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E-consumers' Attribute Non-Attendance Switching Behavior: Effect of providing information on attributes

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Abstract

E-consumers' non-attendance to key website attributes continues to curtail adoption of, and advocacy for, an environmentally-clean e-commerce. This research investigates e-consumers' attribute non-attendance switching behavior when extra information on attributes is provided. To model the changes in attribute attendance behavior, we propose that an attribute's attendance probability depends on its previous attendance pattern. Applying the proposed method on webshop stated preference data, we find that the model gives a better fit compared to standard approaches and that provision of extra information results in significantly higher attendance probabilities for the investigated attributes. Additionally, our results show that socio-economic and attitudinal factors affect e-consumers' shifts in attribute attendance behavior. We provide insights into how our results can help managers, marketeers and policy makers provide an environmentally-friendly e-commerce framework.

Keywords:
E-commerce, Switching ANA, DCE, Websites, Attitudes

1. Introduction

Internet usage continues to spread across many sectors in consumers' lives. Retailing has been among the biggest beneficiaries of consumers' and retailers' internet enthusiasm. Online retailing, broadly referred to as e-commerce, has curved a significant niche in the retail business. E-commerce is estimated to account for over 17% of all global retail sales by 2021 [15]. E-commerce's remarkable compound annual growth rate, which holds more than a three-to-one margin compared to offline retailing [14, 38], poses important questions for businesses concerning customer attraction and retention in the face of stiffer competition worldwide.

The importance of the internet in retailing has triggered extensive research on it, both from consumers' and retailers' perspectives. Probably the more pressing question, for all concerned players, remains how to attract and retain customers on e-retailing platforms. Throughout this article, e-retailing platforms will be interchangeably referred to as 'webshops' or just 'websites'. Like brick-and-mortar businesses, consumers are attracted (and tend to be loyal) to webshops that resonate with their preferences. Webshops attract their prospective customers through their characteristics/attributes. Prior studies have investigated how webshop attributes influence e-consumers' web experience and motivate e-purchase intentions [7, 6, 30], the dynamics of consumer preferences [29, 27, 37, 36, 38] and the effects of e-commerce on the environment [13, 50, 31] and on other socio-economic settings [39, 11, 25].

Originally, the choice experiments literature assumed that consumers process all the information provided when selecting their preferred alternatives. However, recent evidence shows that consumers often simplify their choice tasks by ignoring some attributes [20, 44]. This tendency to ignore part of the information when making decisions is known as attribute non-attendance (ANA). Whereas choice studies acknowledge changes in consumer preferences and tendencies to exhibit ANA behavior, the majority do not incorporate changes in consumers' ANA behavior. Consequently, changes in attributes' impacts on purchase intentions and factors that influence ANA behavior changes are rarely reported. Yet, consumer behavior regarding which piece of information (i.e., the attribute) is important when decision-making is highly dynamic. Attribute relevance may depend on economic conditions, shifts in attribute levels, availability of extra information on attributes or consumer learning/fatigue. This dynamism is especially key in e-retailing where the ever-changing technological factors (e.g., trust, user-privacy and security), web usability and shopping factors (e.g., delivery cost and time, conditions for returning items), and environmental effects of e-commerce have been identified as important website attributes that influence online purchase intentions [58, 32, 6, 24, 50, 45]. This paper fills this modeling gap by using webshop preference data and investigating changes in (and drivers of) the ANA behavior among e-customers.

Changes in ANA behavior can be seen in real-life online purchases. Consider consumers with limited technical knowledge of website characteristics like presence of trust certificates. The limited understanding of purchasing on certified websites - for instance reliable and secure online purchases -

means that consumers, unknowingly, undervalue certified webshops. Hence, attendance probability towards such a crucial attribute will be low. However, when the importance of purchasing on certified sites (symbolized through trust labels) is explained, consumers are likely to give higher importance to trust-labeled websites. So the attendance probability to the trust label attribute post-information will be higher. Similarly, eco-conscious consumers may show ANA behavior changes to the distance attribute once information on the environmental impacts of shipping ordered items over long distances is explained. Consumers' focus on attributes may also evolve over time. This evolution may result from changes in factors that affect their preferences (e.g., income changes or acquiring more knowledge about a product and/or attribute). Equivalently, some choice experiment methods like agent interdependency in group decision making [43], provide settings where changes in attribute preferences and attendance behavior are expected because of more information. While attributes may appear unimportant to individual agents when making decisions, new information from peers may shift attributes' importance markedly. Thus, accounting for changes in both preferences and ANA could help to better understand the impact of attributes on e-purchasers' behavior.

Literature on preference evolution (e.g., [29, 27, 10, 34, 37, 36, 38]) and ANA behavior (e.g., [23, 46, 5, 19]) tends to exist in parallel. However, it is possible for consumers' ANA behavior and taste parameters to change simultaneously. Modeling ANA behavior changes presents two problems: the modeler neither observes the ANA patterns across attributes nor interchanges between ANA patterns over time, choice sets or information regimes in experiments. Various approaches have been suggested to identify ANA [22, 40, 46, 44]. The more prominent approaches are *Stated* and *Inferred* ANA. In stated ANA, respondents are asked to state whether or not they attended to the attributes when making their choices. The attribute attendance questions may be asked after an entire experiment, referred to as *Serial* stated ANA [5]. Alternatively, the attendance questions may be asked after every choice task, *Choice Task* stated ANA [5]. In inferred ANA, econometric models based on latent class models are used to estimate the probability of attribute attendance without the need to collect the attendance data directly from the respondents. We aim for the inferred ANA since it is less demanding in terms of respondent effort and infrastructure needed to carry out the experiment.

The state of the art in modeling ANA presupposes that it is *static*. That is, ANA behavior does not change throughout the experiment. However, some experimental situations can prompt changes in ANA behavior. This paper extends existing choice models to capture changes in ANA behavior. The proposed model introduces a Markovian structure [4, 55] on the endogenous attribute attendance model [23] to reveal changes in ANA behavior. Markov models have been used in behavioral sciences to model changes in consumer preferences [29, 37, 36]. These models assume that consumers' behavior at a given point depends on past behavior. Typically, this dependence is limited to an order of one i.e., behavior at the previous time point. This dynamic ANA formulation makes it possible to obtain more refined results than assuming a static ANA behavior. First, it is possible to obtain inferred results that are similar to the *choice task* stated ANA by assuming that the ANA behavior changes in every choice set. Second, the model can be used to explore factors that drive changes in ANA behavior.

We apply the proposed model formulation to a website preference dataset. The aim of this study was to investigate the impacts of website attributes on the online purchase intentions for Belgian e-consumers. Mid-way through the experiment, extra information on three attributes was provided: *Trust-label* which describes whether a trust label is present or absent on a website, *Headquarter* which explains whether the webshop has its headquarters in Belgium or not, and *Distance* which expresses the distance items have to travel to reach e-consumers. Presence of a trust label implies that the webshop has been verified by an independent third party for reliable e-purchases and guaranteed personal and financial privacy. Information for trust-labelled webshops on privacy, the stiff competition that Belgian-based webstores face when competing against established foreign webshops, and the environmental impact of transporting packages over long distances was provided in the course of the experiment. Traditionally, choice models with shifts in taste parameters would be used to account for the information impact. We instead reveal this impact by modeling the changes in ANA behavior.

