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Online Consumers' Attribute Non-Attendance Behavior: Effects of Information Provision

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ABSTRACT

In online shopping, e-consumers often choose one among many websites on which to place their orders. The choice depends on key attributes such as trust labels. Presence of such a label shows that the website has been independently certified for online security and privacy. However, consumers may not search for websites with security and privacy seals if they do not know the importance of trust certificates. This behavior of ignoring attributes is called attribute non-attendance. Consumers' attention to attributes can be increased through provision of information. We investigate the attribute non-attendance switching behavior when information on attributes is provided. Studies have modeled the impact of providing attribute information through changes in preference parameters. We show that an alternative approach is to model the impact via changes in attendance probabilities. We propose that an attribute's attendance probability post-information depends on its attendance pattern pre-information. Applied to webshop choice data, we find that the proposed model gives a better fit compared with standard approaches. Providing information on attributes led to increases in consumers' attention to the concerned attributes. Additionally, we found that consumer characteristics affect the shifts in attribute attendance behavior. We show that when assessing effects of providing information, considering the effect on attributes' attention is important. We provide evidence that availing information on key attributes can give brands a competitive advantage.

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. Boosted by the increasing internet use, online retailing has progressively curved a significant niche in the retail business [21, 37, 48]. Retail e-commerce sales were estimated to account for more than 20 percent of all global retail sales by 2019, nearly triple the 7 percent estimated for 2015 [61]. The high annual growth rate of e-commerce, which holds a three-to-one margin to offline retailing [37, 61], poses important questions for businesses. Fundamental among these questions is how firms can attract and retain customers on their websites despite the stiff competition [37, 38].

The importance of the internet in retailing has triggered extensive research on it, both from consumers' and retailers' perspectives. An important research question, especially for e-retailers, is how to position their websites so that they are chosen more often by e-customers. The

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underlying logic being that prepurchasing, online customers first choose websites on which to place their orders [5, 41, 61, 62]. Like in brick-and-mortar businesses, customers are attracted and tend to be loyal to websites that resonate with their preferences. Websites attract their customers through their characteristics/attributes. Some attributes show measures taken to enhance security when making e-payments—for example, presence of a trust label or trust-mark [48, 59, 62]. Other attributes characterize benefits of ordering items on a given website. For instance, some websites offer discounts to customers when they make repeat purchases. Websites may also differentiate themselves by offering subsidized and quicker item delivery and return services. These attributes individually contribute to a maximizable customer utility that determines a website choice.

In recent years, extensive research has investigated different aspects of e-commerce. Factors that promote customers' online shopping experiences have also been explored. Part of the research has investigated how website attributes influence customers' web experience and motivate e-purchase intentions [7, 12, 47, 60]. Other studies have explored the dynamics of choice-making [39, 55, 56, 67] and e-customers' website preferences [5, 41, 61]. Some other studies have focused on the environmental [19, 49] and socio-economic [2, 76] effects of e-commerce. A lesser researched, yet central, aspect of e-customers' behavior is website choices. Closely associated with website choices is customers' attribute non-attendance (ANA) behavior [26, 68]. While ANA has been extensively studied in choice experiments [26, 31, 40, 68, 70, 71], there is a dearth in its application in e-commerce.

Modeling ANA in website choices is an important step, since ignoring its existence leads to biased coefficients and thus biased policy decisions. Available studies present ANA as a *static* process. This implies that choice-makers' ANA behavior remains the same throughout the experiment. However, considering changes in choice-makers' behavior when information on key attributes is provided [67] and e-consumers' *window-shopping* for webshops that most satisfy their preferences [41, 61], it is possible that these behavioral dynamics are accompanied by changes in attention towards key attributes (i.e., changes in ANA behavior). We explore and model this extension of e-consumers' ANA behavior when information on key attributes is provided.

Another aspect related to website choices is consumers' information. Information is vital in website choices since many prospective customers are not yet comfortable engaging in online purchases. The discomfort is mainly due to safety, reliability, and privacy concerns when buying online. Some of these uncertainties result from limited understanding of how the e-market operates and unawareness of e-retailers' efforts to ensure safety and privacy when shopping on their websites. Information can also influence e-consumers' behavior in other ways. For example, consumers' willingness to accept online merchants has been reported to be determined by their information about the online shopping activities [7, 22, 83]. Studies in other choice-making contexts also found significant effects of information on choices through changes in their preferences [43, 67] and in their attribute attendance behavior [70].

When information on attributes is provided, the primary target is often to seek consumers' attention toward the attributes or the product as a whole. Consumers who concretely understand and attend to the key attributes of a product are understood to make more informed decisions. Although this flow of events seems natural, prior studies modeling the effects of information often overlooked its effect on changes in consumers' attribute attendance behavior. We suggest that providing information on attributes affects

website choices via changes in customers' attention to the attributes. To support this suggestion, we analyze a stated preference Discrete Choice Experiment (DCE) on website choices. First, we apply ANA behavior in e-commerce using an existing inferential approach [31]. Then, we propose an extension that models attributes' attendance probabilities post-information conditional on attendance (or non-attendance) pre-information. Last, we explore how customer characteristics influence their ANA behavior changes when information is provided. Particularly, we investigate how consumers' environmental [18] and nationalistic [34] attitudes inform their website choices. The former attitude points toward environmental effects of e-commerce [19, 49], whereas the latter explores socio-economic advantages of ordering from domestic webshops [2, 76].

Discrete Choice Experiments and ANA Behavior

DCEs are quantitative techniques used to investigate customers' preferences when making choices [77]. DCEs are based on the random utility theory framework [52]. In a stated preference DCE, alternatives (websites, in this case) are hypothesized using unique combinations of attribute levels. Respondents (e-customers) are then presented with several scenarios (choice sets) of hypothesized websites to choose from. Underlying a website choice is a latent utility. This utility is known to a customer but unknown to researchers. To model customers' choice behavior, modelers construct a utility where every website attribute is assumed to have a quantifiable contribution. It is assumed that in every choice set, customers select websites that maximize their utilities. Details on modeling consumers' choices are provided in the statistical modelling subsection.

