Journal of Choice Modelling 45 (2022) 100375

Contents lists available at ScienceDirect

Journal of Choice Modelling

journal homepage: www.elsevier.com/locate/jocm

Seen but not considered? Awareness and consideration in choice analysis

Anna Kristina Edenbrandt [a,*], Carl-Johan Lagerkvist [a], Malte Lüken [b], Jacob L. Orquin [c]

[a] *Department of Economics, Swedish University of Agricultural Sciences, Sweden*
[b] *Netherlands eScience Center, Amsterdam, the Netherlands*
[c] *Department of Management, Aarhus University, Denmark*

ARTICLE INFO

Keywords:
Eye-tracking data
Consideration set formation
Visual consideration
Choice experiment
Decision process

ABSTRACT

Consideration set formation (CSF) is a two-stage decision process in which people first select a subset of products to consider and then evaluate and choose from the selected subset of products. CSF models typically use stated consideration or infer it from choice data probabilistically. This study explores CSF by means of eye-tracking and evaluates how measures of visual consideration compare to stated consideration. We develop a model of CSF behavior, where stated and visual consideration are embedded in the specification of the utility function. We propose three different measures of visual consideration and show that one third of respondents (~34%) use CSF behavior and that stated consideration diverges substantially from visual consideration. Surprisingly, many product types stated as not considered receive *more* visual attention, not less. Our findings suggest that stated consideration may be in part a measure of preferences rather than of consideration, implying concerns with endogeneity when including stated consideration data in choice models. Accounting for CSF in discrete choice analysis increases our understanding of the decision process, and can target concerns with biased estimates when analyzing data from two-stage decision processes.

1. Introduction

The assumption that individuals evaluate all available alternatives prior to making a decision is imperative for the validity of discrete choice analysis. If individuals instead consider only a subset of alternatives when forming their decision, the assumption of compensatory behavior is violated, and it is necessary to detect and adapt the analysis to obtain unbiased estimates. Models that accommodate for such consideration set formation (CSF) have been applied in choice analysis studies in different fields (Andrews and Srinivasan, 1995; Oscarsson and Rosema, 2019; Roberts and Lattin, 1997; Thiene et al., 2017; Van Nierop et al., 2010). Recognition of CSF postulates a two-stage decision process in which people first select a subset of products to consider and then evaluate and choose from the selected subset of products. The CSF process is interesting to explore from a behavioral insights perspective; should consideration be accommodated in discrete choice models to better understand consumer behavior? Incorporating CSF behavior in discrete choice analysis does not only target a potential bias but can also provide insights into this decision process.

* Corresponding author.
E-mail addresses: anna.edenbrandt@slu.se (A.K. Edenbrandt), carl-johan.lagerkvist@slu.se (C.-J. Lagerkvist), malte_lueken@arcor.de (M. Lüken), jalo@mgmt.au.dk (J.L. Orquin).

https://doi.org/10.1016/j.jocm.2022.100375
Received 20 April 2021; Received in revised form 9 June 2022; Accepted 29 July 2022
Available online 18 August 2022
1755-5345/

There are two main methods to account for CSF: stated CSF, where deterministic methods are typically applied in the analysis, and inferred CSF, where the probability of consideration is estimated (Aribarg et al., 2017; Carson and Louviere, 2015). We propose a third method based on eye-tracking data, which we will refer to as visual CSF. Eye-tracking data measures visual attention to alternatives and may provide insights into the CSF and choice processes. There are several eye-tracking studies on visual attribute-non-attendance, i.e. when certain aspects of products are not attended to in the decision process (Balcombe et al., 2015; Chavez et al., 2018; Dudinskaya et al., 2020; Van Loo et al., 2018; Yegoryan et al., 2019). However, there is to the best of our knowledge no research on the potential of using eye-tracking to infer CSF behavior.

We therefore aim to examine visual CSF behavior based on eye-tracking measures and to evaluate the concordance between visual and stated CSF methods. We collect data from a discrete choice experiment while measuring visual attention with eye-tracking equipment. We develop a model of CSF behavior and test it with three visual CSF measures: *dwell share*, which provides information about the distribution of attention to the products, *last exit time* (LET) which provides information about how late in the decision process a product was examined, and a *combined measure* of dwell share and LET (DwLET). The DwLET measure assumes that choice options that are attended late in the decision process and simultaneously receive relatively more attention are more likely to be considered. Finally, we test the model against stated consideration.