This research contributes to the literature by investigating the tendency for e-consumers to change their ANA behavior with respect to website attributes. While attributes importance differs depending on many factors, accounting for the resulting changes in preferences and ANA behavior remains under-researched. We model consumers' tendency to change their ANA behavior depending on the preceding attendance pattern. We illustrate the importance of explaining essential attributes to consumers and how more information impacts consumers' attribute attendance behavior. We find that taking the ANA switching behavior into account provides a better model fit compared to the more standard approaches of handling additional information in choice experiments. We also investigate e-consumers' socio-economic and attitudinal factors that influence changes in attribute attendance behavior.

The rest of the article is organized as follows. The next section describes the data and methods. Empirical results are provided in the third section while section 4 provides the discussion, concluding remarks and limitations.

2. Data and Methods

2.1. Choice experiment

A discrete choice experiment was used to investigate the impact of website attributes on online purchase intentions. Eight attributes were used to hypothesize webshops: delivery time and price of the e-purchased item, whether the cost of returning items was borne by the e-consumer (own cost) or the e-retailer (free), web usability and friendliness rating, discount offered on next purchases, presence of trust labels, whether the webshop had Belgian or non-Belgian headquarters and the shipping distance for purchased items. These eight are among the more influential webshop attributes known to influence online purchase intentions [7, 6, 30]. The choice of the headquarters and distance attributes was partly motivated by the Belgians' considerable readiness to purchase items from foreign webshops [17, 1], as well as to investigate the opportunities and challenges towards the EU Digital Single Market policy agenda [17]. The study's attributes and attribute level descriptions are provided in Table 1.

A D-efficient design for estimating multinomial logit models was generated in NGENE [35]. The prior values for the eight attributes (from Delivery time to Distance as ordered in Table 1) were -0.15, -0.05, -0.5, 0.15, 0.05, 0.4, 0.4 and -0.001. The prior utility for opting out was 1.8. The resulting design comprised of twelve choice sets of three webshops and an opt-out option. Table 2 shows an example of a choice set used in the study.

2.2. Survey and Questionnaire

Participants were provided with questionnaires divided into three sections. The first section was concerned with online purchases frequency and behavior. Respondents were asked to indicate how often they made online purchases (with response options: daily, weekly, monthly, every three months, every six months, once per year, less than once per year and never). They were then asked to indicate the categories in which they placed most of their online purchases (clothing, travel & leisure, computer & electronics among others). Lastly, they were asked to indicate why they purchased or have not yet purchased items online.

Table 1: Attributes descriptions and attribute levels

Attribute	Notation	Description	Attribute levels
Delivery time	x_1	Duration (in days) for item delivery	1, 3, 6
Delivery price	x_2	Cost (in €s) for item delivery	0, 4, 8
Returns	x_3	Shipping costs of item returns	Free (0), Own cost (1)
Rating	x_4	Website ease of usability rating (out of 5)	1, 2, 3, 4, 5
Discount	x_5	Discount (in %) on the next purchase	0, 5, 15
Trust label	x_6	Webshop certified by an independent agency & is reliable	No (0), Yes (1)
Headquarters	x_7	Webshop's head office location	Not Belgian (0), Belgian (1)
Distance	x_8	Shipping distance (in kms) for the item	100, 300, 1000

Table 2: Choice set example

Webshop	**A**	**B**	**C**
Delivery time (days)	6	1	6
Delivery price (€)	4	0	8
Returns	Free	Own cost	Free
Rating (1 = very bad, 5 = very good)	3	1	5
Discount (%)	0	15	5
Trust label	Yes	No	Yes
Headquarters	Belgian	Belgian	Not Belgian
Distance (kms)	1000	100	300

At which web store would you prefer to make your online purchase?

◦ Webshop A ◦ Webshop B ◦ Webshop C ◦ None

The second part comprised of the choice experiment. A series of twelve choice sets of three webshop alternatives and an opt-out option was used. The twelve choice sets were further divided into two blocks: Block 1 consisted of choice sets 1-6, and Block 2 choice sets 7-12. To assess changes in taste preferences and ANA behavior, additional information on trust label, headquarters and distance attributes was provided between the two blocks of choice sets. Table 3 shows the attributes and the information given after the first block.

Table 3: Additional information given on trust label, headquarters and distance attributes

Attribute	Information
Trust label	Some websites have a trust label. This label shows that online purchase is reliable at this website (Federal Public Service - FPS - Economy, 2018). The payment is secure and your data will not be misused
Headquarters	Scientific studies also show that online and offline stores with Belgian headquarters are facing hard times. This is because they have to compete against foreign webshops such as Zalando, Bol.com, Amazon,.... These foreign e-commerce webshops collected 5.5 billion euros in sales in the Belgian market in 2018 alone. Yet, purchases at foreign webshops do not contribute to the Belgian economy
Distance	Scientific studies show that e-commerce is not very sustainable. The greater the distance a package must travel to reach the consumer, the greater the impact on the environment

The third section comprised of socio-economic and attitudinal questions. The socio-economic questions asked for respondent's age, sex, education level, current employment status, income and the number of family members in their households.

The New Environmental Paradigm (NEP) scale [12] was used to elicit environmental concerns. The NEP scale comprised of the fifteen items as presented by Dunlap et al. [12]. The even-numbered items were reversed so that the scale indicates pro-environmentalism. Respondents with higher pro-environmental concerns were expected to attend more to the shipment distance attribute. The nationalism scale comprised of three items [26] which were adapted for Belgium and are shown in Table 4. Respondents with higher nationalism views were expected to attend more to the headquarters attribute and prefer purchasing from firms with Belgian head-offices.

Table 4: Nationalism views [26]

Item description
1. I would prefer to be a citizen of Belgium
2. Belgium is a better country than most
3. You should support your country even when it is wrong

The NEP and nationalism scales were both translated to Dutch. Respondents were then asked to indicate on a nine-point Likert scale whether they strongly disagreed (value 1) or strongly agreed (9) with each of the scale's statements. To maximize information from each scale, we performed a principal components analysis and retained the first component. The reliability scores [57, 28] of the first principal components for the NEP and nationalism scales were 0.84 and 0.77 respectively.

2.3. Data collection and Sample characteristics

Participants were recruited via the Qualtrics online survey tool [41]. Master of Business administration students at the university were invited to participate in the survey using emails and social media by two students who were collecting the data as part of their theses [49, 18]. The recruits were then asked to invite potential participants from amongst their social circles. Privacy assurances on the anonymity and usage of the collected data was provided as part of the survey preamble.

In total there were 452 participants, of which 256 completed the survey. 203 of these were used in the analyses after excluding those who chose the opt-out option more than once. The exclusion was done to minimize effects from responses that were done with minimal trade-offs among the alternatives. The 53 excluded profiles showed patterns of selecting all the opt-outs in one block or in later choice sets in blocks. These may imply decreasing interest in choice making, which is a behavioral dimension that is beyond the scope of this article. Sensitivity analyses on the results showed that although the coefficients differed slightly depending on the criteria used to exclude respondents, neither the model selected via the Bayesian Information criterion (BIC) nor the conclusions changed substantially.

An overview of the socio-demographic and online purchasing frequency is provided in Table 5. Close to 70% were females while the youngest (oldest) participant was 14 (74) years old. Slightly over 60% had a post-high school diploma. Over 80% purchased items online at least every three months. This implies habitual online purchases in this sample. The three most common reasons for purchasing online were: home delivery service (chosen by 62.1%), save time (58.6%) and 24-hour clock purchase possibilities (46.3%). Most respondents placed their online orders in clothing (69%) followed by computer & electronics (38%) and travel & leisure (33.5%).

