The Use of Neutralisation Techniques in the Context of Responsible Online Shopping: A Latent Profile Analysis

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Although many consumers use various neutralisation techniques to eliminate the anticipated guilt that results from not engaging in responsible consumption, the use of such techniques in the context of responsible online shopping has attracted little attention in prior research. In this study, we aim to address this gap by examining (1) whether it is possible to segment consumers in terms of their use of neutralisation techniques to eliminate the anticipated guilt that results from not engaging in responsible online shopping and (2) how these segments potentially differ from each other in terms of demographics (e.g., gender, age, and income), online shopping frequency, and anticipated guilt. The examination is based on 478 responses from Finnish consumers that were collected in spring 2023 and are analysed with latent profile analysis. Our findings suggest the existence of four distinct consumer segments with several differences between them in terms of demographics and anticipated guilt.

Keywords:
responsible consumption, responsible online shopping, neutralisation techniques, anticipated guilt, latent profile analysis

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1 Introduction

Today, more and more consumers are engaging in *responsible consumption*, which refers to consumption that has a less negative or more positive impact on the environment, society, self, and others (Ulusoy, 2016). Because of this, it is not surprising that responsible consumption has attracted more and more attention also in academic research (Nangia et al., 2024) and has been predicted to remain a prominent research topic also concerning the consumption environments of tomorrow, such as the novel metaverse marketplaces (Pellegrino et al., 2023) that can be seen as digitally mediated spaces that immerse users in shared, real-time experiences (Hadi et al., 2024). According to prior studies (e.g., Onwezen et al. 2013, 2014a, 2014b; Antonetti & Maklan, 2014a, 2014b; Theotokis & Manganari, 2015; Lindenmeier et al., 2017), one main driver for consumers to engage in responsible consumption is their *anticipated guilt*, which refers to the feelings of guilt that arise from contemplating a potential deviation from one's standards (Rawlings, 1970), such as engaging in consumer behaviour that cannot be considered responsible. However, despite this driver, there are still many consumers who do not commonly engage in responsible consumption, for which one explanation may be the various neutralisation techniques suggested in the neutralisation theory by Sykes and Matza (1957) that consumers may use to eliminate their anticipated guilt. Prior studies (e.g., Strutton et al., 1994; Chatzidakis et al., 2007; McGregor, 2008; Antonetti & Maklan, 2014b; Gruber & Schlegelmilch, 2014) have shown the use of such techniques among consumers to be relatively common. However, their use in the specific context of online shopping has attracted little attention in prior information systems (IS) and marketing research.

In this study, we aim to address the aforementioned gap in prior research. More specifically, in order to differentiate the study from prior studies on the topic, our objective is to focus less on the potential effects of the use of neutralisation techniques on other constructs, such as anticipated guilt (cf. Makkonen et al., 2023), and more on the precise use patterns of neutralisation techniques among consumers. As such, we examine (1) *whether it is possible to segment consumers in terms of their use of neutralisation techniques to eliminate the anticipated guilt that results from not engaging in responsible online shopping* and (2) *how these segments potentially differ from each other in terms of demographics (e.g., gender, age, and income), online shopping frequency, and anticipated guilt.* The examination is based on 478 responses from Finnish consumers that were collected in spring 2023 and are analysed by using latent profile analysis (cf. Ferguson et al., 2020) as the main analysis method.