Originally, the choice experiments literature assumed that consumers use every attribute when selecting their preferred alternatives. However, recent evidence suggests that consumers often simplify their choice tasks by ignoring some attributes [26, 68]. Thus, some attributes play a role in a consumer's utility (when they are not ignored), whereas others do not. The tendency to ignore some attributes when making decisions is often referred to as ANA. Details on and modifications to choice models to account for consumers' ANA behavior are provided in the statistical modelling subsection.

Study Background and Literature Review

Information and Choice-Making

Information plays an important role in choices made by decision-makers [10, 43, 67]. A better informed decision-maker is more likely to look out for a perfectly fitting item. Informed customers are also more willing to pay a premium for products that they like [43]. In random utility frameworks, attributes provide the first source of information on alternatives. Attributes such as sustainability labels and trustmarks are often displayed on websites to reduce the information asymmetries with users [11, 59, 67]. Respondents are assumed to trade all the attributes so that they select an option that maximizes their utility. However, respondents sometimes ignore these information signals when making choices [26, 68, 78]. The non-use of some attributes in choices could stem from misunderstanding their significance. For instance, Sandorf et al. [70] found that respondents' attributes' attendance depended on knowledge of the choice context. This evidence (i.e., [70]) suggests that unawareness of the e-commerce context could be associated with

consumers' non-attendance to crucial website attributes. Indeed, whereas e-retailers often detail their privacy practices in their online privacy policies, customers rarely read and understand the policies [78]. Therefore, strategies to mitigate consumers' non-use of information should be prioritized [9, 36, 48, 78]. Strategies such aslike provision of information on attributes, which has been linked with positive and significant effects on consumers' preferences [67], should be explored. For e-retailers, providing information on their websites and e-commerce could have several effects. First, information can reduce asymmetries by increasing customers' awareness of key website attributes [11, 36, 48]. Second, information can bridge the long-standing trust issues that consumers have with e-commerce [28, 30, 42, 54, 83]. Third, explaining the important attributes can lead to the retailers' website being chosen more often for (repeat) e-purchases [38, 75, 78].

The question for this study is, When information on attributes is provided, how should researchers model its impact? Should the influence be assessed through changes in preference parameters (as done in [67])? Or can the effect(s) be modeled via changes in ANA behavior? Which way of modeling information impact (preference parameter vs. ANA changes) would describe the behavioral changes better? Our work draws parallels with Sandorf et al. [70], who modeled the knowledge effect on ANA in environmental choices. Sandorf et al. [70] found a link between respondents' ANA behavior and their knowledge level. In this study, unlike [70], we provide information on attributes to reinforce customers' existing knowledge on website characteristics. For website choices, providing information in the study may be more effective, as respondents' familiarity with technical website attributes can be low. We contrast this finding with modeling the information impact via changes in preference parameters.

Behavioral Changes and ANA

In the recent past, there has been a rise in choice experiments modeling changes in consumers' preferences (e.g., [5, 15, 35, 39, 41, 43, 55, 56, 61, 67]). Similarly, save for e-commerce, choice studies investigating ANA behavior have been on the rise [26, 31, 40, 68, 70, 71]. While modeling changes in preferences, on one hand, and modeling ANA, on the other, have become commonplace, modeling changes in consumers' ANA behavior has not. Consequently, changes in attributes' attention and factors that influence ANA behavior changes are rarely reported. Yet, consumer behavior regarding which attribute is important when decision-making is highly dynamic. Attribute relevance may depend on consumers' knowledge of the attribute, economic and policy conditions or learning/fatigue effects in a study. The dynamism in attribute relevance is especially important for websites and e-commerce. This is because websites/e-commerce operate in an ever-evolving technological and policy system. For example, the policies governing user-privacy and online security before and after the introduction of the General Data Protection Regulation in the EU are different. This implies that attention to a website attribute on data privacy post–General Data Protection Regulation was bound to change. Such changes in attention can similarly occur to other attributes that are important in influencing website choices [7, 33, 36, 49, 51, 60]. Modeling changes in web users' attention to attributes affected by such changes when making choices is a useful but unresearched question. This paper fills this modeling gap by analyzing webshop choice data and investigating changes in (and drivers of) the ANA behavior among e-customers.

Changes in ANA behavior can also be seen in many real-life choices. Consider ill-informed consumers on website characteristics such as presence of trustmarks. Websites with trustmarks seek to inform customers that they have been independently certified for quality, reliability and security [48, 59, 62]. The limited understanding of trustmark attributes means that users, unknowingly, undervalue certified webshops. Hence, the attendance probability toward such a crucial attribute will be low. However, when the importance of purchasing on certified sites (symbolized by trust labels) is explained, consumers are likely to be more interested in trust-labeled websites. So the attendance probability to the trust label attribute post-information will be higher. Similarly, eco-conscious consumers may show attendance 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 [35]. This evolution may result from changes in factors that affect their preferences (e.g., income or knowledge about attributes). Experiments like agent interdependency in group decision-making [66] can be prime for changes in attributes' attendance behavior. An agent in such experiments may ignore an attribute for lack of information. However, when peers provide newer information, the agent's attention to the attribute(s) may change. Accounting for ANA changes in such cases could help to better explain decision-makers' behavior changes.

Literature on preference evolution (e.g., [5, 15, 39, 41, 53, 55, 56, 61, 67]) and ANA behavior (e.g., [4, 25, 31, 70, 71]) tends to exist in parallel. However, it is possible that consumers' behavioral changes, which have previously been modeled by preference changes, could manifest as changes in ANA behavior. In this study, we propose an ANA switching behavior model for modeling consumers' behavioral changes when attribute information is given. To explain consumers' behavioral changes, we compare modeling via ANA changes with modeling via preference parameter changes.

