement facilitated by real human presence. The findings support the notion that effectively tailored, emotionally resonant, and personalized communication strategies are essential to promote sustainable household waste management practices. Future research should explore combining emotional appeals with sustained informational reinforcement and community-driven initiatives to achieve lasting behavioral changes.

Despite the comprehensive nature of the research design, several limitations must be acknowledged. First, the online survey was distributed exclusively via digital platforms, thereby restricting participation to individuals with access to the internet and a baseline level of digital literacy. This limitation may have introduced a sampling bias, particularly by underrepresenting certain demographic groups, such as older adults or individuals in rural areas with limited technological access.

Second, the emotion analysis component was confined to participants physically present in Sumy, Ukraine, where the Behavioral Laboratory and the requisite biometric equipment were located. This geographical constraint limited the diversity of the experimental sample and may have impacted the generalizability of the findings across broader populations.

While the study effectively compared AI-generated and human-acted video content, it did not account for other potentially influential variables such as cultural background, socio-economic status, or pre-existing attitudes toward environmental issues, all of which could mediate audience responses to pro-environmental messaging. Future research should incorporate a more diverse and stratified sample and consider longitudinal designs to assess behavioral changes over time.

The potential error caused by the general stress of respondents due to the war (overall background, bombings, etc.) was not taken into account.

CONCLUSION

The study aimed to assess how different types of video content (featuring humans versus AI-generated characters) affect the pro-environmental behavioral intentions of Ukrainian residents. The survey results revealed significant variability in responses based on demographic segmentation, identifying four distinct respondent clusters. Cluster 1, comprising primarily young women, showed positive reactions to real-person videos but limited behavioral change. Cluster 2, consisting entirely of women aged 26–35, responded positively to both video types, with strong behavioral intentions, especially after viewing real-person content. Cluster 3, primarily men, demonstrated moderate engagement and occasional waste-sorting behavior, showing some responsiveness to both video types. Cluster 4, mainly highly educated women, exhibited the least positive responses and minimal behavioral change intentions.

Emotion analysis findings showed that both video types evoked a range of emotions, predominantly contempt and joy. Real-person videos elicited significantly stronger emotional responses, notably higher levels of joy and contempt. Conversely, AI-generated videos triggered higher levels of anger but generally resulted in weaker overall emotional engagement. These emotional insights underscore the effectiveness of human authenticity and relatability in enhancing viewer engagement and potentially influencing sustainable behavior.

In conclusion, this study highlights the greater effectiveness of videos featuring real people in promoting emotional engagement and behavioral intentions toward household waste sorting among Ukrainian youth. Future research should explore integrating such emotionally compelling content with sustained educational efforts, economic incentives, and community involvement strategies to encourage long-term behavioral change. These findings provide valuable guidance for developing targeted and emotionally resonant communication campaigns to promote sustainable environmental practices.

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Methodology: Serhiy Lyeonov, Svitlana Bilan, Liliia Khomenko, Anzhela Kuznyetsova, Iuliia Myroshnychenko, Nataliia Letunovska.
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Writing – original draft: Anna Rosokhata, Liliia Khomenko, Nataliia Letunovska.
Writing – review & editing: Serhiy Lyeonov, Svitlana Bilan, Iuliia Myroshnychenko.

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APPENDIX A
QUESTIONNAIRE

1. Did you manage to watch the entire Video 1 at the link from beginning to end?

- ☐ Yes.
- ☐ No.

2. Rate how much you were interested in Video 1.

From 1 to 5, where 1 – Not interested at all, 5 – Very interested.

3. Is the main idea of Video 1 clear to you?

- ☐ Of course.
- ☐ Somewhat clear.
- ☐ Neutral.
- ☐ It is difficult to understand.
- ☐ It is unclear.

4. Choose emotions you had during or as a result of watching Video 1?

- ☐ Joy.
- ☐ Sympathy.
- ☐ Inspiration.
- ☐ Motivation.
- ☐ Certainty.
- ☐ Surprise.
- ☐ Interest.
- ☐ Indifference.
- ☐ Anger.
- ☐ Abomination.
- ☐ Concern.
- ☐ Displeasure.
- ☐ Other.