Table 5: Socio-economic characteristics and online-purchasing behaviour.

Characteristic	%	Characteristic	%
Female	69.0	Social status	
		Unemployed	2.5
Age groups		Independent	9.4
14-24	43.3	Housewife/husband	2.5
25-29	6.9	Retired	6.4
30-44	18.2	Student	32.5
45-54	17.2	Employed	42.9
55-74	14.3	Other	3.9
Education level		Online purchasing behaviour	
Primary	1.5	Daily	1.0
Secondary	34.5	Weekly	10.8
College	29.1	Monthly	41.4
University- BSc	16.3	Every 3 months	28.6
University- MSc	17.3	Every 6 months	11.3
Other	1.5	Once/year	4.9
		< Once/year	1.5
Net family income (€)		Never	0.5
< 1500	13.3		
1500-3000	30.5	Main reasons for e-purchasing	
3000-4500	16.7	Home delivery	62.1
>4500-	13.4	Time saving	58.6
No answer	26.1	24-hr clock purchasing	46.3

2.4. Statistical modeling

Four models were estimated. We first fit a multinomial logit (MNL) model [33, 51] with interaction effects for the three attributes (x_6 - x_8 in Table 1) where information was provided after the first block of choice sets.

These interaction effects (denoted as α_6, α_7 and α_8) were used to show the modifying effects of providing additional information on consumers' taste parameters. Positive and significant interaction effects imply positive shifts in the taste parameters attributable to the information provided.

The second model embeds *static* inferred ANA [23] into the MNL model with shifts in taste parameters as in the first model. All attributes were assumed to be subject to *static* ANA. The third MNL model allows switching ANA behavior for the three attributes where information was provided. The remaining five attributes were subject to static ANA. Unlike in the first two models where interaction effects were used to account for changes in taste preferences, in the third model, changes in ANA behavior were used to account for changes in preferences post-information. The initial attendance probabilities were confined to the first block of six sets, while a transition matrix of probabilities caters for ANA behavior post-information. The fourth model investigates the effects of socio-economic and attitudinal factors on the initial and transition attendance probabilities. The BIC and the likelihood ratio test were used for model comparisons. We formalize the models next.

2.4.1. Model 1: Multinomial logit model with shifts in taste parameters

The multinomial logit is a standard and widely used model for analysing choice data. MNL models are based on random utility theory, with the assumption that an alternative's unobservable true utility can be divided into two summable parts: a deterministic and a random component. Assuming the deterministic utility component (denoted as V_{ms}) is a linear function in the attribute parameters, and that the random component is identically and independently distributed following a type-I extreme value distribution, the probability of a consumer selecting webshop m in choice set s [33] is as shown in Equation 1:

$$p_{ms} = \frac{e^{V_{ms}}}{\sum_{m'=1}^{M} e^{V_{m's}}} \tag{1}$$

In line with notation introduced in Table 1, the deterministic components of the utility functions for the first and second block of choice sets are shown in Equation 2.

$$\begin{aligned} V_{ms} &= \beta_0 \mathrm{OptOut}_{ms} + \sum_{j=1}^{5} \beta_j \mathrm{x}_{jms} + \sum_{j=6}^{8} \beta_j \mathrm{x}_{jms} \ , \quad s \leq 6 \\ V_{ms} &= \beta_0 \mathrm{OptOut}_{ms} + \sum_{j=1}^{5} \beta_j \mathrm{x}_{jms} + \sum_{j=6}^{8} (\beta_j + \alpha_j) \mathrm{x}_{jms} \ , \quad s > 6 \end{aligned} \tag{2}$$

where OptOut equals 1 when the opt-out option is selected and 0 when a webshop is selected. The value x_{jms} refers to the j^{th} attribute for the m^{th} webshop in choice set s. Thus, x_{311} is the returns attribute value for webshop A in the first choice set and x_{839} is the distance attribute value for webshop C in the ninth choice set. The β_j's and α_j's are taste and interaction parameters respectively.

2.4.2. Model 2: Multinomial logit model with shifts in taste parameters and static ANA

Latent class models have for long been used to incorporate consumer heterogeneity in choice models [22, 46, 23]. In latent class modeling of ANA behavior, consumers are assumed to be divisible into a number of classes or subgroups (denoted as D) that differ in attributes' attendance behavior. A latent variable, denoted by Z_{ij} for an attribute where no extra information was provided and by K_{ij} for an attribute where information was provided, is usually defined for each attribute. The variables Z_{ij} and K_{ij} equal 1 when consumer i attends to attribute j and equal 0 when the attribute is not attended to. In this study, we assume that the probability to attend to attribute j is the same for all consumers and is denoted by θ_j. We also introduce pattern $\boldsymbol{k}_i$ (and $\boldsymbol{z}_i$ in brackets) for consumer i's indicator latent variables. Where $\boldsymbol{k}_i$ ($\boldsymbol{z}_i$) is the attendance pattern for the three (five) attributes where information was (not) provided. Conditional on the ANA latent class, consumers are then assumed to choose an alternative that maximizes their utility.

Equation 3 presents the deterministic components of the utility functions in the two blocks of choice sets when ANA patterns are included

$$\begin{aligned} V_{ms}|\boldsymbol{z}_i, \boldsymbol{k}_i &= \beta_0 \mathrm{OptOut}_{ms} + \sum_{j=1}^{5} \beta_j z_{ij} \mathrm{x}_{jms} + \sum_{j=6}^{8} \beta_j k_{ij} \mathrm{x}_{jms} \;\;, \quad s \le 6 \\ V_{ms}|\boldsymbol{z}_i, \boldsymbol{k}_i &= \beta_0 \mathrm{OptOut}_{ms} + \sum_{j=1}^{5} \beta_j z_{ij} \mathrm{x}_{jms} + \sum_{j=6}^{8} (\beta_j + \alpha_j) k_{ij} \mathrm{x}_{jms}, \quad s > 6 \end{aligned} \tag{3}$$

Attribute j contributes to consumer i's utility if z_{ij} or k_{ij} equals one. Otherwise, the attribute's contribution is constrained to zero. As a result, $V_{ms}|\boldsymbol{z}_i, \boldsymbol{k}_i$ only contains terms related to attributes that are attended to in the attendance pattern of consumer i. Consequently, the estimated taste parameters are conditional on the consumers attending to the attributes. We also extend the choice probability in Equation 1 to be dependent on a consumer's attribute attendance pattern. Detailed definitions of the updated choice probabilities, the probabilities to belong each of the latent classes and the unconditional probabilities of observing a sequence of webshop choices are provided in the Appendix.

2.4.3. Model 3: Multinomial logit model with changing ANA behavior for attributes where information was provided

This model targets the switching behavior in attribute attendance and is based on a first-order Markov model. The model comprises a static inferred ANA component for attributes where no information was provided. It also includes a Hidden Markov model (HMM) component [55, 4] that describes the ANA changes for the three attributes where information was provided mid-way through the experiment. The difference between this model and those in subsections 2.4.1 and 2.4.2 is the utilization of the ANA behavioral changes to reveal the impact of extra information.