2. Choice process

Consideration is a stage in the choice process, and to define it we must demarcate it from other stages in the process. Among the many studies applying CSF methods in, for instance, marketing, transport economics, and environmental economics, many different definitions have been applied to consideration sets (Stocchi et al., 2016). For this reason, we first define the stages of the choice process, how these are incorporated in the CSF literature, and which definitions will be used in this study.

The global choice set refers to all the alternatives available in a choice situation. This could be all brands or services on the market within a specific category such as cars, computers, or red wines. The awareness set consists of the products that individuals are aware of, for instance, all brands within the relevant product category that a person is familiar with. The awareness set is the base from which the consideration set develops, and the consideration set is constructed purposefully to satisfy the goals of the choice occasion (Shocker et al., 1991). While Shocker and colleagues further distinguish the consideration set from the choice set (the set immediately prior to making the decision), they note that this is not commonplace in empirical studies, and here we do not distinguish between the two.

Discrete choice analysis, based on Random Utility Theory, assumes a compensatory decision process. This implies that all alternatives are attended to and considered such that the global set = awareness set = consideration set. If the assumption of compensatory behavior is violated, for instance, if individuals only consider a subset of alternatives, this should be incorporated in the econometric analysis to obtain unbiased estimates (Li et al., 2015). Different methods have been developed to distinguish between the global set, awareness set, and consideration set. This study investigates non-compensatory behavior in a discrete choice modeling framework. We recognize that consumer search models also explore behavior when certain alternatives are not evaluated. Aribarg et al. (2017) provide a review and discussion on the differences.

2.1. Awareness set formation

In complex choice tasks, or under time pressure, individuals may adopt heuristics to make the decision less costly in terms of time and effort. One heuristic could be to only attend to a subset of the available alternatives e.g., products on particular shelves in the supermarket (Chandon et al., 2009). This type of behavior violates the assumption of compensatory decision-making. A number of studies have assumed that people use simplifying heuristics, and based on researcher-defined assumptions, certain alternatives are excluded from the choice set in the discrete choice model (Hicks and Strand, 2000; Peters et al., 1995).

In this study, we define the awareness set as the set of products that are visually attended (fixated on). This is in line with the definition of alternative-non-attendance in (Grebitus and Roosen, 2018). We hypothesize that individuals adopt non-compensatory decision rules by not attending all alternatives. Based on previous studies we expect that the likelihood of a product being included in the awareness set i.e., being visually attended, is affected by the position. While the position of an alternative in stated preference studies has been found to affect choice probabilities (Scarpa et al., 2011), there are relatively few studies that have analyzed the impact of position on the choice process. There is evidence of more attention (fixation length) on alternatives to the left compared to the right (Ryan et al., 2018), and this tendency to give more attention to alternatives to the left holds in countries where reading from left to right (Orquin et al., 2018). In a best-worst study, Campbell and Erdem (2015) find a *top-bias*, where trust in different institutions was affected by the position in the choice task. Chandon et al. (2009) find that products placed in the top and middle rows are attended to visually more than products on the bottom row, but the position of the product has less impact on the likelihood of the product being chosen (for a review see Orquin et al. (2021)). Based on this, we expect that products in the center and top of the screen are more likely to be visually attended than products at the bottom.

2.2. Consideration set formation

Another way individuals can simplify choice tasks is by adopting non-compensatory decision rules in the consideration stage (Shocker et al., 1991). For example, imagine a person purchasing dinner for his/her family. In the aisle with meat products, the person is faced with a large number of products to choose from. To simplify the decision, he/she only considers familiar brands, which means that if a brand is unfamiliar, no further attention is paid to its attributes, such as its price, quality, or production method, etc. In such a situation, a traditional choice model would infer that the negative preference for unfamiliarity is not compensated by other attributes. However, the attributes of the unfamiliar brand were not even evaluated. Hence, CSF is described as a decision process of first selecting from the awareness set which alternatives to consider and then making a choice among the considered alternatives. It is often assumed that the first stage is based on some heuristic process, while the second stage is made in a fully compensatory manner (Aribarg et al., 2017; Roberts and Lattin, 1997). If the CSF is not accounted for in discrete choice models when present, it may cause biased estimates (Li et al., 2015).