2 Theoretical Foundation

Table 1: Neutralisation techniques examined in the study

Name	Reference	Description
Denial of responsibility (DOR)	Sykes & Matza (1957)	Claiming not to be responsible for the deviant behaviour
Denial of injury (DOI)	Sykes & Matza (1957)	Claiming that the deviant behaviour caused no injury
Condemnation of the condemners (COC)	Sykes & Matza (1957)	Claiming that those who condemn the deviant behaviour engage themselves in similar behaviour
Appeal to higher loyalties (AHL)	Sykes & Matza (1957)	Claiming that the deviant behaviour was due to actualising a higher-order ideal or value
Metaphor of the ledger (MOL)	Klockars (1974)	Claiming that the previous good behaviour counterbalances the present bad behaviour
Defence of necessity (DON)	Minor (1981)	Claiming that the deviant behaviour was necessary
Claim of relative acceptability (CRA)	Henry & Eaton (1999)	Claiming that the deviant behaviours of others are even worse than my deviant behaviour
Claim of individuality (COI)	Henry & Eaton (1999)	Claiming not to care about what others think of me or my behaviour
Justification by comparison (JBC)	Cromwell & Thurman (2003)	Claiming that the deviant behaviour is still better in comparison to some other behaviours
Claim of entitlement (COE)	Coleman (2005)	Claiming to have the right to engage in the deviant behaviour and to gain the benefits from it

The theoretical foundation of the study is based on the neutralisation theory by Sykes and Matza (1957), which suggests that when individuals engage in deviant behaviour, they may try to eliminate the resulting feelings of guilt or shame by using various justifications for the deviant behaviour that are referred to as *neutralisation* *techniques*. Although originally developed for the context of juvenile delinquency, the neutralisation theory has later been applied to also other contexts, such as inappropriate consumer behaviour (Strutton et al., 1994), fair trade (Chatzidakis et al., 2007), immoral and unethical consumption (McGregor, 2008), employee IS security policy violations (Siponen & Vance, 2010), software piracy (Siponen et al., 2012), music piracy (Riekkinen & Frank, 2014), sustainable consumption (Antonetti & Maklan, 2014b; Gruber & Schlegelmilch, 2014), shadow IT use (Silic et al., 2017), employee unauthorised computer access (Lin et al., 2018), and responsible online shopping (Makkonen et al., 2023). Of the various neutralisation techniques proposed in prior literature, this study focuses specifically on the ten neutralisation techniques in Table 1. These have all been found to be used by consumers in the context of sustainable consumption by Gruber and Schlegelmilch (2014), which is why we assume them to be relevant for consumers also in the closely connected context of responsible online shopping.

3 Methodology

The data for the study was collected from Finnish consumers between February and March 2023 with an online survey conducted by using the LimeSurvey service. The survey respondents were recruited by promoting the survey on social media and via the communication channels of Finnish universities and student associations. As an incentive for responding, all the respondents who completed the survey were able to take part in a prize drawing of ten gift boxes worth about 25 € each. In the survey questionnaire, the use of the ten neutralisation techniques was measured with two items each. These were developed for the study based on the studies by Siponen and Vance (2010) as well as Gruber and Schlegelmilch (2014). In turn, anticipated guilt was measured with three items. These were adapted from the guilt inventory by Kugler and Jones (1992) as exemplified by Onwezen et al. (2013, 2014a, 2014b). The wordings of these 23 items are reported in Appendix A, and before presenting them to the respondents, we also provided a brief definition of responsible online shopping as "making consumption choices that take various ecological and ethical values (e.g., sustainable development and fair trade) into account while shopping online". The measurement scale of all the aforementioned items was the traditional five-point Likert scale (1 = strongly disagree, 2 = disagree, 3 = neither agree nor disagree, 4 = agree, and 5 = strongly agree). In contrast, gender, age, income, and online shopping frequency were measured with only one item each, with age being measured on a continuous scale and the other variables on a categorical scale. To avoid forced responses, the respondents also had the option to skip any item in the survey.