5. Did you have the desire to change your behavior after watching Video 1?

- ☐ Yes, exactly.
- ☐ Perhaps.
- ☐ Uncertain.
- ☐ Unlikely.
- ☐ No, I definitely will not.

6. Will Video 1 influence your future decisions about waste management?

- ☐ Very likely.
- ☐ Probably.
- ☐ Not sure.
- ☐ Unlikely.
- ☐ It will not affect me at all.

7. Should this and similar videos with real people on a given topic be shown to a broader audience?

- ☐ Yes, definitely.
- ☐ Yes, maybe.

- ☐ Neutral.
- ☐ Unlikely.
- ☐ No, it is not worth it at all.

8. Has your attitude to the topic changed after watching Video 1?

- ☐ Yes, much improved.
- ☐ Yes, it has improved a bit.
- ☐ Nothing has changed.
- ☐ Yes, it got a little worse.
- ☐ Yes, it has worsened significantly.

9. Did you manage to watch the entire Video 2 at the link from beginning to end?

- ☐ Yes.
- ☐ No.

10. Rate how much you were interested in Video 2.

From 1 to 5, where 1 – Not interested at all, 5 – Very interested

11. Is the main idea of Video 2 clear to you?

- ☐ Of course.
- ☐ Somewhat clear.
- ☐ Neutral.
- ☐ It is difficult to understand.
- ☐ It is unclear.

12. Choose from the list the emotions you had during or as a result of watching Video 2?

- ☐ Joy.
- ☐ Sympathy.
- ☐ Inspiration.
- ☐ Motivation.
- ☐ Certainty.
- ☐ Surprise.
- ☐ Interest.
- ☐ Indifference.
- ☐ Anger.
- ☐ Abomination.
- ☐ Concern.
- ☐ Displeasure.
- ☐ Other.

13. Did you have the desire to change your behavior after watching Video 2?

- ☐ Yes, exactly.
- ☐ Perhaps.
- ☐ Uncertain.
- ☐ Unlikely.
- ☐ No, I definitely will not.

14. Will Video 2 influence your future decisions regarding waste management?

- ☐ Very likely.
- ☐ Probably.
- ☐ Not sure.

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- ☐ Unlikely.
- ☐ It will not affect me at all.

15. Should this and similar videos with real people on a given topic be shown to a broader audience?
    - ☐ Yes, definitely.
    - ☐ Yes, maybe.
    - ☐ Neutral.
    - ☐ Unlikely.
    - ☐ No, it is not worth it at all.
16. Has your attitude to the topic changed after watching Video 2?
    - ☐ Yes, much improved.
    - ☐ Yes, it has improved a bit.
    - ☐ Nothing has changed.
    - ☐ Yes, it got a little worse.
    - ☐ Yes, it has worsened significantly.
17. How often do you sort waste?
    - ☐ Constantly.
    - ☐ Often.
    - ☐ Sometimes.
    - ☐ Never.
18. If you answered "Constantly," "Often," or "Sometimes" to the previous question, then choose the types of waste by which you sort them:
    - ☐ Paper and cardboard.
    - ☐ Glass.
    - ☐ Metal and Artificial materials (including plastic).
    - ☐ Organic waste (food waste, garden waste).
    - ☐ Electronic waste (batteries, accumulators).
    - ☐ Textiles and clothing.
    - ☐ Wood and furniture.
    - ☐ Hazardous waste (chemicals, paints).
    - ☐ Medical waste.
    - ☐ Waste electrical equipment.
    - ☐ Building materials.
    - ☐ Mixed waste (that which is not subject to another category).
19. What, in your opinion, is the reason for not sorting waste, or partially sorting it, or only sometimes? (Choose the answer options that are the most appropriate for you).
    - ☐ There is not enough information about the correct sorting of waste.
    - ☐ No special containers or bags for sorting nearby.
    - ☐ No time to sort waste.
    - ☐ There is not enough space to store different types of waste at home.
    - ☐ Lack of incentives to waste sorting.
    - ☐ Low level of awareness of environmental problems.
    - ☐ Distrust of the waste recycling system (belief that waste is mixed anyway).
    - ☐ Irregular schedule for removal of sorted waste.
    - ☐ High costs associated with waste sorting.
    - ☐ Social pressure or lack of support from others.
    - ☐ Lack of habit or tradition of waste sorting.