To operationalize the ANA switching behavior, we assume that consumers can switch to any of the latent ANA states in the second block conditional on the ANA state in the first block of choice sets. The states are mutually exclusive and jointly exhausitive per block. The ANA state in the second block is determined by the attributes where information was provided since the rest are assumed to have non-changing ANA. To distinguish the role of the latent variable K_{ij} in the utilities and the attributes' attendance patterns in the two blocks, we introduce an index t ($t = 1, 2$) to K_{ij} such that K_{ijt} is a latent variable indicating whether consumer i attends to attribute j in block t or not. Along this line, $\boldsymbol{k}_{i1}$ is consumer i's attendance pattern for the three attributes where information was provided in the first block. The HMM structure comprises of two sets of probabilities - the initial attendance probabilities in the first block and the transition attendance probabilities in the second block of choice sets.

The initial attendance probability describes consumers' ANA states in the first block. A consumer's initial probability to belong to an ANA class is determined by the initial attendance probabilities and the consumer's initial attribute attendance pattern. Similar to section 2.4.2, attribute j's initial attendance probability is assumed to be the same for all consumers and is denoted by θ_j. Taking into account the initial attendance patterns, the updated deterministic utility in the first block is shown in Equation 4.

$$V_{ms}|\boldsymbol{z}_i, \boldsymbol{k}_{i1} = \beta_0 \mathrm{OptOut}_{ms} + \sum_{j=1}^{5} \beta_j z_{ij} \mathrm{x}_{jms} + \sum_{j=6}^{8} \beta_j k_{ij1} \mathrm{x}_{jms} \quad , \quad s \leq 6 \qquad (4)$$

In the second block of choice sets, we anticipate changes in the attendance probabilities for the three attributes where information was provided. These changes are driven by transition attendance probabilities which are probabilities of attending to attributes in the second block conditional on the attendance pattern in the first block. For the transition attendance probabilities, a pair of probabilities are possible per attribute depending on whether the attribute was attended to or not attended to in the first block. First, an attribute j can be attended to in the second block having not been attended to in the first block. We assume that this probability is the same for all consumers and denote it by $\delta_{j|0}$. Second, attribute j can be attended to in the second block having been attended to in the first block. Similarly, we assume that this attendance probability is the same for all consumers and denote it by $\delta_{j|1}$. Overall, the attendance probability for attribute j in the second block is the sum of the pair of transition probabilities weighted by the initial attendance probability. We denote this marginal probability by δ_j and show in Equation 5 how it is derived.

$$\begin{aligned} P(K_{ij2} = 1) = \; & P(K_{ij2} = 1 | K_{ij1} = 0) P(K_{ij1} = 0) \; + \\ & P(K_{ij2} = 1 | K_{ij1} = 1) P(K_{ij1} = 1) \\ \delta_j = & \delta_{j|0}(1 - \theta_j) + \delta_{j|1}\theta_j \qquad\qquad \forall j \in 6, 7, 8 \end{aligned} \tag{5}$$

Adapting the utility component in Equation 4 for the second block of choice sets, the updated deterministic utility equals:

$$V_{ms} | \boldsymbol{z}_i, \boldsymbol{k}_{i2} = \beta_0 \mathrm{OptOut}_{ms} + \sum_{j=1}^{5} \beta_j z_{ij} \mathrm{x}_{jms} + \sum_{j=6}^{8} \beta_j k_{ij2} \mathrm{x}_{jms} \;\; , \;\; s > 6 \tag{6}$$

We discuss the initial, transition, updated conditional and unconditional choice probabilities in greater detail in the Appendix.

2.4.4. Model 4: Including factors influencing changes in attribute attendance behavior

To investigate the effects of socio-economic and attitudinal factors on consumers' attribute attendance behavior, we model the logit of attendance probabilities as a linear function of the socio-economic and attitudinal factors. The logit of an attendance probability is the logarithm of the ratio of the attendance and the non-attendance probabilities. Explicit functions are shown in the Appendix. In line with past literature [12, 48, 42, 26, 21], we investigated the effects of age and sex on attendance to the trust label, age and nationalism on headquarters and pro-environmentalism on attendance to the distance attribute.

Pre-analysis, consumers' age was standardized to conform to NEP and nationalism principal components which were accordingly standardized. All the models were estimated using the Latent Gold software [54]. To select the best local maximum, each model was estimated using 100 runs with random starting values.

3. Results

3.1. Model comparison

Table 6 shows fit statistics for the estimated models. The results show that the ordering for *Model 1* to *Model 3* was the same for all the presented fit measures. We compare the models using the BIC values since it penalizes for the number of parameters and is also appropriate when models are not nested. Improvement in BIC was achieved when static ANA was included to *Model 1* (4687 vs 4337). Modeling changes in ANA lowered the BIC to 4312. Further, since providing information on the three attributes was likely to have knock-on effects on the remaining five, we also fit a model where the attendance probabilities for all the attributes were allowed to change. This model had a BIC value of 4331. The higher BIC (4331 vs 4312) shows that the increased attendance for the three attributes where information was provided was not accompanied by significant changes in the attendance probabilities for the other five. These results show that including and appropriately modeling the ANA behavior progressively lowers the BIC values, indicating better model fits.

Table 6 also shows that fit measures that penalize for model complexity (i.e, cAIC and BIC) gave lower values for *Model 3* compared to *Model 4*. In contrast, measures that do not penalize for complexity (e.g., AIC) preferred *Model 4*. Indeed, given *Model 3* is nested in *Model 4*, a likelihood ratio test in favour of *Model 3* was conclusively rejected (LR-stat = 33.33, p-value <0.01). The preference for *Model 4* to *Model 3* implies that the attendance probabilities can be explained by the underlying consumer heterogeneity.

3.2. Preference estimates

When interpreting the parameter estimates, it is necessary to note that estimates in models without and models with ANA are not directly comparable. This is because taste parameters in models without ANA hold for the entire sample while the parameters are conditional on accounting for all attributes when ANA is included. To provide direct comparisons, parameter estimates for models with ANA in Tables 7 and 8 and have been adjusted for attendance probability in columns annotated as Coef^{a} (SD).

Table 6: Model fit statistics

Model (*Model number*)	Par	LL	AIC	cAIC	BIC
MNL (*1*)	12	-2311.37	4646.75	4698.51	4686.51
MNL + static ANA (*2*)	20	-2115.43	4270.87	4357.13	4337.13
MNL + changing ANA (*3*)	23	-2095.07	4236.14	4335.35	4312.35
MNL + changing ANA + covariate effects (*4*)	38	-2078.41	4232.81	4396.72	4358.72

Notes:
Par: Number of parameters in the model
LL: log likelihood value
AIC: Akaike Information Criterion.
cAIC: AIC corrected for the number of parameters.
BIC: Bayesian Information Criterion.

Table 7 shows that in the MNL model without ANA, the impacts of the attributes on e-purchase intentions differred greatly. The utility from choosing an optout, as is in the other three models, was negative and significant. This implies that e-consumers benefit more from choosing among webshop alternatives than from opting-out. Webshops that were trust-labelled, were Belgian-based, had higher ratings for ease of use and user-friendly interfaces and offerred discounts on the next e-purchase were preferred. Longer delivery time, higher delivery costs, longer transportation distances and consumer-borne return costs were not preferred. *Model 1* also shows that the interaction effects for the trust label and distance attributes were significant. The direction of these interaction effects indicate that providing information reinforced the preference for trust-labelled webshops and non-preference for longer item delivery distances.