Stated CSF models incorporate information about which alternatives were considered, as indicated by the individuals in surveys or experiments (Jang et al., 2012; Oskarson et al., 2016). Alternatively, consideration is based on a researcher-defined proxy for realistic consideration sets e.g., only include brands that have been purchased in the past or only include sites that are within a certain proximity. The awareness set and consideration set are typically confounded in stated CSF studies, assuming that all alternatives that the individual is aware of are also considered (Peters et al., 1995). Stated CSF data is typically analyzed with deterministic methods (Oscarsson and Rosema, 2019; Parsons et al., 2000; Rekker and Rosema, 2019). Alternatives that are indicated as non-considered, or assumed to be non-considered by the researcher, are commonly excluded in deterministic CSF models (Hicks and Strand, 2000; Honka et al., 2017; Jang et al., 2012; Peters et al., 1995), although this approach is likely associated with sample selection problems (Carson and Louviere, 2015). Stated consideration has also been included in the form of self-reported thresholds for specific attributes (Swait, 2001). Others have used additional information to deterministically form the consideration set, such as availability (Ben-Akiva and Boccara, 1995), and acceptability of alternatives (Hensher and Ho, 2015). Recently, stated consideration has been included as a dependent variable, to account for the potential endogeneity bias (Capurso et al., 2019). Bergantino et al. (2019) include stated consideration as indicators in an integrated choice and latent variable model, to overcome the potential endogeneity bias from the stated consideration measures.

Although beyond the scope of this study, which focuses on visual CSF and how it compares to stated CSF, we note that a different stream of research incorporates CSF behavior stochastically in the choice model. Building on the two-stage decision model proposed by Manski (1977), the consideration set is inferred from the choice data (Andrews and Srinivasan, 1995; Gilbride and Allenby, 2004; Martínez et al., 2009; Swait and Ben-Akiva, 1987; Swait and Erdem, 2007).

We note that non-attendance behaviors can be divided into two areas; attribute-non-attendance (ANA) and screening of alternatives (i.e., CSF). While CSF concerns non-consideration of entire alternatives (columns in a choice experiment), ANA rather concerns non-consideration of attributes (rows in choice experiments). The two fields have evolved independently, and while the CSF literature has often been applied to revealed preference data e.g., scanner data or travel data, the ANA literature has mostly been applied to stated preference data. However, as noted by Li et al. (2015), the issues of CSF also apply to stated preference data.

3. Method

3.1. Experimental design

Much of the literature on CSF is applied to observed choice data, but the collection of visual attention data requires some form of controlled environment. We collect data in a choice experiment in an eye-tracking lab. Respondents were asked to choose among nine different types of minced meat, described by the attributes price, carbon footprint, production method (organic/conventional), and level of animal welfare. Attribute levels are displayed in Table 1. Vegetarian and vegan individuals were screened out, and only individuals that indicated that they purchase the product regularly are included in the analysis. The experiment did not include the option of not purchasing any product. While the possibility to opt-out is important for welfare measures and total willingness to pay estimates, this study rather investigates decision processes, and we did not consider it necessary in this study.

Products were presented in a 3*3 matrix. Price levels were generated based on market prices in Denmark during the period of the study. Carbon footprint levels were selected based on a recent life cycle analysis review (Clune et al., 2017), and the levels varied around the means for each meat type. The organic label in Denmark is familiar to most consumers, but we decided against using this

Table 1
Minced meat types and attribute levels in the choice experiment.

Alternatives	Attributes			
	Price (DKK)[a]	Carbon Footprint[b]	Organic	Animal Welfare[c]
Beef	20, 32, 44, 56, 68	22, 31	0, 1	0, 1, 2, 3, 4
Lamb	20, 32, 44, 56, 68	22, 31	0, 1	0, 1, 2, 3, 4
Veal	20, 32, 44, 56, 68	22, 31	0, 1	0, 1, 2, 3, 4
Beef & pork 70/30	20, 32, 44, 56, 68	16, 22	0, 1	0, 1, 2, 3, 4
Beef & pork 30/70	20, 32, 44, 56, 68	10, 16	0, 1	0, 1, 2, 3, 4
Beef & Soy 50/50	20, 32, 44, 56, 68	10, 16	0, 1	0, 1, 2, 3, 4
Pork	20, 32, 44, 56, 68	5, 10	0, 1	0, 1, 2, 3, 4
Pork & Soy 50/50	20, 32, 44, 56, 68	3, 5	0, 1	0, 1, 2, 3, 4
Chicken	20, 32, 44, 56, 68	3, 5	0, 1	0, 1, 2, 3, 4