Modeling ANA behavior changes presents two challenges. First, we do not observe attributes' ANA patterns. Second, we do not observe interchanges between attributes' ANA patterns pre- and post-information. For the first challenge, approaches have been suggested to identify ANA [63, 68, 71]. The more prominent approaches are *stated* and *inferred* ANA. In stated ANA, respondents are asked to state whether 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 [4]. Alternatively, the attendance questions may be asked after every choice task—*choice task* stated ANA [4]. The stated ANA approach entails answering extra questions making the choice exercise bulkier. Stated ANA is also prone to misreporting and may be a source of endogeneity if stated ANA variables are included in the utility function [32]. In inferred ANA, econometric models based on latent class models are used to estimate the probability of attribute attendance without collecting the attendance data directly from the respondents. In light of stated ANA's shortcomings, we modeled inferred ANA. Inferred ANA is also 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. To address the second challenge, this paper extends existing choice models to handle changes in ANA behavior. The proposed model introduces a Markovian structure [3, 82] on the endogenous attribute attendance

model [31, 32]. Markov models have been used in behavioral sciences to model changes in consumer preferences [41, 55, 56]. These models assume that consumers' behavior at a given point depends on past behavior. Typically, the dependence is limited to an order of one, that is, behavior at the previous point. This dynamic ANA formulation makes it possible to obtain more refined results than assuming a static ANA behavior. The model can also be used to explore factors that drive changes in ANA behavior.

We apply the proposed model formulation to a stated choice experiment on website choices for Belgian e-consumers. Initially, the data were collected to investigate the impacts of website attributes on website choices. However, the innovative way in which the data were collected makes it a good candidate for investigating the impact of information on ANA in website choices. This is because midway through the experiment, extra information was provided on three attributes. First was the *trustlabel* attribute. The trustlabel describes whether a trust label is present or absent on a website. 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. Second was the *headquarter* attribute, which explains whether the webshop has its headquarters in Belgium. Information on headquarter described the economic impact of the stiff competition that Belgium-based webstores face when competing against foreign well-established webshops. Third, information was given on the *distance* attribute. Distance expresses the distance (in kilometers) that items have to be transported to reach e-consumers. In this regard, information on the environmental impact of transporting packages over long distances was provided. The motivation for providing information on these attributes was to investigate trust in e-commerce, preference for local webshops, and environmentalism and sustainability in e-commerce. Traditionally, choice models with shifts in preference parameters would be used to account for the information impact (e.g., [67]). We instead reveal this impact by modeling the changes in ANA behavior.

This research contributes to the literature in several ways. First, we augment the evidence that providing information on attributes may alter customers' behavior when selecting websites. This implies that for companies whose websites have differential attributes like trustmarks, informing customers by prominently displaying and explaining its importance may increase selection chances for their webshops [38, 78]. Second, we model ANA in an e-commerce setting. In doing so, we show that the consequences of not modeling ANA (e.g., inaccurate estimates and conclusions) that have been reported in other settings apply to e-commerce choice experiments. We find that customers did not always attend to the attributes when choosing websites. Additionally, the estimates and conclusions for models that modeled ANA were not always the same as for those that did not model ANA. Third, we investigate tendencies for e-consumers to change their ANA behavior. Although attributes' importance may change because of availability of information or over time, accounting for possible changes in 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 accounting for ANA switching behavior provides a better model fit compared with the more standard approaches of handling additional information in choice experiments. We also find significant socio-economic and attitudinal factors' effects on changes in e-consumers' attribute attendance behavior.

Hypotheses

Customers choose websites by considering many attributes simultaneously. According to behavioral theory, website choices are related to their attributes. Attributes are assumed to have quantifiable contributions to utilities. Customers aggregate attributes' individual contributions into a utility and choose a website that maximizes their utility. The overarching principle in this decision-making process is that customers understand and consider all the attributes presented to them. However, this is not always the case. Decision-makers do not always consider all attributes [26, 68, 78]. Customers' understanding of the choice context may differ [43, 70]. Similarly, some customers may need information on the importance of some attributes [67]. Therefore, there is a need to investigate the attendance behavior of decision-makers, especially when attribute information is provided.

Provision of attribute information enhances consumers' awareness of the attributes. The impact of information can be captured through changes in attributes' parameters in the utility. This has been the standard theoretical and modeling approach (e.g., [39, 43, 67]). However, this impact can also express itself as changes in consumers' attention to the attributes. We propose the latter and contrast it with the former way of modeling the impact of information in choice experiments. We propose the following hypothesis:

Hypothesis 1: Providing information about attributes increases the corresponding attributes' attendance probabilities.

We build up toward the hypothesis starting with a model that assesses the information impact through changes in preference parameters. We then introduce ANA using methods that assume static ANA behavior. We discuss how including ANA improves the model fit and affects estimates and conclusions in website choices. Next, we alternatively model the information effects through changes in ANA behavior. Statistical fit statistics are used to compare the modeling approaches.

Further, we investigate the effect of customers' idiosyncrasies on their ANA changing behavior. Studies have shown that consumers' interactions with the internet and e-commerce can be linked to their characteristics (e.g., [11, 22, 28, 30, 36, 44, 74, 79]). For instance, Hoffmann et al. [30] and Herrando et al. [28] found that users' internet engagement relies on trust and that trust differed based on age cohorts. Younger online users are usually more experienced in using computers and the internet [28, 30, 36]. As a result, they are more likely to be aware of cues on websites' privacy policy positions before choosing websites for orders. Older informed consumers are, however, more likely to be concerned about their online privacy [28, 30]. Therefore, we expect that older consumers will be more attentive to the presence of a trust label when making webshop choices post-information. We propose the following hypotheses:

Hypothesis 2A: Younger consumers are more likely to attend to the trust label attribute pre-information.