The collected data was analysed in three phases. First, we calculated a composite score for each neutralisation technique construct and the anticipated guilt construct by averaging the scores of the individual items that were measuring them as well as assessed their reliability in terms of internal consistency by using Cronbach's alphas and their validity in terms of discriminant validity by using disattenuated correlations as suggested by Rönkkö and Cho (2022). Second, we used the Mplus 8.8. statistical software (Muthén & Muthén, 2024) to conduct a latent profile analysis for the neutralisation technique constructs by estimating multiple models with a varying number of profiles and assessing their goodness of fit with the data. To estimate the models, we used the robust maximum likelihood (MLR) estimator, with the full information maximum likelihood (FIML) estimator used for handling the potential missing values. In turn, to assess model fit, we used four information criteria and two likelihood ratio tests recommended in recent methodological literature (e.g., Nylund-Gibson & Choi, 2018; Ferguson et al., 2020; Weller et al., 2020). The four information criteria were the consistent Akaike information criterion (CAIC) by Bozdogan (1987), the Bayesian information criterion (BIC) by Schwarz (1978), the sample-size adjusted Bayesian information criterion (SABIC) by Sclove (1987), and the approximate weight of evidence (AWE) by Banfield and Raftery (1993). In the case of these all, a lower value suggests a better fitting model, thus typically resulting in the selection of the model with the lowest value. Or, if the values continue to decrease while increasing the number of profiles, then the model after which the improvements in model fit become only marginal may also be selected (Nylund-Gibson & Choi, 2018). In turn, the two likelihood ratio tests were the Vuong-Lo-Mendell-Rubin adjusted likelihood ratio test (VLMR-LRT) by Vuong (1989) and Lo et al. (2001) as well as the bootstrapped likelihood ratio test (BLRT) by McLachlan and Peel (2000). These are used to compare a model with k profiles against a model with $k - 1$ profiles to see whether the additional profile provides a statistically significant improvement in model fit or whether the model with fewer profiles is sufficient. In addition, we also diagnosed the quality of the estimated models by examining their entropy (Celeux & Soromenho, 1996), in the case of which a value that is greater than 0.8 is commonly considered to suggest sufficient differentiation between the profiles (Nylund-Gibson & Choi, 2018). Third, we used the IBM SPSS

Statistics 28 software to conduct post-hoc analyses of the potential differences between the members of each profile in terms of their gender, age, income, online shopping frequency, and anticipated guilt based on the most likely profile membership. In the case of gender, income, and online shopping frequency, this was done by using cross-tabulation analysis, whereas in the case of age and anticipated guilt, this was done by using one-way analysis of variance.

4 Results

In total, we received 478 valid responses to the conducted online survey. The descriptive statistics of this sample in terms of the gender, age, yearly personal taxable income, socioeconomic status, and average online shopping frequency of the respondents are reported in Table 2. As can be seen, most of the respondents were women and students as well as had a relatively low income, which was not surprising when considering how they were recruited. The age of the respondents ranged from 19 to 75 years, with a mean of 28.3 years and a standard deviation of 9.0 years. Most of the respondents (68.8%) were also relatively active online shoppers who shopped online at least monthly on average.

Table 2: Sample statistics (N = 478)

	N	%		N	%
Gender			**Socioeconomic status**		
Man	88	18.4	Student	341	71.3
Woman	364	76.2	Employee or self-employed	132	27.6
Other	26	5.4	Unemployed or unable to work	10	2.1
Age			Pensioner	4	0.8
Under 25 years	206	43.1	Other	4	0.8
25–49 years	253	52.9	**Online shopping frequency**		
50 years or over	19	4.0	At least weekly	31	6.5
Yearly personal taxable income			At least monthly	298	62.3
Under 15,000 €	286	59.8	At least yearly	139	29.1
15,000–29,999 €	71	14.9	Less frequently than yearly	8	1.7
30,000 € or over	98	20.5	Has never shopped online	1	0.2
No response	23	4.8	No response	1	0.2

4.1 Construct Reliability and Validity

Table 3 reports for each neutralisation technique construct and the anticipated guilt construct the mean (M) and standard deviation (SD) of its composite score as well as its Cronbach's alpha (on-diagonal) and disattenuated correlations (off-diagonal). Of them, Cronbach's alphas of at least 0.7 are commonly considered to suggest sufficient construct reliability in terms of internal consistency (Nunally & Bernstein, 1994). This criterion was met by all the constructs except for the claim of individuality, which was also so close to meeting the criterion that we decided not to drop it. In turn, disattenuated correlations of less than 0.85 are commonly considered to suggest sufficient construct validity in terms of discriminant validity (Rönkkö & Cho, 2022). This was met by all the constructs.