The results from *Model 2* in Table 7 show that the direction and significance of attributes, except for the time of delivery attribute, remained unchanged when static ANA was modelled. For the unadjusted coefficients, the trust label, headquarters and returning attributes had the highest impacts on e-purchase intentions. When the attributes were adjusted for attendance, the significance of the discount attribute was lost. Unlike in *Model 1* where two of the interaction effects were significant, in *Model 2*, only the interaction effect for the trust label remained significant. The effect of providing information on trust labelled webshops in *Model 2* was double the effect realized in *Model 1*. The differences in coefficient sizes and conclusions from models 1 and 2 are in line with findings in the literature showing that failure to model ANA behaviour may lead to unreliable results.

Table 8 shows that for *Model 3* where the switching ANA behavior was modelled, the trust label, headquarters, returning and distance attributes had the highest impact in the e-purchase intentions. Like in models 1 and 2, the attribute impacts differred considerably, the non-significance of the delivery time and the attendance-adjusted discount attributes remained. In addition, the significance of the distance attribute in the first block was lost when adjusted for the initial attendance probability. The non-significance of the distance attribute when adjusted for the initial attendance probability shows that pre-information, these consumers were less concerned about the negative environmental impacts of transporting items over long distances.

3.3. Attribute non-attendance

From the static ANA model in Table 7, these e-consumers mostly attended to the cost-related and the trust label attributes. The delivery price attribute was attended to by 42% of the consumers, while 51% and 46% respectively attended to the returning and trust label attributes. The least attended to attributes were distance (8%) and discount (2%).

Table 8 shows that except for the trust label, headquarters, distance and delivery time attributes, the proportion of consumers that initially attended to the remaining attributes in the switching ANA model were similar to those in the static ANA model. Initially, the trust label, headquarters and distance attributes were taken into account by 24%, 9% and 5% of the consumers respectively. After providing information on trust-labelled websites, the economic impacts of foreign-based webshops and the environmental impacts of long distance items transfers, the marginal share of consumers that attended to the trust label, headquarters and distance attributes increased to 43%, 12% and 10% respectively. The transition attendance probabilities in the second block of choice sets, which constitute the building blocks for these marginal proportions, are provided in Table 9 and are discussed next.

Table 9 shows that 28% of the consumers that did not attend to the trust label attribute in the first block attended to it in the second block of choice sets. This proportion was 6% and 5% for the headquarters and distance attributes respectively. The 95% confidence intervals for these conditional attendance proportions did not include zero. These results imply that for e-consumers that did not initially attend to the three attributes, their attendance probabilities were significantly higher post-information. On the other

Table 7: Multinomial logit (MNL) models without and with *Static* ANA results

	MNL (*Model 1*)	MNL with Static ANA (*Model 2*)		
Attribute	Coef (SD)	Coef^{na} (SD)	Attendance (θ_j) prob (L, U)	Coef^{a} (SD)
OptOut	-3.46 (0.22)	-3.84 (0.23)	-	-3.84 (0.23)
Delivery time	-0.07 (0.01)	-0.11 (0.12)	0.29 (0.02, 0.91)	-0.03 (0.01)
Delivery price	-0.13 (0.01)	-0.36 (0.03)	0.42 (0.33, 0.52)	-0.15 (0.02)
Returning	-0.60 (0.05)	-1.44 (0.21)	0.51 (0.33, 0.69)	-0.74 (0.08)
Rating	0.13 (0.02)	0.46 (0.10)	0.22 (0.11, 0.40)	0.10 (0.02)
Discount	0.01 (0.00)	0.21 (0.06)	0.02 (0.01, 0.08)	0.00 (0.00)
Trust label	0.79 (0.08)	1.73 (0.17)	0.46 (0.37, 0.55)	0.79 (0.10)
Headquarters	0.36 (0.07)	2.50 (0.56)	0.12 (0.07, 0.21)	0.31 (0.08)
Distance	-0.03 (0.01)	-0.28 (0.07)	0.08 (0.04, 0.15)	-0.02 (0.01)
Interactions (α_6 - α_8)				
Trust label	0.48 (0.12)	2.10 (0.36)		0.96 (0.15)
Headquarters	-0.01 (0.12)	0.83 (0.78)		0.10 (0.10)
Distance	-0.04 (0.01)	-0.19 (0.13)		-0.01 (0.01)

Notes:
Coef^{na} (SD) implies that the Coefficient has not been adjusted for attendance probability. SD is the Standard Deviation
Attendance prob (L, U) are the lower (L) & upper (U) 95% confidence interval limits for the attendance probabilities.
Coef^{a} (SD) implies that it has been adjusted for attendance probability i.e., $\text{Coef}^{\text{a}} = \text{Coef}^{\text{na}} * \text{attendance probability}$
Greyed out numbers reflect non-significance at α = 0.05

hand, the proportion of consumers that attended to the trust label, headquarters and distance attributes in the second block having also attended to them in the first block were 91%, 76% and 96% respectively. These results indicate that consumers that initially attended to each of the three attributes almost certainly attended to the attribute in the second block.

Table 8: Multinomial logit model with switching ANA (*Model 3*)

		Choice sets 1 - 6		Choice sets 7 - 12	
Attribute	$\mathrm{Coef}^{\mathrm{na}}$ (SD)	Initial (θ_j) attendance prob (L, U)[1]	$\mathrm{Coef}^{\mathrm{a}}$ (SD)	Marginal (δ_j) attendance prob (L, U)[2]	$\mathrm{Coef}^{\mathrm{a}}$ (SD)
OptOut	-4.04 (0.24)		-4.04 (0.24)		
Delivery time	-0.40 (0.23)	0.04 (0.00, 0.34)	-0.02 (0.01)		
Delivery price	-0.37 (0.02)	0.48 (0.39, 0.58)	-0.18 (0.02)		
Returning	-1.70 (0.25)	0.50 (0.32, 0.67)	-0.84 (0.10)		
Rating	0.51 (0.09)	0.21 (0.11, 0.36)	0.11 (0.02)		
Discount	0.23 (0.06)	0.02 (0.01, 0.07)	0.01 (0.00)		
Trust label	4.54 (0.35)	0.24 (0.17, 0.32)	1.07 (0.16)	0.43 (0.28, 0.56)	1.95 (0.29)
Headquarters	4.22 (0.87)	0.09 (0.05, 0.16)	0.38 (0.11)	0.12 (0.04, 0.27)	0.51(0.19)
Distance	-0.52 (0.12)	0.05 (0.02, 0.12)	-0.03 (0.02)	0.10 (0.03, 0.24)	-0.05 (0.03)
				4312.3	

Notes:
$\mathrm{Coef}^{\mathrm{na}}$ (SD) implies that the Coefficient has not been adjusted for attendance probability.
SD is the Standard Deviation.
Attendance prob (L, U)[1] are the lower (L) & upper (U) 95% confidence interval limits for the initial attendance probabilities in the first block of choice sets.
$\mathrm{Coef}^{\mathrm{a}}$ (SD) implies that it has been adjusted for attendance probability i.e., $\mathrm{Coef}^{\mathrm{a}} = \mathrm{Coef}^{\mathrm{na}} *$ attendance prob.
Attendance prob (L, U)[2] are the lower (L) & upper (U) 95% confidence interval limits for the marginal attendance probabilities in the second block of choice sets.
Greyed out numbers reflect non-significance at $\alpha = 0.05$

Table 9: Transition probabilities for the switching attribute attendance behavior model

	Attendance in choice sets 7-12 given:	
Attribute	Non-attendance in choice sets 1-6 ($\delta_{j\|0}$'s)	Attendance in choice sets 1-6 ($\delta_{j\|1}$'s)
Trust label	0.28 (0.20, 0.37)	0.91 (0.69, 0.98)
Headquarters	0.06 (0.02, 0.14)	0.76 (0.36, 0.94)
Distance	0.05 (0.02, 0.14)	0.96 (0.30, 1.00)

3.4. Factors influencing changes in attribute attendance behavior

Table 10 shows estimates and significances for *Model 4* investigating socio-economic and attitudinal factors' effects on changes in ANA. As a preliminary step, we tested and found no significant effects of socio-economic and attitudinal factors on the attendance probabilities of attributes where no information was provided. For the trust label, initial probabilities were significantly influenced by consumers' age (p-value 0.034) while sex was not significant (p-value 0.15). Table 10 shows that for an increase of one standard deviation (SD) in age, the logit of the initial probability of attending to the trust label decreases by 0.49 units. Hence, initially, older consumers were less likely to account for the trust label attribute. Neither age nor sex significantly influenced the conditional attendance probabilities in the second block.