20. In your opinion, what types of waste should be sorted for efficient removal, processing, and disposal? (Choose all that apply).

- ☐ Paper and cardboard.
- ☐ Glass.
- ☐ Metal and Artificial materials (including plastic).
- ☐ Organic waste (food waste, garden waste).
- ☐ Electronic waste (batteries, accumulators).
- ☐ Textiles and clothing.
- ☐ Wood and furniture.
- ☐ Hazardous waste (chemicals, paints).
- ☐ Medical waste.
- ☐ Building materials.
- ☐ Waste electrical equipment.
- ☐ Mixed waste (that which is not subject to another category).

21. What do you think most influences people's behavior when making decisions about waste sorting? (Choose the answer options that are the most appropriate for you).

- ☐ The convenience of access to containers for sorting (for example, containers for sorting waste at the exit from your entrance house).
- ☐ Awareness of the importance and rules of sorting (for example, posters at waste collection points with a detailed description of the rules of sorting).
- ☐ Personal beliefs about environmental protection.
- ☐ Financial incentives or the opportunity to save (for example, points of reception of sorted waste with receipt of monetary compensation).
- ☐ Influence of family, friends, and colleagues.
- ☐ Influence of influencers, bloggers, and mass media.
- ☐ Programs and regulations that support sorting and proper disposal (for example, free bags or containers for collecting sorted waste for your household).
- ☐ The cost of waste sorting and removal services (for example, the reduced cost of utility services for the removal and disposal of sorted waste).
- ☐ Availability of technologies and places for handing in waste (for example, machines for accepting plastic bottles in supermarkets, with the possibility of compensating the given waste in the bill for paying for products).

22. Your age (whole years).

- ☐ Up to 18 years old.
- ☐ From 18 to 25 years old.
- ☐ From 26 to 35 years old.
- ☐ From 36 to 45 years old.
- ☐ From 46 to 60 years old.
- ☐ More than 60 years.

23. Your gender.

- ☐ Male.
- ☐ Female.

24. Level of education.

- ☐ Basic secondary school (9th grade).
- ☐ Complete secondary school (11th grade).
- ☐ Vocational and technical (school/lyceum).

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- ☐ Vocational higher education (unfinished higher education).
- ☐ Higher education (bachelor's, specialist's, master's degree).
- ☐ Availability of a scientific degree and/or scientific title (candidate of sciences, Ph.D., doctor of sciences, associate professor, professor, etc.).
- ☐ Other.

25. Your occupation:

- ☐ Hired specialist.
- ☐ Middle manager.
- ☐ Head of business, institution, organization.
- ☐ Civil servant.
- ☐ Self-employed person (Individual entrepreneur).
- ☐ A person studying.
- ☐ Unemployed.
- ☐ Pensioner.
- ☐ Other.

APPENDIX B

Table B1. Emotion analysis table for all respondents (video 1)