Table 3: Construct statistics

	N	M	SD	Cronbach's alphas and disattenuated correlations										
				DOR	DOI	COC	AHL	MOL	DON	CRA	COI	JBC	COE	AG
DOR	478	2.134	1.118	0.932										
DOI	476	1.913	0.943	0.476	0.889									
COC	460	2.548	1.164	0.554	0.455	0.870								
AHL	478	4.271	0.794	0.274	0.228	0.311	0.882							
MOL	477	1.932	0.901	0.418	0.486	0.543	0.285	0.786						
DON	475	4.024	0.931	0.149	0.028	0.056	0.355	0.138	0.847					
CRA	469	2.457	1.090	0.553	0.444	0.754	0.414	0.657	0.196	0.720				
COI	478	2.690	1.058	0.399	0.627	0.509	0.332	0.434	0.031	0.428	0.695			
JBC	478	2.522	1.088	0.607	0.638	0.663	0.315	0.522	0.088	0.713	0.611	0.833		
COE	476	2.532	1.159	0.350	0.572	0.514	0.365	0.368	0.005	0.457	0.716	0.591	0.881	
AG	470	3.310	1.057	-0.322	-0.446	-0.245	-0.279	-0.196	0.012	-0.210	-0.520	-0.366	-0.428	0.838

4.2 Latent Profile Analysis

Table 4 reports the log-likelihood (LL) value, the values of the four information criteria (i.e., CAIC, BIC, SABIC, and AWE), the p-values of the two likelihood ratio tests (i.e., VLMR-LRT and BLRT), and the entropy value of the estimated models in which the number of profiles (k) ranged from one to seven. The values of the four information criteria are also plotted graphically in Appendix B. The four information criteria all suggested the selection of the four-profile model because both CAIC and AWE reached their lowest value in the case of this model and also the values of BIC and SABIC showed only marginal decreases when increasing the number of profiles beyond four. This suggestion was also supported by VLMR-LRT, which showed that increasing the number of profiles from four to five would not result in a statistically significant improvement in model fit (p = 0.232). Despite the lack of support from BLRT, we thus decided to proceed with the four-profile model. This model also had a very high entropy value of 0.927, which suggests good differentiation between the profiles.

Table 4: Fit and entropy of the estimated models

k	LL	CAIC	BIC	SABIC	AWE	VLMR-LRT	BLRT	Entropy
1	-5,994.406	12,447.667	12,383.667	12,180.539	12,479.667	< 0.001	< 0.001	–
2	-5,890.131	12,317.983	12,242.983	12,004.942	12,355.483	0.002	< 0.001	0.933
3	-5,813.364	12,243.315	12,157.315	11,884.361	12,286.315	0.046	< 0.001	0.929
4	-5,764.002	12,223.456	12,126.456	11,818.590	12,271.956	0.232	< 0.001	0.927
5	-5,727.538	12,229.394	12,121.394	11,778.615	12,283.394	0.354	< 0.001	0.928
6	-5,686.565	12,226.314	12,107.314	11,729.622	12,285.814	0.601	< 0.001	0.925
7	-5,662.880	12,257.809	12,127.809	11,715.205	12,322.809	0.508	< 0.001	0.918