Both age (p-value 0.01) and nationalistic attitudes (p-value 0.08, at 10% significance level) significantly affected consumers' propensity to initially attend to the headquarters attribute. Without controlling for age, the significance of nationalistic attitudes was stronger (p-value 0.02). This suggests presence of some collinearity between the nationalism and age effects in this sample. An increase of 1 SD in age and nationalism scores respectively led to increases of 0.76 and 0.15 units in the logit of the initial probability of attending to the headquarters attribute. These results indicate that pre-information, the interest in local-based webshops was higher for older and more nationalistic consumers. Neither age nor nationalism influenced the conditional attendance probabilities in the second block.

Pre-information, pro-environmental views were not significant for the probability of attending to the distance attribute (p-value 0.51). Post-information, the effect of pro-environmentalism was significant for the probability of non-attendance in the first to attendance in the second block (p-value 0.02). Here, a 1 SD increase in NEP increases the logit of probability of attending to the distance attribute by 0.21 units. Therefore, provision of environmentally-themed information led to stronger increases in the conditional attendance probabilities for eco-friendly e-consumers.

Table 10: *Model 4* showing covariate effects on initial and transition attendance probabilities

		Initial prob. θ_j	Transition probabilities $\delta_{j\|0}$	$\delta_{j\|1}$
Attribute	Covariate	Coef(SD)	Coef(SD)	Coef(SD)
Trust label	Intercept	-1.76 (0.43)	-1.45 (0.42)	3.20 (3.36)
	Sex	0.68 (0.47)	0.65 (0.49)	-0.75 (3.50)
	Age	-0.49 (0.23)	0.17 (0.21)	0.20 (1.00)
Headquarters	Intercept	-2.22 (0.36)	-2.61 (0.64)	2.89 (3.35)
	Age	0.76 (0.27)	0.39 (0.64)	1.62 (3.86)
	Nationalism	*0.15* (0.09)	-0.02 (0.14)	0.35 (0.56)
Distance	Intercept	-3.06 (0.44)	-2.94 (0.55)	3.11 (2.14)
	NEP	-0.06 (0.09)	0.21 (0.09)	-0.04 (0.38)

Notes:
θ_j is the initial attendance probability for attribute j.
$\delta_{j|0}$ is the probability of attending to attribute j in choice sets 7-12 conditional on non-attendance in choice sets 1-6.
$\delta_{j|1}$ is the probability of attending to attribute j in choice sets 7-12 conditional on attendance in choice sets 1-6.
Coef (SD) is the Coefficient (Standard Deviation).
Greyed out numbers reflect non-significance at α = 0.05
Italicized numbers reflect significance at α = 0.10
NEP is a short form for New Environmental Paradigm scale

4. Discussion and conclusion

4.1. Theoretical implications

The primary theoretical contribution of this paper is the implementation of a dynamic attribute non-attendance model. Attribute non-attendance has often been modelled as a *static* process, where regardless of the prevailing experimental conditions, consumers are assumed to belong to a single state. However, changes in ANA behavior can be expected in some cases: e.g., longitudinal experiments, where behavior-changing information on key attributes becomes available, consumers learning and/or fatigue in lengthy experiments. Therefore, there is a need to appropriately model changes in attribute attendance behaviors.

The more standard way of handling additional information in a choice experiment is to include interaction terms between dummy variables indicating presence of information and the attributes. Significance of the interaction terms then implies that the information leads to changes in the taste parameters. However, as we show in this article, an alternative to assessing the information impact is by evaluating attribute attendance behavior changes. Our results show that determining the information impact by estimating shifts in attribute attendance behavior provides a better model fit than modelling shifts in taste coefficients. From Tables 7 and 8, while two-thirds of the interactions in the *static* ANA model were not significant, the changing ANA model provided significant transition probability changes. Additionally, marginal changes in coefficient estimates were observed, albeit with similar in conclusions.

4.2. Research findings

Consumers' online purchase intention is influenced by webshop factors that ensure a great, comfortable and secure shopping experience. The relevance and importance of these webshop characteristics vary among consumers, as does the probability to attend to them when making e-purchase decisions. We investigate the impact of common webshop attributes on intention to purchase, consumers' chances of accounting for attributes when constructing their utilities, effects of providing extra information and factors that influence changes in consumers' attribute attendance behavior.

The impact of attributes in determining webshop preferences differ greatly. Trust label, headquarters, returning and distance attributes carried the most weight in consumers' intention to make online purchases in this sample. Trust has for long been an influential factor in the B2C relationships in e-commerce [8, 53, 6, 3]. The trust issues stem from diverse challenges related to consumer behavior, technology and knowledge [56, 6]. Whereas ways to enhance and factors affecting trust in e-commerce have been suggested [8, 3], the knowledge effect on consumers' attention to the trust label remains an unstudied option. From a policy and managerial perspective, it is necessary that efforts to improve the consumer-webshop relationship are correctly perceived by the targeted consumers and taken into account when selecting webshops. Our results show that initially, about a quarter of the consumers took presence of a trust label into account when selecting a webshop for shopping. Providing information had a positive and significant effect on consumers' interest in the trust attribute. Further, older consumers were more likely to be hesitant in attending to the trust attribute.

Delivery of discrepant items because they were over-hyped or are damaged [45], the ensuing costs, complex item return procedures and unawareness of available channels for online dispute resolutions [9] are some of the reasons for consumers' e-purchases apathy. This particularly affects cross-border e-commerce, where the associated risks result in preference for domestic markets [16, 52]. The high impact and attendance probability of the product returns services attribute is therefore unsurprising. This is because it affects many important but unresolved e-commerce challenges. First, despite the frequent needs by e-consumers to return e-purchased products, only a few e-retailers offer free return services [45]. The retailers' unwillingness to meet return costs presents consumers with an unwelcome risk of incurring extra charges. Second, the procedures for item returns are sometimes unclear, unknown and complex or are country-specific. These motivates consumers to favour domestic sites where they are more familiar with the linguistic, legal and credibility barriers that often undermine cross-border e-commerce. To overcome, efforts to improve consumer awareness and unify regional digital markets like the EU's Digital Single Market [17] policy agenda should be prioritised. Third, lengthy and costly item returns procedures discourage consumers further weakening the B2C trust. Lastly, failed deliveries and consumer returns involve additional travelling, warehousing, picking and packaging activities. These extra handling activities carry unwanted environmental implications [31].