Hypothesis 2B: The rate of change in attendance probability to the trust label attribute post-information increases with age.

Customers' involvement in e-commerce can also depend on their gender [30, 44, 79]. Despite the moderating effects of gender on e-commerce involvement leveling out [44],

male internet users are still considered to be more cautious in their choice of online privacy tools and tend to exhibit higher computer self-efficacy [30]. Therefore, we expect male e-consumers to be keener on the presence of a trustmark when choosing websites. We suggest the following hypotheses:

Hypothesis 3A: Male consumers are more likely to attend to the trust label attribute pre-information.

Hypothesis 3B: The rate of change in attendance probability to the trust label attribute post-information is higher for males.

Pro-environmental consumers prefer buying items in a way that is consistent with their eco-conservation attitudes. For these consumers, eco-conscious webshop operations like bulk transportation or far-off firms establishing local outlets to limit transporting few orders over long distances would be more appealing. This is because ordering items on webshops whose stores are far away involves elaborate transportation that is negative to the environment [19, 49]. We propose the following hypotheses:

Hypothesis 4A: Pro-environmental consumers are more likely to attend to the distance attribute pre-information.

Hypothesis 4B: The rate of change in attendance probability to the distance attribute post-information increases with increasing pro-environmental scores.

Nationalistic consumption is a consumer behavior of favoring products and brands from one's own country and rejecting those from other countries [1, 24, 84]. This may be because of activism, insecurity, or campaigns promoting domestic buying. Nationalistic e-consumers can reject foreign brands as a way of promoting domestic brands. In this case, an influx of foreign brands is seen as a threat to the growth of domestic brands. Additionally, nationalistic consumers belief that domestic firms contribute directly to the local economy in terms of job opportunities and remittances compared to foreign firms [1, 24]. Because nationalistic attitudes can influence the attendance probability to attributes on webshop headquaters, we propose the following:

Hypothesis 5A: Nationalistic consumers are more likely to attend to the headquarters attribute pre-information.

Hypothesis 5B: The rate of change in attendance probability to the headquarters attribute post-information increases with increasing nationalistic attitudes scores.

Preference for domestic firms can also be mediated by consumers' age. Studies have profiled younger consumers as cosmopolitan digital natives who are more open to foreign brands [24, 30]. On the other hand, older consumers tend to be more conservative and less inclined toward foreign brands [24, 30]. Because consumers' age can influence preference for domestic brands, we investigate how attention to the headquarters attribute varies with age. We suggest the following hypotheses:

Hypothesis 6A: Older consumers are more likely to attend to the headquarters attribute pre-information.

Hypothesis 6B: The rate of change in attendance probability to the headquarters attribute post-information increases with age.

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

Data and Methods

Choice experiment

A discrete choice experiment was used to investigate the impact of website attributes on website choices. Eight attributes were used to hypothesize webshops. The *delivery time* and *delivery price* attributes indicated how fast and at what cost items ordered on the webshop could be delivered. The *returns* attribute indicated whether customers had to incur extra costs in returning items. This may happen in case customers ordered on the webshop and were not happy with the delivered item. The other attributes were webshop's usability and friendliness *rating, discount* offered on repeat orders on the webshop, presence of *trust labels* on the webshop, whether the webshop had Belgian or non-Belgian *headquarters*, and the shipping *distance* for e-purchased items. These eight are among the more influential webshop attributes known to influence online purchase intentions [7, 12, 47, 80]. The choice of the headquarters and distance attributes was partly motivated by the Belgians' considerable readiness to purchase items from foreign webshops [23, 79], as well as to investigate the opportunities and challenges toward the EU Digital Single Market policy agenda [23, 37, 79]. 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 [8]. 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 resulting design comprising 12 choice sets of three webshops and an opt-out option. The prior utility for opting out was 1.8. All participants got the same 12 choice sets in the same order. Table 2 shows an example of a choice set used in the study.

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 when ordered on the webshop	0, 4, 8
Returns	x_3	Shipping costs of item returns when ordered on the webshop	Free (0), Own cost (1)
Rating	x_4	Webshop ease of usability rating (out of 5)	1, 2, 3, 4, 5
Discount	x_5	Discount (in %) offered on a repeat purchase on the webshop	0, 5, 15
Trust label	x_6	Webshop certified by an independent agency and is reliable	No (0), Yes (1)
Headquarters	x_7	Webshop's head office location	Not Belgian (0), Belgian (1)
Distance	x_8	Shipping distance (km) for the item	100, 300, 1,000

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 (km)	1,000	100	300

At which web store would you prefer to make your online purchase?
○ Webshop A ○ Webshop B ○ Webshop C ○ None

Survey and Questionnaire

Participants were provided with questionnaires divided into three parts. The first part was concerned with online purchases frequency and behavior. Respondents were asked to indicate how often they made online purchases (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). Last, they were asked to indicate why they purchased or have not yet purchased items online.

The second part comprised the choice experiment. A series of 12 choice sets of three webshop alternatives and an opt-out option was used. The 12 choice sets were further divided into two blocks: block 1 for choice sets 1 to 6, and block 2 for choice sets 7 to 12. To assess changes in consumer 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.

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

The New Environmental Paradigm (NEP) scale [18] was used to elicit environmental concerns. The NEP scale comprised the 15 items as presented by Dunlap et al. [18]. The even-numbered items were reversed so that the scale indicates pro-environmentalism. Respondents with higher pro-environmental concerns were expected to be more attentive to the shipment distance attribute. The nationalism scale comprised three items [34] that 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 webshops with Belgian head offices.

Table 3. Information Given on Trust Label, Headquarters, and Distance Attributes.

Attribute	Information
Trust label	Some websites have a trust label. This label shows that online purchases are reliable at this website (Federal Public Service - FPS - Economy, 2018). The presence of a label implies that payments are secure and your data will not be misused.
Headquarters	Scientific studies 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 on 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.