Table 5: Estimation results of the four-profile model

	Mean score (from 1 to 5)				Result of the Wald test (p-value)					
	LP1 (62.8%)	LP2 (23.4%)	LP3 (7.5%)	LP4 (6.3%)	LP1 vs. LP2	LP1 vs. LP3	LP1 vs. LP4	LP2 vs. LP3	LP2 vs. LP4	LP3 vs. LP4
DOR	1.634	3.917	1.616	1.389	< 0.001	0.902	0.046	< 0.001	< 0.001	0.193
DOI	1.794	2.522	1.665	1.314	< 0.001	0.440	< 0.001	< 0.001	< 0.001	0.071
COC	2.342	3.384	2.552	1.637	< 0.001	0.424	< 0.001	0.002	< 0.001	0.001
AHL	4.387	4.583	4.229	2.157	0.007	0.354	< 0.001	0.050	< 0.001	< 0.001
MOL	1.816	2.400	1.879	1.511	< 0.001	0.709	0.038	0.006	< 0.001	0.082
DON	4.253	4.257	1.922	3.416	0.973	< 0.001	0.004	< 0.001	0.005	< 0.001
CRA	2.325	3.171	2.364	1.609	< 0.001	0.862	< 0.001	< 0.001	< 0.001	0.003
COI	2.590	3.145	2.858	1.899	< 0.001	0.239	< 0.001	0.244	< 0.001	< 0.001
JBC	2.315	3.395	2.204	1.873	< 0.001	0.621	0.007	< 0.001	< 0.001	0.200
COE	2.428	2.989	2.791	1.669	< 0.001	0.211	< 0.001	0.499	< 0.001	< 0.001

Table 5 reports the estimation results of the four-profile model in terms of the mean scores of the neutralisation technique constructs in each of the four latent profiles (LP1–LP4) and the p-values of the Wald test for the pairwise comparisons of the differences in the mean scores between the profiles. The mean scores are also plotted graphically in Appendix C, with each line representing a particular profile. In addition, Table 5 and Appendix C report the relative sizes of the profiles based on the most likely profile membership. Here, LP1 was found as the largest of the four profiles with a 62.8% share of the respondents, followed by LP2 with a 23.4% share, LP3 with a 7.5% share, and LP4 with a 6.3% share. Of the profiles, LP2 consisted of the most active users of neutralisation techniques, with the mean scores of all the constructs being either the highest or at least equally high as in the other three profiles. The highest mean scores concerned the appeal to higher loyalties and the defence of necessity constructs as well as the denial of responsibility construct, of which the latter was a unique feature of this particular profile. In contrast, LP4 consisted of the least active users of neutralisation techniques, with the mean scores of all the constructs being either the lowest or at least equally low as in the other three profiles except for the defence of necessity construct, in the case of which the mean score was higher than in LP3 but lower than in LP1 and LP2. Finally, LP1 and LP3 were situated between these two extremes. These two profiles were practically identical to each other except for the defence of necessity construct. That is, LP1 was characterised by the high mean scores of both the appeal to higher loyalties and the defence of necessity constructs but relatively low mean scores of all the other constructs. In contrast, LP3 was characterised by the high mean score of only the appeal to higher loyalties construct, whereas the mean scores of the defence of necessity construct and all the other constructs remained relatively low.

4.3 Post-Hoc Analyses

Table 6 reports the relative distributions of gender, income, and online shopping frequency in the four profiles and in the entire sample as well as the results of the χ^2 test for testing the statistical significance of the differences in these distributions between the profiles. The χ^2 test suggested statistically significant differences in the case of gender ($p = 0.002$) and income ($p = 0.003$) but not in the case of online shopping frequency ($p = 0.797$). To examine these differences more closely, Table 6 also reports (in parenthesis) the adjusted standardised residuals of which values higher than 1.960 or lower than -1.960 (in bold) suggest a statistically significant difference between the distribution of a particular profile and the distribution of the entire sample at the level of $p < 0.05$ (Agresti, 2012). Here, in the case of gender, LP1 was found to have a higher proportion of women and a lower proportion of men than the entire sample, whereas LP2 was found to have a higher proportion of men and a lower proportion of women than the entire sample. In addition, LP4 was found to have a higher proportion of individuals who did not identify themselves as either men or women, although this finding must be taken with caution because of the low number of such individuals in the entire sample. In turn, in the case of income, LP1 was found to have a lower proportion and LP3 and LP4 were found to have a higher proportion of respondents with a yearly personal income of 30,000 € or over than the entire sample, and LP3 was also found to have a lower proportion of respondents with a yearly personal income of under 15,000 € than the entire sample.