The results of this study show that consumers preferred webshops headquartered in Belgium. Additionally, providing more information on economic impacts of preferring foreign to local webshops appears to raise interest in the headquarters attribute. Considering the high attention to the trust label and return attributes, this result may also reflect respondents' comfort to resolve possible products returns in a legal, linguistic and social context they are more familiar with. Older consumers and those with higher nationalistic views were more attentive to the economic impacts of shopping on foreign webshops. Thus, to realize regional digital integration and boost adoption of e-commerce, it appears necessary that policy formulators and implementors address concerns of these consumer groups. Similarly, foreign webshops seeking to expand their operations may want to contribute to local economies by setting up stores in those countries. This would give webshops opportunities to contribute to local economies by engaging locals in their operations. Local stores for foreign webshops would also minimize environmental impacts of returned and undelivered items by collecting and transporting in batches.

Consumers' limited knowledge and inattention to key e-commerce characteristics [56, 6, 3, 2] does not only explain their reluctance to trust and adopt e-commerce, or pursue delivered but unsatisfactory items. It also explains some of the environmentally-insensitive purchase decisions. Despite the recent literature surge on the environmental impacts of e-commerce [13, 50, 31], the penetration of this knowledge to consumers is still low. However, results of this study show that providing extra information can be an effective way of raising awareness and influencing consumers' decision-making. Explaining the environmental impacts of long-distance product deliveries significantly improved the keenness of respondents who were initially indifferent. Pro-environmental consumers were more likely to account for the distance attribute after provision of information.

4.3. Managerial and policy implications

Results from this sample suggest that webshops attributes with the highest impact on e-consumers intent for online purchase are: presence of trustmarks, Belgian headquarters, free item return services and shipment distance. Therefore, to attract and retain e-consumers, webshop managers and e-commerce marketeers should consider guaranteeing trust through payments and data security, contribution to domestic economies, provision of free item returns and environmental-friendliness as key differentials. Similarly, to ensure that all citizens are on board for the success of EU's Digital Single Market, it is essential that policy makers address concerns from pro-domestic e-consumers driven by economy concerns. Given that the distance (and partly, headquarter) attribute(s) provide tacit environmental concerns, these results recommend e-commerce's development and policy making to be environmentally-conscious in its operations.

Attribute attendance in this sample, like in many choice behavioral studies, was low. Previous studies show that limited knowledge is a leading barrier to the acceptance of (cross-border) e-commerce as well as pro-environmental consumption behaviors. In the current study, we find that providing information on important attributes changes their attribute attendance behavior. Thus, for webshop marketeers, environmental and digital single market policy makers to realize their objectives, there is a need to continuously provide key information to potential consumers. This can be done via consumer awareness forums, advertisements and explaining strength characteristics on webshops.

Our findings also suggest that e-consumers' perception, attention and reaction to information on attributes depends on their age and environmental and nationalistic attitudes. To address the trust challenges in e-commerce, policy makers need, beyond providing information on trust, to satisfy the innate trust concerns from the older generation. Our results also show that older and nationalistic consumers are keener on domestic e-shopping. Thus, to promote cross-border e-commerce which is a core objective in the Digital Single Market agenda, these groups of consumers will require more persuasion. Similarly, environmentally-conscious consumers were more likely to attend to the shipment distance attribute after provision of information. This result provides a good launch-pad for pro-environmental policies. It shows that enlightened consumers are more receptive of business innovations that are environmentally-friendly. On a broader scale, the significance of age and attitudinal factors imply that e-commerce segmentation and marketing efforts should be conscious of extant consumer heterogeneity.

4.4. Limitations and future research

There remains substantial gaps for future studies relating to this work. First, we provided additional information on attributes mid-way through the experiment. This effectively divided the choice sets into two blocks, a block of six choice sets each before and after the information. Thus, investigation of changes in attribute attendance was only done in the second block of choice sets. However, changes in attribute attendance behavior can occur in each choice set throughout the experiment. While *choice task stated* ANA studies exist [47, 5], to our knowledge, their inferred counterparts do not yet exist. The approach proposed in this article can be tailored for *choice task inferred* ANA by assuming that changes occur at every choice task. The *choice task inferred* ANA can be a useful tool to investigate consumers' learning and fatigue effects [10] especially in lengthy experiments.

Secondly, while a multinomial logit kernel was used, other models that allow greater flexibility and heterogeneity e.g., mixed multinomial models could be used. These extensions, which are conceptually straightforward, are left for future research. Thirdly, e-consumers are known to visit multiple webshops before making their e-purchases [29, 38]. Whereas the switching behaviors [29] and purchase paths and conversion dynamics [38] across webshops have been studied, to our knowledge, there does not exist a study that has investigated the dual switching behavior across webshops and attribute attendance behavior on realized preferences data. We encourage future studies to allow for these model extensions.

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Appendix A

A.2.4.2. Multinomial logit model with shifts in taste parameters and static ANA

We define two sets of binary latent variables; five Z_{ij}'s for attributes where no extra information was provided and three K_{ij}'s for those where information was provided. Z_{ij} and K_{ij} equal 1 if consumer i attends to attribute j at all occasions, 0 otherwise. The mathematical notations are $Z_{ij} \sim \text{Bern}(\theta_j)$ (j = 1, 2, .., 5) and $K_{ij} \sim \text{Bern}(\theta_j)$ (j = 6, 7, 8), where θ_j is the Bernoulli probability of attending to attribute j. Thus, consumer i's attendance probability for attribute j is $P(Z_{ij} = 1) = \theta_j$. Similarly for attributes where information was provided, $P(K_{ij} = 1) = \theta_j$. Consumer i's probability to belong to one of the ANA patterns is then a product of individual attributes' Bernoulli probabilities due to the independence assumption of Z_{ij}'s and K_{ij}'s [23]:

$$p(\boldsymbol{z}_i, \boldsymbol{k}_i|\boldsymbol{\theta}) = \prod_{j=1}^{5} \theta_j^{z_{ij}} (1-\theta_j)^{1-z_{ij}} \prod_{j=6}^{8} \theta_j^{k_{ij}} (1-\theta_j)^{1-k_{ij}} \qquad \text{(A1)}$$

The conditional deterministic components of the utility that consumer i

derives from selecting webshop m in set s given a *static* ANA pattern are:

$$\begin{aligned} V_{ms}|\boldsymbol{z}_i,\boldsymbol{k}_i =& \beta_0 \mathrm{OptOut}_{ms} + \sum_{j=1}^{5} \beta_j \mathrm{z}_{ij} \mathrm{x}_{jms} + \sum_{j=6}^{8} \beta_j \mathrm{k}_{ij} \mathrm{x}_{jms}, \quad s \le 6 \\ V_{ms}|\boldsymbol{z}_i,\boldsymbol{k}_i =& \beta_0 \mathrm{OptOut}_{ms} + \sum_{j=1}^{5} \beta_j \mathrm{z}_{ij} \mathrm{x}_{jms} + \sum_{j=6}^{8} (\beta_j + \alpha_j) \mathrm{k}_{ij} \mathrm{x}_{jms}, \quad s > 6 \end{aligned} \tag{A2}$$

Attribute j contributes to consumer i's utility if z_{ij} or k_{ij} equals one. Otherwise, the attribute's contribution is constrained to zero. Consequently, the estimated taste parameters are conditional on the consumers attending to the attributes. From Equation A2, the conditional probability of consumer i choosing webshop m in set s, denoted by $p_{ms}|\boldsymbol{z}_i,\boldsymbol{k}_i$, is given by:

$$p_{ms}|\boldsymbol{z}_i,\boldsymbol{k}_i = \frac{e^{V_{ms}|\boldsymbol{z}_i,\boldsymbol{k}_i}}{\sum_{m'=1}^{M} e^{V_{m's}|\boldsymbol{z}_i,\boldsymbol{k}_i}} \tag{A3}$$

Combining the probabilities to belong to the latent classes and the conditional choice probabilities, and recognizing that every e-consumer can belong to each of the D attribute attendance latent classes, the unconditional probability of observing a sequence of webshop choices over choice sets is;

$$p_i = \sum_{\boldsymbol{z}_i,\boldsymbol{k}_i \in D} p(\boldsymbol{z}_i,\boldsymbol{k}_i|\boldsymbol{\theta}) \prod_s \prod_m (p_{ms}|\boldsymbol{z}_i,\boldsymbol{k}_i)^{y_{ims}} \tag{A4}$$

Where y_{ims} equals 1 if webshop m in choice set s is chosen by consumer i, 0 otherwise.