[a] 1€ ~ DKK 7.5.
[b] CO2 – equivalents.
[c] Number of 'leafs' where 4 represents the highest animal welfare standard.

label. If a product is non-organic there is no label to visually attend, and we would not able to distinguish if the respondent visually ignored the production method or if there was merely no information to attend. The production method was therefore presented with the plain letter "Ø" for organic and a "K" for conventional, and this was explained to participants prior to taking the survey. The animal welfare label ranges from 1 to 4 leaves with 4 leaves being the highest welfare level. For products that only fulfill the Danish legal requirements, no animal welfare label is presented in stores. However, we included an empty leaf symbol to represent the base level. This approach provides more reliable data since we know if participants visually ignored base levels, but this is achieved at the expense of ecological validity.

Based on input from two focus group sessions and initial tests using eye-tracking equipment, the experimental setup was formed. A pilot study was conducted and the final experimental design was generated in Ngene 1.2.0 using the d-efficiency criteria and including priors from the pilot study (ChoiceMetrics, 2012). The design consisted of 40 choice tasks, where the order of tasks was randomized. Each of the choice tasks included nine alternatives, where the position of the alternatives was randomized, as this enables us to estimate separate effects for the alternatives, as described by their attributes, and the position itself. An example choice task is presented in Fig. 1.

The data collection was conducted in two stages. The first set of data was collected in spring 2019 and subsequently analyzed. Following valuable suggestions from Editor and Reviewer, additional data were collected in October 2021–February 2022. Prior to data collection, the study was pre-registered, including specifications of the models included in the study. In total, 104 participants were recruited from the laboratory's participant panel (38 in the first data collection and 66 in the additional data collection).

The study was approved by the Human Subjects Committee at the Cognition and Behavior Lab, Aarhus University. Participants were required to have normal vision and did not wear glasses or contact lenses. Further, vegetarians and vegans were screened out, due to the focus on meat product selection. Participants gave written informed consent and were provided compensation (60DKK~8EURO) for taking part in the experiment which lasted approximately 30 min. The sample was not representative of the Danish population, but since the main interest of the study is a behavioral question and not to predict demand, this should not be a concern. Prior to the eye-tracking session, respondents answered questions concerning food-related attitudes and frequency of purchasing the different types of minced meat included in the experiment. The questionnaire was provided on a computer in the lab. A trial task was presented prior to the experiment, where participants indicated which products they found acceptable. This was to familiarize participants with the alternatives available and was not used for analysis. Following the eye-tracking session, participants completed a short follow-up survey, where they indicated their consideration of the alternatives in the choice tasks, to be used in the stated CSF analysis. Another option is to ask participants to indicate their consideration after each choice task, as done in some studies on ANA (Caputo et al., 2018; Scarpa et al., 2013). We decided against this, as it may distort respondents' visual attention behavior.

The eye-tracking part of the experiment was implemented in Python using the PsychoPy2 library (Peirce et al., 2019). For the eye-tracking data collection, we used an EyeLink 1000 (SR Research, 2009) desktop setup eye-tracker with the camera on the left and the illuminator on the right side. The EyeLink 1000 has an accuracy of 0.5° and a precision of 0.05° for an average calibration (Orquin and Holmqvist, 2018). A chin rest was used and the distance between monitor (model: Dell P2210; size: 473.76 × 296.1 mm; resolution: 1680× 1050 px; refresh rate: 60 Hz) and the participant's eyes was approximately 60 cm. The tracker was set to 500 Hz and recorded the movements of the participant's dominant eye. We used a 9-point calibration and obtained an average validation error of M = 0.27° (app 10 pixels or 2.8 mm) and SD = 0.05 for the first data collection and M = 0.37° (app 14 pixels or 3.9 mm) and SD = 0.08. The default SR algorithm which is based on velocity and acceleration was used to detect fixations. Between the choice tasks, a fixation cross was displayed on a uniformly random position on the screen for a duration of a uniformly random time interval between 0.5 and