Respondent	Average max emotions, points						
	Anger	Disgust	Contempt	Joy	Fear	Distress	Surprise
1	0.24	0.08	0.2	0.026	0.24	20	0.06
2	4	0.04	0.24	0.026	4	0.128	2
3	0	0	2	0	0.8	1.6	0.2
4	0	0.08	2.4	0.024	1.6	8	0.058
5	0.4	0.2	0.8	2	0.4	1.6	0.08
6	2	0.08	0.16	0.028	0.4	0.16	0.16
7	0.8	0.4	20	8	0	0.08	0.16
8	0	0.08	80	0.04	4	16	0.4
9	0.16	0.032	0.2	0.026	0.16	0.14	0.06
10	0	0.028	2	0.024	1.6	8	0.08
11	20	0.032	2	0.024	0	8	80
12	0.2	0.02	40	1.6	0.8	2	0
13	0.16	0.04	0.2	0.024	0.16	0.128	0.069
14	0	0.024	0.8	0.04	4	0.14	2
15	0	0.032	2	0.024	2	20	0.08
16	0.4	0.4	0.4	0.025	0.4	0.4	0.2
17	4	0.024	1.6	0.024	0.8	0	0.06
18	1.6	0.4	0	80	0	0	8
19	0.8	80	0	80	16	0	20
20	0.2	0.04	80	40	0.2	0.2	0.06
21	4	0.08	80	80	0	8	0
22	80	4	2	0	2	80	0.08
23	4	0.04	2	0.024	1.6	8	0.058
24	2	0.024	0.32	0.024	4	0.16	2
25	0.8	0.4	80	0.026	0.4	0.4	0.056
26	4	0.8	4	80	2	0.8	0.8
27	2	0.02	80	2	4	0.16	2
28	0.4	0.028	0.24	0.024	0.16	0.136	0.08
29	1.6	0.026	0.8	0.024	0.8	2	0.12
30	2	0.028	0.4	0.025	2	0.4	0.8
31	0.12	0.024	0.2	0.024	0.16	0.16	0.08
32	0.4	0.08	40	40	0.2	0.8	0.08
33	0.14	0.028	0.2	0.028	0.136	0.128	0.057
34	0.2	0.024	0.2	0.026	0.4	0.128	0.16
35	0.08	0.02	0.8	2	0.08	0.08	2

APPENDIX C

Table C1. Emotion analysis table for all respondents (video 2)

Respondent	Average max emotions, points						
	Anger	Disgust	Contempt	Joy	Fear	Distress	Surprise
1	0	0.08	2	80	0.2	0	0.2
2	2	1.6	0.2	0.025	0	40	2
3	0.4	0.024	0.4	0.16	0.4	0.4	0.12
4	8	0.04	2.3	0.024	1.6	10	0.056
5	0.3	0.08	0.4	0.032	0.3	0.14	0.06
6	0.4	0.08	20	80	0.2	0.2	0.06
7	0.4	0.16	0.24	0.028	0.4	0.16	0.16
8	40	0.04	2	0.026	1.6	8	0.064
9	0.024	0.026	0.22	0.025	0.14	0.16	0.057
10	0.2	0.026	0.4	0.024	0.24	0	0.064
11	4	0.032	0.24	0.024	8	0.16	4
12	0.4	0.02	2	0.2	0.4	0.4	0.2
13	0.24	0.04	0.2	0.028	0.16	0.14	0.08
14	0.8	0.024	2	0.032	0.8	0.14	0.4
15	2	0.024	1.6	0.026	2	20	0.12
16	0.2	0.04	8	0.16	0.24	0.2	0.08
17	0	0	80	0.032	0.8	4	0.06
18	0	0	4	80	0.2	0.2	0.064
19	0.4	0.2	0.24	0.028	0.16	0.16	0.056
20	0.16	0.024	40	0.2	0.16	0.16	0.056
21	2	0.04	80	40	0.8	4	0.4
22	80	80	2	0	2	40	0.2
23	2	0.025	0.8	0.024	0.8	4	0.056
24	2	0.024	0.24	0.024	4	0.16	4
25	0.16	0.025	80	0.028	0.16	0.16	0.056
26	4	0.2	20	80	2	0.2	1.6
27	2	0.032	40	0.024	4	0.2	2
28	0.16	0.032	0.2	0.024	0.16	0.136	0.08
29	0.2	0.024	2	0.028	0.24	0.2	0.057
30	0.24	0.026	0.24	0.025	0.16	0.24	0.07
31	0.128	0.024	0.2	0.024	0.14	0.14	0.064
32	0.24	0.04	0.2	0.024	0.24	0.16	0.064
33	0.132	0.026	0.2	0.025	0.132	0.128	0.058
34	0.3	0.04	0.192	0.025	0.4	0.128	0.16
35	0.132	0.026	0.22	0.028	0.128	0.132	0.064

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