Table 4. Nationalism Views. [34]

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 (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 [50, 85] of the first principal components for the NEP and nationalism scales were 0.84 and 0.77, respectively.

Data Collection and Sample Characteristics

Participants were recruited via the Qualtrics online survey tool [64]. Master of Business Administration students at the university were invited to participate in the survey using e-mails and social media by two students who were collecting the data as part of their theses. 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.

There were 452 participants, of which 256 completed the survey. Of these, 203 were used in the analyses after excluding those who chose the opt-out option more than once. The exclusion minimized 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 beyond the scope of this paper. 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 sociodemographic and online purchasing frequency is provided in Table 5. Close to 70 percent were female, and the youngest (oldest) participant was 14 (74) years old. Slightly more than 60 percent had a post–high school diploma. More than 80 percent 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 percent), save time (58.6 percent), and 24-hour clock purchase possibilities (46.3 percent). Most respondents placed their online orders in clothing (69 percent), followed by computer and electronics (38 percent) and travel and leisure (33.5 percent).

Statistical Modeling

Four models were estimated. We first fit a multinomial logit (MNL) model [52, 77] with interaction effects for the three attributes (x_6 - x_8 in Table 1) where information was provided

Table 5. Socio-economic Characteristics and Online-Purchasing Behavior.

Characteristic	%	Characteristic	%
Female	69.0	Social status	
Age groups		Unemployed	2.5
14–24	43.3	Independent	9.4
25–29	6.9	Housewife/husband	2.5
30–44	18.2	Retired	6.4
45–54	17.2	Student	32.5
55–74	14.3	Employed	42.9
Education level		Other	3.9
Primary	1.5	Online purchasing behavior	
Secondary	34.5	Daily	1.0
College	29.1	Weekly	10.8
University- BSc	16.3	Monthly	41.4
University- MSc	17.3	Every 3 months	28.6
Other	1.5	Every 6 months	11.3
Net family income (€)		Once/year	4.9
< 1,500	13.3	< Once/year	1.5
1,500–3,000	30.5	Never	0.5
3,001–4,500	16.7	Main reasons for e-purchasing	
>4,500	13.4	Home delivery	62.1
No answer	26.1	Time saving	58.6
		24-hr clock purchasing	46.3

after the first block of choice sets. These interaction effects (denoted as $\alpha_6 - \alpha_8$) were used to show the modifying effects of providing additional information on consumers' preference parameters. Positive and significant interaction effects imply positive shifts in the preference parameters attributable to the information provided.

The second model embeds static inferred ANA [31] into the MNL model with shifts in preference 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. The first two are standard choice models that use interaction effects to model the impact of providing information on attributes (e.g., [67]). In the third model, changes in ANA behavior are used to account for consumers' behavioral changes post-information. The initial attendance probabilities were confined to the first block of six sets, whereas 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.

Model 1: Multinomial Logit Model With Shifts in Preference 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 that 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 [52] is as shown in Equation 1:

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

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.

$$V_{ms} = \beta_0 \text{OptOut}_{ms} + \sum_{j=1}^{5} \beta_j x_{jms} + \sum_{j=6}^{8} \beta_j x_{jms}, s \leq 6$$

$$V_{ms} = \beta_0 \text{OptOut}_{ms} + \sum_{j=1}^{5} \beta_j x_{jms} + \sum_{j=6}^{8} (\beta_j + \alpha_j) x_{jms}, s > 6 \tag{2}$$

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 jth attribute for the mth 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 preference and interaction parameters, respectively.

Model 2: Multinomial Logit Model with Shifts in Preference Parameters and Static ANA

Latent class models have long been used to incorporate consumer heterogeneity in choice models [31, 32, 40, 71]. In latent class modeling of ANA behavior, consumers are assumed to be divisible into a number of classes or subgroups (denoted as D). The subgroups 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 $\mathbf{k}_i$ (and $\mathbf{z}_i$ in brackets) for consumer i's indicator latent variables. Where $\mathbf{k}_i(\mathbf{z}_i)$ 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:

$$V_{ms}|\mathbf{z}_i, \mathbf{k}_i = \beta_0 \text{OptOut}_{ms} + \sum_{j=1}^{5} \beta_j z_{ij} x_{jms} + \sum_{j=6}^{8} \beta_j k_{ij} x_{jms}, s \leq 6$$

$$V_{ms}\bigg|\mathbf{z}_i, \mathbf{k}_i = \beta_0 \text{OptOut}_{ms} + \sum_{j=1}^{5} \beta_j z_{ij} x_{jms} + \sum_{j=6}^{8} (\beta_j + \alpha_j) k_{ij} x_{jms}, s > 6 \tag{3}$$

Attribute j contributes to consumer i's utility if z_{ij} or k_{ij} equals 1. Otherwise, the attribute's contribution is constrained to zero. As a result, $V_{ms}|\mathbf{z}_i, \mathbf{k}_i$ only contains terms related to attributes that are attended to in the attendance pattern of consumer i. Consequently, the

estimated preference 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 to each of the latent classes, and the unconditional probabilities of observing a sequence of webshop choices are provided as Equations (A1) to (A4) in the supplemental material available online.

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 component [3, 82] that describes the ANA changes for the three attributes where information was provided midway through the experiment. The difference between this model and models 1 and 2 is the use 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 exhaustive 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-changingANA. 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}. Therefore, K_{ijt} is a latent variable indicating whether consumer i attends to attribute j in block t. Along this line, $\mathbf{k}_{i1}$ is consumer i's attendance pattern before information was provided. The Hidden Markov model structure comprises 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. 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:

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

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 conditional on attendance 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.

$$
P(K_{ij2} = 1) = P(K_{ij2} = 1 | K_{ij1} = 0)P(K_{ij1} = 0) + P(K_{ij2} = 1 | K_{ij1} = 1)P(K_{ij1} = 1)
$$
$$
\delta_j = \delta_{j|0}(1 - \theta_j) + \delta_{j|1}\theta_j, \quad j \in 6, 7, 8 \tag{5}
$$

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

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

We discuss the initial, transition, updated conditional and unconditional choice probabilities in greater detail in Equations (A5) to (A11) in the supplemental online material. A lower BIC value for this model to that for Model 2 is theoretically important. It indicates that assessing the information effects via ANA changes describes consumers' behavioral changes better than via preference parameter changes.