Table 6: Results of cross-tabulation analysis

Variable	Category	Relative distributions					Result of the χ^2 test		
		LP1	LP2	LP3	LP4	Sample	χ^2	df	p
Gender (N = 478)	Man	**14.0% (-3.230)**	**25.9% (2.335)**	30.6% (1.955)	20.0% (0.232)	18.4%	21.111	6	0.002
	Woman	**81.0% (3.230)**	**68.8% (-2.100)**	69.4% (-0.982)	63.3% (-1.702)	76.2%			
	Other	5.0% (-0.550)	5.4% (-0.044)	0.0% (-1.496)	**16.7% (2.801)**	5.4%			
Income (N = 455)	Under 15,000 €	66.1% (1.853)	66.4% (0.856)	**37.1% (-3.277)**	48.1% (-1.631)	62.9%	20.185	6	0.003
	15,000–29,999 €	16.4% (0.634)	11.2% (-1.431)	25.7% (1.715)	11.1% (-0.663)	15.5%			
	30,000 € or over	**17.5% (-2.738)**	22.4% (0.256)	**37.1% (2.337)**	**40.7% (2.503)**	21.5%			
Online shopping frequency (N = 477)	At least weekly	7.0% (0.602)	4.5% (-0.999)	5.6% (-0.239)	10.0% (0.804)	6.5%	3.098	6	0.797
	At least monthly	61.2% (-0.742)	67.0% (1.122)	66.7% (0.540)	53.3% (-1.068)	62.5%			
	Less frequently than monthly	31.8% (0.456)	28.6% (-0.642)	27.8% (-0.438)	36.7% (0.690)	31.0%			

Table 7 reports the means (M) and standard deviations (SD) of age and anticipated guilt in the four profiles and in the entire sample as well as the results of one-way analysis of variance (ANOVA) for testing the statistical significance of the differences in these means between the profiles. More specifically, we employed Welch's (1951) one-way ANOVA because Levene's (1960) test did not support the hypothesis on equal variances across the profiles in the case of either age ($p = 0.011$) or anticipated guilt ($p = 0.038$). Welch's one-way ANOVA suggested statistically significant differences in the case of both age ($p = 0.031$) and anticipated guilt ($p <$

0.001). These differences were examined more closely with multiple comparisons conducted by using the Games-Howell (1976) test because of the unequal variances across the profiles. Here, in the case of age, the multiple comparisons initially suggested no statistically significant differences between any of the profiles, although the mean age seemed to be lower in LP1 and LP2 than in LP3 and LP4. Thus, we repeated Welch's one-way ANOVA after merging LP1 with LP2 and LP3 with LP4, and its result confirmed that the observed difference in the mean age between the two former and two latter profiles was indeed statistically significant ($p = 0.003$). In contrast, in the case of anticipated guilt, the multiple comparisons immediately suggested several statistically significant differences between the profiles. More specifically, anticipated guilt was found to be higher in LP4 than in LP1 ($p < 0.001$), LP2 ($p < 0.001$), and LP3 ($p = 0.003$) as well as higher in LP1 than in LP2 ($p < 0.001$).