A.2.4.3. Multinomial logit model with changing ANA behavior for attributes where information was provided

We introduce an extra index t, $t = 1, 2$, to the latent binary variable K_{ij}, so that K_{ijt} equals 1 if consumer i attends to webshop attribute j in block t, 0 otherwise. The Z_{ij} are as defined in section A.2.4.2.

A.2.4.3.1. Initial state probability

In line with the independence assumption amongst the latent variables, the initial ANA pattern probability for e-consumer i is the product of initial attributes' attendance probabilities:

$$p(\boldsymbol{z}_i,\boldsymbol{k}_{i1}|\boldsymbol{\theta}) = \prod_{j=1}^{5} \theta_j^{z_{ij}} (1-\theta_j)^{1-z_{ij}} \prod_{j=6}^{8} \theta_j^{k_{ij1}} (1-\theta_j)^{1-k_{ij1}} \tag{A5}$$

A.2.4.3.2. Transition probabilities

They are denoted as $p(\boldsymbol{k}_{i2}|\boldsymbol{k}_{i1}, \boldsymbol{\delta})$ and are limited to the three attributes where information was provided. Where $\boldsymbol{\delta}$ is a vector of transition attendance probabilities. The $\boldsymbol{\delta}$ vector contains a pair of conditional attendance probabilities per attribute, depending on whether the attribute was attended to or not attended to in the first block:

$$\begin{aligned}\delta_{j|0} =& P(K_{ij2} = 1|K_{ij1} = 0)\\ \delta_{j|1} =& P(K_{ij2} = 1|K_{ij1} = 1)\end{aligned} \tag{A6}$$

The probability to attend to the three attributes in the second block is:

$$p(\boldsymbol{k}_{i2}|\boldsymbol{k}_{i1}, \boldsymbol{\delta}) = \prod_{j=6}^{8} \left(\delta_{j|1}^{k_{ij2}}(1-\delta_{j|1})^{1-k_{ij2}}\right)^{k_{ij1}} \left(\delta_{j|0}^{k_{ij2}}(1-\delta_{j|0})^{1-k_{ij2}}\right)^{1-k_{ij1}} \tag{A7}$$

A.2.4.3.3. Posterior marginal attendance probability in the second block (δ_j)

The δ_j's are sums of the conditional probabilities weighted by the attendance probability in the first block.

$$\begin{aligned}\theta_j =& P(K_{ij1} = 1)\\ \delta_j =& P(K_{ij2} = 1|K_{ij1} = 1)P(K_{ij1} = 1) + P(K_{ij2} = 1|K_{ij1} = 0)P(K_{ij1} = 0)\\ =& \delta_{j|1}\theta_j + \delta_{j|0}(1-\theta_j)\end{aligned} \tag{A8}$$

A.2.4.3.4. Utilities and choice probabilities

Extending Equation A2 to allow for the two blocks of choice sets, the updated webshop utilities are as shown below:

$$\begin{aligned}V_{ms}|\boldsymbol{z}_i, \boldsymbol{k}_{i1} =& \beta_0 \mathrm{OptOut}_{ms} + \sum_{j=1}^{5} \beta_j \mathrm{z}_{ij} \mathrm{x}_{jms} + \sum_{j=6}^{8} \beta_j \mathrm{k}_{ij1} \mathrm{x}_{jms}, \quad s \leq 6\\ V_{ms}|\boldsymbol{z}_i, \boldsymbol{k}_{i2} =& \beta_0 \mathrm{OptOut}_{ms} + \sum_{j=1}^{5} \beta_j \mathrm{z}_{ij} \mathrm{x}_{jms} + \sum_{j=6}^{8} \beta_j \mathrm{k}_{ij2} \mathrm{x}_{jms}, \quad s > 6\end{aligned} \tag{A9}$$

Similarly, extending Equation A3, the conditional choice probability is:

$$p_{ms}|\boldsymbol{z}_i, \boldsymbol{k}_{it} = \frac{e^{V_{ms}|\boldsymbol{z}_i, \boldsymbol{k}_{it}}}{\sum_{m'=1}^{M} e^{V_{im's}|\boldsymbol{z}_i, \boldsymbol{k}_{it}}} \tag{A10}$$

The subscript index t equals 1 (2) for the first (second) block of choice sets. Combining $p(\boldsymbol{z}_i, \boldsymbol{k}_{i1}|\boldsymbol{\theta})$, $p(\boldsymbol{k}_{i2}|\boldsymbol{k}_{i1}, \boldsymbol{\delta})$ and $p_{ms}|\boldsymbol{z}_i, \boldsymbol{k}_{it}$, and recognizing that choice probabilities are correlated through the underlying Markov formulation, the unconditional probability of observing the sequence of webshop choices is a sum over all possible ANA paths consumers can take;

$$p_i = \sum_{\boldsymbol{z}_i, \boldsymbol{k}_{i1} \in D} \sum_{\boldsymbol{k}_{i2} \in D_2} p(\boldsymbol{z}_i, \boldsymbol{k}_{i1} | \boldsymbol{\theta}) p(\boldsymbol{z}_i, \boldsymbol{k}_{i2} | \boldsymbol{k}_{i1}, \boldsymbol{\delta}) \prod_m \prod_s \prod_t (p_{ms} | \boldsymbol{z}_i, \boldsymbol{k}_{it})^{y_{ims}} \tag{A11}$$

With $D = 2^8$ possible attendance patterns in the first six choice sets. In the last six choice sets, there are $D_2 = 2^3$ patterns corresponding to the three attributes where information was provided.

A.2.4.4. Including factors influencing changes in attribute attendance behavior

To include a factor that influences the initial attribute attendance probabilities, we specify θ_j as

$$\theta_j = \frac{\exp(\gamma_j w_i)}{1 + \exp(\gamma_j w_i)} \tag{A12}$$

Where w_i and γ_j are a consumer i characteristic and the parameter to be estimated respectively. Similarly, for the ANA transition probability from non-attendance to attendance, we define

$$\delta_{j|0} = \frac{\exp(\gamma_{j|0} w_i)}{1 + \exp(\gamma_{j|0} w_i)} \tag{A13}$$

Where $\gamma_{j|0}$ is a parameter to be estimated. $\delta_{j|1}$ can be similarly defined:

$$\delta_{j|1} = \frac{\exp(\gamma_{j|1} w_i)}{1 + \exp(\gamma_{j|1} w_i)} \tag{A14}$$

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