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 probability. Explicit functions are shown as Equations (A12) to (A14) in the supplemental online material. In line with past literature [18, 28, 30, 34, 65, 73, 79], we investigated the effects of age and gender on attendance to the trust label, age, and nationalism on headquarters and pro-environmentalism on attendance to the distance attribute.

Preanalysis, 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 [81]. To select the best local maximum, each model was estimated using 100 runs with random starting values.

Results

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 fit measures. We compare the models using BIC values since they penalize for the number of parameters. BIC is also appropriate when models are not nested. Improvement in BIC was achieved when static ANA was included to Model 1 (4,687 vs. 4,337). Modeling changes in ANA lowered the BIC to 4,312. The lower BIC for

Table 6. Model Fit Statistics.

Model (Model number)	Par	LL	AIC	cAIC	BIC
MNL+parameter shifts (1)	12	−2311	4647	4699	4687
MNL+parameter shifts+static ANA (2)	20	−2115	4271	4357	4337
MNL+ changing ANA (3)	23	−2095	4236	4335	4312
MNL+ changing ANA + covariate effects (4)	38	−2078	4233	4397	4359

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.

Model 3 suggests that modeling the information impact via ANA changes describes consumers' behavioral changes more closely than via preference parameter changes. Further, since providing information on the three attributes was likely to have knock-on effects on the remaining five, we also fit a model with changes in attendance probabilities for all the attributes. This model had a BIC value of 4,331. The higher BIC (4,331 vs. 4,312) 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 more for model complexity (i.e., Akaike information criterion corrected for the number of parameters and BIC) gave lower values for Model 3 compared with Model 4. In contrast, measures that penalize less for complexity (e.g., Akaike information criterion) preferred Model 4. Indeed, given Model 3 is nested in Model 4, a likelihood ratio test in favor of Model 3 was conclusively rejected (LR-stat = 33.33, $p < .01$). The preference for Model 4 to Model 3 implies that the attendance probabilities can be explained by consumer heterogeneity.

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. Preference parameters in models without ANA hold for the entire sample. However, when ANA is included, the parameters are conditional on accounting for all attributes. To provide direct comparisons, parameter estimates for models with ANA in Tables 7 and 8 have been adjusted for attendance probability in columns annotated as Coef [a](SD).

Table 7 shows that in the MNL model without ANA, the impact of attributes on webshop choices differed greatly. The utility from choosing an optout, similar to the other three models, was negative and significant. This implies that e-consumers benefited more from choosing among webshop alternatives than from opting out. Webshops that were trust-labelled, were Belgium based, had higher ratings for ease of use and user-friendly interfaces, and offered discounts on repeat purchases were preferred. Webshops with 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 nonpreference for longer item delivery distances.

Table 7. 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 ($a_6 - a_8$)				
Trust label	0.48 (0.12)	2.10 (0.36)		0.96 (0.15)
Headquarters	−0.01 (0.12)	0.83 (0.78)		−0.01 (0.01)
Distance	−0.04 (0.01)	−0.19 (0.13)		−0.01 (0.01)

Notes: Grayed-out numbers reflect nonsignificance at $\alpha = 0.05$. Coef (SD) is the coefficient (standard deviation). Coef [na](SD) implies that the coefficient has not been adjusted for attendance probability. Coef [a] (SD) implies that it has been adjusted for attendance probability, that is, Coef [a] = Coef [na]× Attendance Probability. Attendance prob (L, U) are the lower (L) and upper (U) 95 percent confidence interval limits for the attendance probabilities. MNL = Multinomial logit.

Table 8. Multinomial Logit Model With Switching ANA (Model 3).

		Choice sets 1–6		Choice sets 7–12	
		Initial (θ_j) attendance prob		Marginal (δ_j) attendance	
Attribute	Coef [na](SD)	(L, U)[1]	Coef [a](SD)	prob (L, U)[2]	Coef [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)

Notes: Grayed-out numbers reflect nonsignificance at $\alpha = 0.05$. Coef (SD) is the coefficient (standard deviation). Coef [na](SD) implies that the coefficient has not been adjusted for attendance probability. Attendance prob (L, U)[1] are the lower (L) and upper (U) 95 percent confidence interval limits for the initial attendance probabilities in the first block of choice sets. Coef [a] (SD) implies that it has been adjusted for attendance probability, that is, Coef = Coef [na]× Attendance Prob. Attendance prob (L, U) [2] are the lower (L) and upper (U) 95 percent confidence interval limits for the marginal attendance probabilities in the second block of choice sets.

Model 2 results in Table 7 show that the direction and significance of most estimates remained unchanged when static ANA was modelled. The delivery time (discount) attribute switched significance when un(adjusted) for ANA. The interaction term for the distance attribute also turned nonsignificant in Model 2. The trust label, headquarters, and returning attributes had the highest impacts on webshop choices. In Model 1, two interaction effects were significant. In Model 2, only the interaction effect for the trust label was significant. The effect of information on trust labelled webshops in Model 2 was double the effect realized in Model 1. Table 7 also shows that the estimates in Models 1 and 2 were often (slightly) different. The significance for some estimates also changed between Models 1 and 2. These observations are in line with findings in the literature showing that failure to model ANA behavior may lead to unreliable results [27, 29, 31, 32, 40, 71].