Table 7: Results of one-way ANOVA

Variable	Profile	N	M	SD	Welch's one-way ANOVA			
					W	df_1	df_2	p
Age (N = 478)	LP1	300	27.827	8.634	3.099	3	78.944	0.031
	LP2	112	27.339	7.629				
	LP3	36	32.028	11.277				
	LP4	30	32.367	12.107				
	Sample	478	28.314	8.998				
Anticipated guilt (N = 470)	LP1	295	3.411	0.991	18.463	3	80.153	< 0.001
	LP2	112	2.850	1.083				
	LP3	36	3.278	1.137				
	LP4	27	4.148	0.742				
	Sample	470	3.310	1.057				

5 Discussion and Conclusion

In this study, we examined (1) *whether it is possible to segment consumers in terms of their use of neutralisation techniques to eliminate the anticipated guilt that results from not engaging in responsible online shopping* and (2) *how these segments potentially differ from each other in terms of demographics (e.g., gender, age, and income), online shopping frequency, and anticipated guilt.* In answer to the first question, we were able to identify four consumer segments (or latent profiles, as they are called in latent profile analysis), each with its characteristic profile for using neutralisation techniques. Of these, the second segment consisted of the most active users of neutralisation techniques, the fourth segment consisted of the least active users of neutralisation techniques, and the first and third segments were situated between these two extremes with only small differences between each other. Overall, we made two interesting findings concerning these segments. On one hand, we found that, in each segment, there was at least one actively used neutralisation technique, meaning that the use of neutralisation techniques is very universal and practically all consumers use them in one way or another. On the other hand, we also found that, in all the segments, the use focused on only a few neutralisation techniques: the appeal to higher loyalties and the defence of necessity in the first segment, the appeal to higher loyalties, the defence of necessity, and the denial of responsibility in the second segment, the appeal to higher loyalties in the third segment, and the defence of necessity in the fourth segment. In other words, consumers most often try to eliminate the anticipated guilt that results from not engaging in responsible online shopping with justifications based on the actualisation of some higher-order ideal or value (e.g., choosing a cheaper but less responsible alternative to be able to provide for one's family), the lack of responsible alternatives, and the fact that they cannot really change anything with their own consumption choices.

In answer to the second question, we found several differences between the segments in terms of gender, age, income, and anticipated guilt, but not in terms of online shopping frequency. In terms of demographics, we found that the active use of neutralisation techniques was most strongly associated with being a man instead of a woman as well as being younger, whereas the inactive use of neutralisation techniques was most strongly associated with being older and having a higher income. These findings are not surprising when considering that prior studies have found men to engage in sustainable consumption less likely than women (e.g., Isenhour & Ardenfors, 2009) and that limited financial resources likely force younger consumers with a lower income to resort to less responsible alternatives more often than older consumers with a higher income. Thus, also the use of neutralisation techniques to eliminate the resulting anticipated guilt is likely to be more common among men and younger consumers with a lower income than among women and older consumers with a higher income. In turn, in terms of online shopping frequency, it was interesting to find no association with the use of neutralisation techniques, suggesting that the mere frequency of having to make consumption choices does not, per se, seem to make one a more or less active user of neutralisation techniques. Finally, in terms of anticipated guilt, our findings suggest a strong negative association with the use of neutralisation techniques because anticipated guilt was found to be lowest in the second segment with the most active users of neutralisation techniques and highest in the fourth segment with the least active users of neutralisation techniques. This finding is not only consistent with the neutralisation theory by Sykes and Matza (1957) but also supports the findings of the prior study by Makkonen et al. (2023) concerning the negative effect of using neutralisation techniques on the anticipated guilt that results from not engaging in responsible online shopping.

To our knowledge, this study is the first to focus on segmenting individuals based on their use of neutralisation techniques, which is why its findings can be seen to contribute to a better understanding of the use of neutralisation techniques not only in the specific context of responsible online shopping but also more generally. This better understanding of the most used neutralisation techniques and the specific segments in which they are being used can be seen as highly valuable in not only theoretical but also practical respects. For example, by better understanding which consumers are most likely to use which neutralisation techniques, the retailers in the traditional online and offline as well as in the novel omnichannel and metaverse environments can better target their actions for limiting the use of neutralisation techniques among consumers, thus nudging them away from less responsible and towards more responsible consumption practices. This, in turn, can be seen as critical for the future survival of our whole planet.