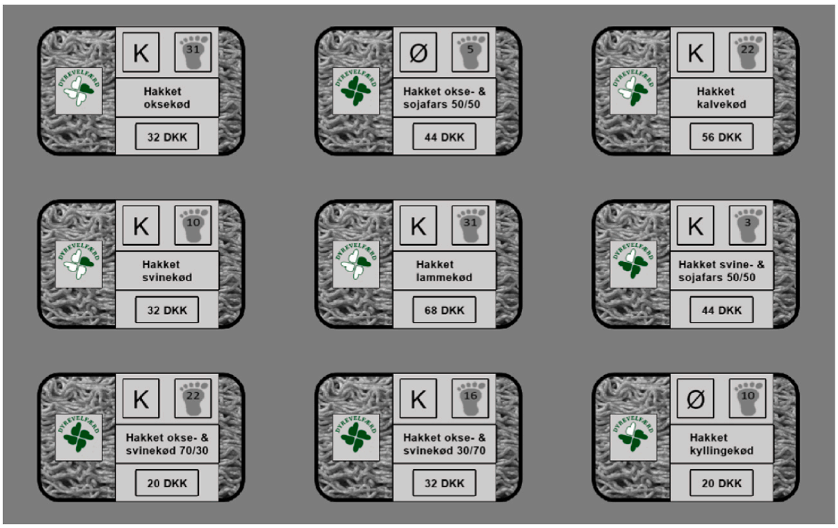

Fig. 1. Example of choice task. Note: The label indicates the type of meat, the footprint indicates carbon footprint, "K" and "Ø" indicate Conventional and Organic, and the four leaf symbol indicates the level of animal welfare.

1 s.

3.2. Defining awareness and consideration measures

Information about whether an individual visually fixated on a product is useful for defining the awareness set. However, while the eye-tracking data gives a direct measure of attention and awareness, visual consideration is not self-evident. There is no standard for this in the literature, so we propose three different measures to explore visual consideration: Dwell share and last exit time, and a combined measure.

Dwell share. We define a dwell on an area of interest (AOI) as the duration of the period from when the eyes fixate within the AOI until the eyes leave the AOI. A dwell can thus consist of several fixations and normally has a longer duration than individual fixations. We sum the durations of individual dwells to each product and normalize the dwell time to get a dwell share measure, such that it ranges from zero to one. Thus, if all products are given a similar amount of attention, the dwell shares will be evenly distributed across products. We propose that, if an individual uses CSF, this should result in some products being screened out, and hence these products should have lower dwell shares.

Last exit time. We define the last exit time (LET) for each product as the time that has elapsed from the beginning of the choice task until the end of the last fixation on that product i.e., the product that receives its last fixation shortly before the individual makes a choice will have a high LET. We compute LET from fixations that last less than 1s and dwells with at least 2 fixations. Since a key feature of CSF is systematically screening out specific products, we expect this to result in an observable attention pattern. Specifically, if a product is actively considered, the individual is likely to continuously fixate the product since fixations are tightly connected to the decision process. The consequence of this narrowing down of attention is that considered products are likely to draw attention until the end of the choice task. Oppositely, screened-out products become less likely to draw attention, as the choice task progresses. This process should result in an eye movement signature, where screened-out products have a low LET and considered products a high LET. We normalize LET (ranging between 0 and 1) to account for individuals spending varying total time on the choice tasks. A possible shortcoming of the LET measure is that, if all alternatives are considered, the individual must stop looking at some alternative first. In this situation, we would expect LETs to be overall high relative to the duration of the choice task as well as being unsystematic across product alternatives.

Combined measure. Finally, we generate a measure that combines the above measures by multiplying the scores from dwell share and LET (DwLET). This combined measure targets a potential concern with the dwell share measure since an unfamiliar product type might receive more fixations even if they are not considered. Moreover, the combined measure also targets a potential shortcoming of the LET measure: a high LET score could happen by chance if a participant forgets that a product has been screened out and therefore attends it again later in the process. This would not necessarily mean that it is considered. The combined measure implies that a product that was both fixated on relatively much *and* fixated on late in the process has a high score, while a product that was fixated on late in the process, but only very briefly, will get a lower score.