Table 8 shows results for Model 3, where the switching ANA behavior was modeled. As in Models 1 and 2, the impacts of attributes on webshop choices differed considerably. The

trust label, headquarters, returning, and distance attributes now have the highest impact on webshop choices. The nonsignificance 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 its initial attendance probability. This shows that pre-information, these consumers were less concerned about the negative environmental impacts of transporting items over long distances.

ANA

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

Table 8 shows that except for the trust label, headquarters, distance, and delivery time attributes, the proportion of consumers who 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 percent, 9 percent, and 5 percent 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 percent, 12 percent, and 10 percent, respectively. The transition attendance probabilities in the second block of choice sets, which are the building blocks for these marginal proportions, are provided in Table 9 and are discussed next.

Table 9 shows that 28 percent of the consumers who 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 percent and 5 percent for the headquarters and distance attributes, respectively. The 95 percent confidence intervals for these conditional attendance proportions did not include zero. This suggests that for e-consumers who did not initially attend to the three attributes, their attendance probabilities were significantly higher post-information. These results support our first hypothesis (H1). On the other hand, the proportion of consumers who attended to the trust label, headquarters, and distance attributes in the second block having also attended to them in the first block were 91 percent, 76 percent, and 96 percent, respectively. These results indicate that consumers who initially attended to each of the three attributes almost certainly attended to the attribute in the second block.

Table 9. Transition Probabilities for the Switching Attribute Attendance Behavior Model.

Attribute	Attendance in choice sets 7–12 given:	
	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)

Table 10. Model 4 Showing Covariate Effects on Initial and Transition Attendance Probabilities.

		Initial prob.	Transition probabilities	
		θ_j	$\delta_{j\|0}$	$\delta_{j\|1}$
Attribute	Covariate	Coef (SD)	Coef (SD)	Coef (SD)
Trust label	Intercept	-1.76 (0.43)	-1.45 (0.42)	3.20 (3.36)
	Male	-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)
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)
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)

Notes: Grayed-out numbers reflect nonsignificance at $a = 0.05$. 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). NEP is New Environmental Paradigm scale.

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 ($p = .017$), whereas gender was not significant ($p = .08$). Table 10 shows that for an increase of 1 standard deviation 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. This could be because older consumers shop online less compared with young and more digital consumers. As a result, they may not be aware of website characteristics such as presence of trust labels. The significance and direction of age on trust label's attendance probability provides support for Hypothesis 2A. However, Hypothesis 3A about gender influence on e-consumers' initial attendance probability to the trust label attribute was not supported.

Hypotheses on rates of change in the attention probabilities post-information are based on the $\delta_{j|0}$'s; these are the probabilities that express the actual changes: from non-attendance to attendance. Both age ($p = .22$) and gender ($p = .10$) were not significant for the rate of change in attention to the trust attribute. These results imply that changes in consumers' attention to the trust attribute depended on neither age nor gender. Thus, Hypotheses 2B and 3B were not supported.

Pre-information, the NEP score was not significantly related to the probability to attend to the distance attribute ($p = .26$). Thus, Hypothesis 4A was not supported. This means that initially, e-consumers who were keen on environmental protection were not as keen on attending to attributes that express the environmental effects of ordering items online. Post-information, the effect of pro-environmentalism was significant for the probability of non-attendance in the first to attendance in the second block ($p = .01$). 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. This result provides support for Hypothesis 4B.

Both nationalistic attitudes ($p = .04$) and age ($p = .002$) significantly affected consumers' propensity to initially attend to the headquarters attribute. Without controlling for age, the significance of nationalistic attitudes was stronger ($p = .01$). This suggests presence of some collinearity between the nationalism and age effects in this sample. An increase of 1 SD in nationalism scores and age, respectively, led to increases of 0.15 and 0.76 units in the logit of the initial probability of attending to the headquarters attribute. Thus pre-information, the interest in local-based webshops was higher for more nationalistic and older consumers. These pair of results provide support for Hypotheses 5A and 6A. Neither nationalism ($p = .45$) nor age ($p = .27$) influenced the rate of change in attention to the headquarters attribute post-information. Therefore, Hypotheses 5B and 6B were also not supported.

Discussion and Conclusion

Research Findings

Consumers' webshop choices are influenced by webshop factors that ensure a great, comfortable, and secure shopping experience. The importance of these webshop attributes varies, as does the probability to attend to them when making choices. First, we investigate the impacts of webshop attributes on webshop choices. Second, we estimate consumers' chances of accounting for these attributes when constructing their utilities. Then we investigate the effects of providing extra information on attributes and the factors that influence changes in consumers' attribute attendance behavior.

The impact of attributes in determining webshop preferences differed greatly. Trust label, headquarters, returning, and distance attributes carried the most weight in consumers' webshop choices. Trust has always been influential in e-commerce's business-to-consumer relationships [6, 7, 13, 20, 36, 46, 80]. The trust issues stem from diverse challenges related to consumer behavior, technology and knowledge [7, 11, 20, 35, 36, 83]. Many consumers are neither aware nor comfortable with how e-commerce operates. This lack of understanding implies that even in cases where steps are taken to improve the online buying experience, the efforts are rarely noticed by the targeted consumers. Trust in e-commerce, as a result, remains low. Ways to enhance and factors affecting trust in e-commerce have been suggested [11, 13, 28, 36, 46, 83]. However, the knowledge effect on consumers' attention to the trust label remains an unstudied option despite studies showing that decision-makers do not always attend to key attributes when making choices (e.g., [78]). Further, some consumer characteristics like trust in e-commerce and attention to attributes are dynamic in nature. A trust relationship mutates based on new experiences and information, such that decision-makers continuously update their information base and their decision to trust or not to trust [35]. Choice experiment studies (e.g., [67]) have reported higher preferences for attributes where information is provided. Higher environmental knowledge has also been associated with higher attribute attendance probabilities [70]. In bolstering this limited literature, our results show that providing information can have a positive and significant effect on consumers' interest in the trust attribute. Further, older consumers were less likely to attend to the trust attribute. From a policy and managerial

perspective, it is necessary that efforts to improve trust are correctly perceived by the consumers and taken into account when selecting webshops for their e-purchases.