6 Limitations and Future Research

We see this study to have three main limitations. First, our sample consisted only of Finnish consumers and was also not fully representative of all Finnish consumers in terms of variables like gender and age. This obviously limits the generalisability of our findings, particularly in terms of the relative sizes and precise compositions of the identified segments, and urgently calls for future replications of this study in other countries and by using more representative samples. Second, in the post-hoc analyses, we focused only on a very limited set of variables that were used to examine the potential differences between the identified segments. Future studies could extend this set with numerous other variables, such as the personality (e.g., Bosnjak et al., 2007), individual values (e.g., Makkonen et al., 2019a), as well as online shopping skilfulness and self-efficacy (e.g., Makkonen et al., 2022) of consumers and the emotions that consumers experience during online shopping (e.g., Makkonen et al., 2019b). Third, in the study, we focused on the use of neutralisation techniques only in the context of responsible online shopping in general. Future studies could focus on their use also in some more specific contexts in which responsible consumption has been found to play an important part, such as fashion retailing (e.g., Kemppainen et al., 2021, 2022).

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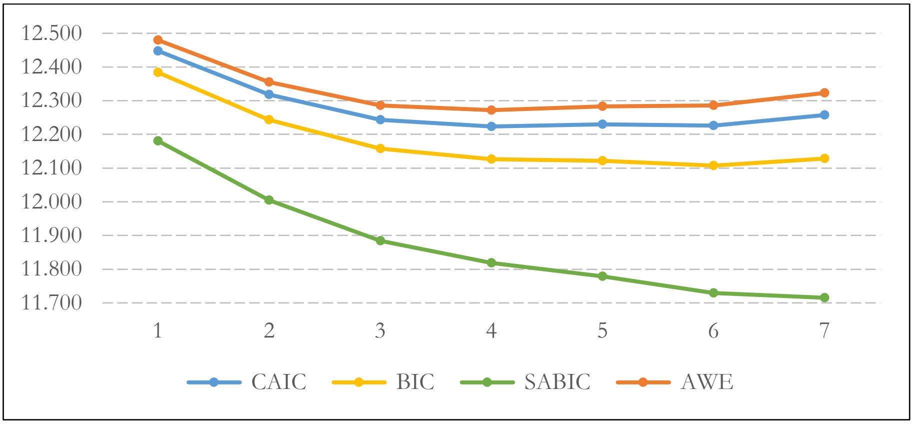
Appendix A: Item Wordings

Item	Wording
	I find that is OK for me not to make responsible consumption choices when shopping online because…
DOR1	… one person cannot really trigger any change with his or her choices.
DOR2	… one person cannot really change anything with his or her choices.
DOI1	… it causes no actual harm to anybody.
DOI2	… it caused no actual damage to anybody.
COC1	… people who call for responsibility from others sometimes do the same.
COC2	… people who call for responsibility from others do not always themselves make responsible choices.
AHL1	… I have to consider also other values or criteria (e.g., price) when making my choices.
AHL2	… I have to take into account also other values or criteria (e.g., price) when making my choices.
MOL1	… I have already made enough responsible choices earlier in my life.
MOL2	… the responsible choices that I have made earlier in my life compensate for it.
DON1	… the lack of responsible alternatives sometimes makes it necessary.
DON2	… responsible alternatives are not always available.
CRA1	… many other people fail to make them even more often than me.
CRA2	… I still fail to make them less often than many other people.
COI1	… I do not care what other people think about my choices.
COI2	… my choices do not belong to other people.
JBC1	… there are far worse things in the world.
JBC2	… it is not a very bad thing compared to many other things.
COE1	… I am entitled to do so if I want to.
COE2	… I have the right to do so if I wish.
	If I do not make responsible consumption choices when shopping online, I feel…
AG1	… guilty.
AG2	… remorseful.
AG3	… bad.

Appendix B: Information Criteria of the Estimated Models



Appendix C: Estimation Results of the Four-Profile Model