Stated measure. Individuals responded ex-post, if they had considered the different meat products, on a 5-point scale from “never” to “always” for each alternative to the question “How often did you seriously consider the following meat types?”. Following conventions in the ANA literature, we constructed a dummy variable taking the value 0, if they indicated to never consider a product, and 1 otherwise.

4. Modeling approach

In the first stage of the analysis, we investigate awareness set formation, and if this is explained by the position of the alternatives. Alternatives that are visually ignored are assumed to be excluded from the awareness set, and the CSF is therefore formed based on the awareness set only. We investigate CSF using a conjunctive rule, where alternatives may be screened out based on the meat type. An example of this is if individuals screen out products including red meat, vegetables, or pork. We construct the consideration measures and the model specifications accordingly. We note that other forms of screening rules could be used to form consideration sets, such as budget constraints or only considering organic products. However, to enable comparisons across visual and stated CSF, we decided to test for screening based on the meat types.

4.1. Random utility model (RUM)

We take departure in random utility theory (McFadden, 1974), where individuals are assumed to choose the product that maximizes utility among all available products. We assume that the utility that individual n derives from product i in choice task t is $U_{nit} = \beta_n' x_{nit} + \varepsilon_{nit}$, where $n = 1, 2, \ldots, N$; $i = 1, 2, \ldots, J$; $t = 1, 2, \ldots, T$. x_{nit} represents the attributes associated with the product and β is a vector of parameters to be estimated. There are $N = 104$ respondents, $T = 40$ choice tasks per respondent, and $J = 9$ alternatives to choose from in each task. The random error terms ε_{nit} are assumed to be iid and type I extreme value distributed with $\sigma^2 = \pi^2/6\lambda^2$, where λ is a scale parameter that is normalized to unity. To allow for unobserved preference heterogeneity, while relaxing the IIA assumption in the MNL model, and accounting for the panel format of the data in this study, we estimate mixed logit (ML) models (Hensher et al., 2015; Train, 2009). The parameter β_n varies across individuals and can be described by a density function $f(\beta)$, which takes the form $\beta_n = b + \sigma\nu_n$, with the population mean b, parameter standard deviation σ, and standard normal error term ν_n. (Train, 2009). Because β_n is unknown, we derive the unconditional distribution of $P(y_n | x_n, \beta)$ by integrating over β, such that the probability of individual n's sequence of choices $y_n = \{i_{n1}, i_{n2}, \ldots, i_{nT}\}$ is:

$$P_{ni} = \int \left(\prod_{t=1}^{T} \left[\frac{\exp\left(\lambda\left(\beta_n^{'} x_{nit)}\right)\right.}{\sum_{j=1}^{J} \exp\left(\lambda\left(\beta_n^{'} x_{njt}\right)\right)} \right] \right) f(\beta|\mathrm{b}, \sigma) d\beta \tag{1}$$

With the ML model, it is possible to obtain posterior parameters for the subpopulation that made a certain sequence of choices, by deriving the conditional distribution of preference parameters based on the individual observed sequences of choices. Let $h(\beta|\boldsymbol{y}, \boldsymbol{x}; \boldsymbol{b}, \sigma)$ be the conditional distribution of β among the individuals that make this particular sequence of choices given some observable characteristics x. Train (2009) shows that, by Bayes' theorem, the posterior distribution of the subpopulations preference parameters can be expressed as:

$$h(\beta|y, x; b, \sigma) = \frac{P\left(y_n | x_{n,} \beta\right) f(\beta|\mathrm{b}, \sigma)}{P(y_n|x_n; \mathrm{b}, \sigma)} = \frac{P\left(y_n | x_{n,} \beta\right) f(\beta|\mathrm{b}, \sigma)}{\int P(y_n|x_n, \beta) f(\beta|\mathrm{b}, \sigma) d\beta} \tag{2}$$

and the mean of the posterior distribution of β can now be estimated as

$$\overline{\beta}_n = \int \beta\, h(\beta|y, x; b, \sigma) d\beta. \tag{3}$$

This expression does not have a closed-form solution, and simulation methods are therefore used to obtain maximum likelihood estimates.

4.2. Visual CSF measures

We explore the relevance of our proposed visual CSF measures. To examine if there are systematic patterns in the visual measure depending on the meat type, we regress the visual measure (Dwell share, LET, DwLET) on the meat type for each individual. We generate a variable for each individual (Fstat) which takes the value of the F-statistic for the joint significance of the meat-type parameters.