Instances of mismatches between items as they appear online and those that are delivered have been discussed in e-commerce [57, 58, 69]. Returning mismatch items can be complicated and costly to retailers and consumers alike. Sometimes, consumers are not even aware of existing channels for online dispute resolutions [14]. These factors particularly affect cross-border e-commerce, where the associated risks result in preference for domestic e-shops [17, 37, 79]. The high-impact and attendance probability of the product returns attribute is therefore unsurprising; it affects important and unresolved e-commerce challenges. First, despite the frequent needs by consumers to return purchased products, e-retailers often offer restricted return services [16, 58]. 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, or country specific. These motivates consumers to favor domestic sites where they are more familiar with the linguistic, legal, and credibility barriers that undermine cross-border e-commerce. To overcome, efforts to improve consumer awareness and unify regional digital markets like the EU's Digital Single Market [23, 37] policy agenda should be prioritized. Third, lengthy and costly item returns procedures discourage consumers further weakening the business-to-commerce trust. Last, failed deliveries and consumer returns involve additional traveling, warehousing, picking, and packaging activities. The extra handling activities pose negative environmental effects [19, 49].

The results of this study show that consumers preferred webshops headquartered in Belgium. Additionally, providing information on the economic impacts of shopping on foreign webshops appeared 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 returns in familiar retailing environments. 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 implementers 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.

Studies have shown that knowledge can affect e-commerce in various ways. First, knowledge can determine consumers' preferences and thus choices [9, 10, 43, 67]. Second, knowledge can affect the probability with which consumers attend to key attributes when making choices [70]. Knowledge can also affect trust in and adoption of e-commerce [7, 22, 36, 78, 83]. Fourth, some consumers make numerous impulsive e-purchases [45, 69] oblivious of the associated effects. Such orders often end up as returns, compounding the environmental distress. We investigate how informing decision-makers of the negative effects of returns on the environment impacts their attention to eco-themed attributes. Despite the recent literature surge on the environmental impacts of e-commerce [19, 49], the penetration of this knowledge to consumers remains low. We supplement the growing evidence that providing information can be an effective way of raising awareness and influencing consumers' decision-making [10, 36, 43, 78]. Explaining the environmental impacts of long-distance product deliveries significantly improved the

keenness of respondents who were initially indifferent. Pro-environmental consumers were also more likely to account for the distance attribute after provision of information.

Theoretical and Methodological Implications

This research makes theoretical and methodological contributions to the choice experiments field. First, the study augments the growing literature on the strategic use of information to influence respondents' choices [9, 43, 67, 78]. While informed decision-makers make more astute choices, it is the mechanism used to model the information impact that most interests us. Existing studies view the effects of providing information as restricted to preference parameter changes. We provide evidence that assessing the effects of information through changes in attributes' attention may represent the respondents' behavioral changes in a better way.

Second, we make a methodological contribution through the implementation of a dynamic ANA model. ANA has often been modeled as a static process. That is, 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: for example, 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 preference parameters. However, as we show in this paper, 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 attribute coefficients. From Tables 7 and 8, whereas two-thirds of the interactions in the static ANA model were not significant, the changing ANA model provided significant transition probability changes. Additionally, marginal differences in coefficient estimates were observed, albeit with similar conclusions.

Managerial and Policy Implications

Results from this sample suggest that attributes with the highest impact on consumers' webshop choices were presence of trustmarks, Belgian headquarters, free return services, and shipment distance. Therefore, to attract and retain e-consumers, webshop managers and e-commerce marketeers need to 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 policymakers address concerns from pro-domestic e-consumers driven by economic 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.

Attribute attendance in this sample, like in many choice behavior 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 choice behaviors. In the current study, we find that providing information on important attributes changed e-customers' 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 prominently displaying strength characteristics on webshops.

Our findings also suggest that e-consumers' perception, attention, and reaction to information on attributes depended on their age and environmental and nationalistic attitudes. To address the trust challenges in e-commerce, policy leaders 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 were keener on domestic e-shopping. Thus, to promote cross-border e-commerce, 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 shows that more informed consumers were more receptive of e-businesses that are environmentally friendly. On a broader scale, the significance of age and attitudinal factors imply that e-commerce marketing strategies should be conscious of extant consumer heterogeneity.

Limitations and Future Research

There remain substantial gaps for future studies relating to this work. First, information was provided on three webshop attributes concerning trust, preference for local webshops, and sustainability in e-commerce. As can be expected, these are not the only attributes and thematic areas where more information to consumers may be needed. We encourage future research to explore more attributes touching on diverse themes in e-commerce and in other areas of study. Second, we provided additional information on attributes midway 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 done only in the second block of choice sets. However, changes in attribute attendance behavior can occur in each choice set throughout the experiment. Although choice-task stated ANA studies exist [4, 72], to our knowledge their inferred counterparts do not. The approach proposed in this paper can be tailored for choice-task inferred ANA by assuming that changes occur in every choice task. The choice-task inferred ANA can be a useful tool to investigate consumers' learning and fatigue effects [15], especially in lengthy experiments.

Third, although a multinomial logit kernel was used, other models that allow greater flexibility and heterogeneity (e.g., mixed multinomial models) could be used. Allowing for preference heterogeneity can provide more reliable attendance probabilities [29, 32]. These extensions, which are conceptually straightforward, are left for future research. Fourth, e-consumers are known to visit multiple sites before choosing webshops for their e-purchases [5, 41, 61]. Research on consumers' switching behavior [41] and purchase conversion dynamics [61] across webshops exists. However, to our knowledge a study that has investigated the dual switching behavior across webshops and attribute attendance behavior does not exist. We encourage future studies to allow for these model extensions.

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