We further examine how individuals' visual consideration measures relate to their preferences. We estimate ML models on the full dataset to obtain individual-level parameters (eq. (3)). To explore how the visual consideration measures relate to the individual-level preference parameters, we generate an adjusted dwell share measure. The alternative with the highest dwell share in a choice task takes the value one and the other alternatives' dwell shares are a proportion of that. The measure is then adapted to the choice model structure, by expressing the adjusted dwell share relative to the base level meat type in the ML model (chicken). This yields the variable *Reference-adjusted dwell share*. Similar variable constructions are done for the LET and DwLET measures. Illustrations of the constructed variables are given in Web Appendix A.

We regress individual-level estimates for the meat types (eq. (3)) on the visual consideration measures for each product in each choice task. We further test if the relation is different among individuals that display systematic behavior (high Fstat-value):

$$\widehat{\alpha}_{sn} = \sum_{s=0}^{S-1} \alpha_{snt} + \delta_a \gamma_{snt} + \delta_b \gamma_{snt} {}^{*} Fstat_n + \rho_n + e \tag{4}$$

where s indicates the meat type (total number of meat types $S = 9$), and γ are the *Reference-adjusted visual measures*. ρ_n are individual fixed effects, and e is an error term with mean zero.

4.3. Accounting for decision processes in discrete choice models

In the standard RUM model, it is assumed that all alternatives in the global set are in the awareness set, and that all alternatives are considered and compared when making the decision. We develop a model to incorporate visual measures (dwell share, LET and DwLET) for CSF. The base model takes the form (individual and time subscripts omitted):

$$V = \alpha_0 beef + \alpha_1 veal + \alpha_2 lamb + \alpha_3 bp73 + \alpha_4 bp37 + \alpha_5 bsoy + \tag{5}$$

$$+\alpha_6 pork + \alpha_7 psoy + \beta_p price + \beta_{cf} carbon + \beta_o organic + \beta_{aw} animal\ welfare = \alpha^{'} + \beta^{'} x$$

We enhance the base model by two parameters to test if the visual measures are associated with different choice probabilities:

$$V = \theta\gamma + \alpha^{'} + \beta^{'} x \tag{6}$$

here, γ is the visual measure that we test in separate models for dwell share, LET, and DwLET, and θ is a free parameter describing how much the visual measures affect choice probabilities. Next, we specify a model that describes the CSF behavior that we investigate. An individual with CSF behavior screens out (does not consider) certain meat types. We therefore expect that the individual will place less or even no importance on the attributes of the screened-out products. This is described in the following model:

$$V = \theta\gamma + \alpha^{'} + (1 - (1 - \gamma)\tau)\beta^{'} x \tag{7}$$

This specification implies that, if $\tau = 0$, the model collapses to eq. (6). On the contrary, if $\tau > 0$, then the attributes for that product will weigh less in the utility function. An individual that has a very low value on the visual measure (γ) for a product will put very little weight on the attributes of that product. Our goal is to test if there are individuals that employ CSF behavior, as identified by visual measures. We propose that an individual can either undertake CSF-behavior or non–CSF–behavior. To stochastically identify if an individual undertakes such CSF behavior or not, we estimate equality constrained latent class (ECLC) models (Scarpa et al., 2009). Previous studies in the inferred CSF literature used a similar approach (Calastri et al., 2019; Campbell et al., 2018). The Independent Availability Logit model includes consideration sets for all possible combinations of alternatives in estimation. To reduce the computational burden from this model, a number of studies have proposed the latent class (LC) logit model, where the possible compositions of alternatives that are considered by an individual are specified prior to estimation. This is similar in this study, where we limit the CSF rule to depend on the meat type. The model includes two classes, where the first class describes non-CSF behavior and τ is constrained to zero, and the second class describes CSF-behavior, and τ has no constraints. The α and β parameters are constrained to be equal for CSF-individuals and non–CSF–individuals. The share of individuals in the second class provides information about the share of individuals that have CSF behavior.

5. Results

5.1. Visual attention data and awareness sets

Inspection of the visual attention data reveals that the number of fixations is highest on the alternative label (meat type) and lower for the attributes (price, organic, carbon footprint): 73% of the meat type labels are visually attended (receive at least one fixation), while it is lowest for animal welfare (32%) and price (32%; see Web Appendix B). The number of fixations decreases rapidly after the first two choice tasks and then becomes more stable (Web Appendix C). We attribute this pattern to subjects familiarizing themselves with the choice task. Similar learning effects in the first choice task are found in other studies (Carlsson et al., 2012).

Only 1209 out of the 33,642 products displayed (3.6%) are non-attended. The rate of products visually ignored is low compared to previous studies using eye-tracking (Chandon et al., 2009; Grebitus and Roosen, 2018). To explore if individuals make the decision easier by ignoring entire alternatives, we investigate if there are systematic patterns in attendance of alternatives depending on the position. The number of non-attended products, displayed in Figure D1 in Web Appendix D, is statistically significantly different depending on the position, with most ignored products in the upper right corner, and least in the lower left corner (Pearson's χ^2 statistic = 89.2, p-value < 0.001). Additional tests for position effects are presented in Web Appendix D.

5.2. Visual CSF measures

In the following section, we explore how well the three different visual measures (Dwell share, LET, DwLET) detect CSF behavior. Given that some of the product types were likely unfamiliar to the participants and the rapid decrease in fixations following the first two choice tasks (as displayed in Figure D1), we exclude the first two choice tasks in further analyses. This implies that there are 38 choice tasks for each individual in the analysis. We also exclude choice sets that have zero dwells on the chosen alternative. These choice tasks have very few recorded fixations most likely to eye-tracking recording errors. In total, 219 choice tasks were excluded for this reason. A graphic presentation of the dwell share and LET for the different meat types, presented for each individual, is provided in Web Appendix E. Inspection of the figures suggests that some individuals vary in their dwell share/LET between meat types, but only to a small extent.

We explore more systematically if the visual measures indicate CSF patterns among individuals in Table 2. As specified in eq. (3), the individual-specific preference parameters are regressed on the visual measure, and this effect interacts with the degree that each individual displayed variation in their visual pattern for the different meat types (*F-stat*). Out of the 104 individuals, there were 30 with systematic differences (F-statistic suggest joint significance at 5% level) in the dwell share, 13 individuals with systematic differences

Table 2
Individual-level preference estimates and visual consideration measures.

	Model 1	Model 2	Model 3			
	Coef.	$\lvert t\text{-}val \rvert$	Coef.	$\lvert t\text{-}val \rvert$	Coef.	$\lvert t\text{-}val \rvert$
δ_a (eq. (4))						
Ref-adjusted dwell share	−0.03	1.13				
Ref-adjusted LET			−0.03	1.29		
Ref-adjusted DwLET					−0.02	0.55
δ_b (eq. (4))						
F-stat* Ref-adjusted Dwell share	0.13***	8.12				
F-stat* Ref-adjusted LET			0.12***	5.98		
F-stat* Ref-adjusted DwLET					0.14***	7.64
P-all zero[a]	<0.001		<0.001		<0.001	

Note: Observations = 33,642. Individuals = 104. Meat type variables are included in all models. *** indicates p-values<0.001, * if p < 0.05, ** if p < 0.01, and *** if p < 0.001.
[a]P-all zero refers to F-test of the null hypothesis that all coefficients are equal to zero.

in the LET and 22 individuals with systematic differences in the DwLET behavior. The correlation between dwell share and LET are presented in Web Appendix F.

While the relation between the individual-level preference parameter for meat-type and dwell share (δ_a) is not different from zero, it is positive and statistically significant for individuals that display a more systematic dwell behavior ($\delta_b > 0$). This holds for all three measures (Dwell, LET and DwLET). This indicates the appropriateness of all three measures for visually measured CSF.

5.3. CSF models

To evaluate the CSF models, we test how the models perform out-of-sample. For this purpose, we divide the sample into an estimation sample and a holdout sample, where the holdout sample consists of 10 randomly chosen choice tasks from each respondent. Hence, out of the 40 choice tasks that each individual did, the first two were excluded from analysis, and 28 remained for the estimation sample.

Results from the in-sample estimations are summarized in Table 3. Models are estimated in R (R Core Team, 2018) using the package Apollo (Hess and Palma, 2019). The model 'Global' is an MNL model, including all products, and assuming fully compensatory choice behavior. The consideration set is formed as a subset of the awareness set. Therefore, in the following analysis using visual measures, we exclude the alternatives that were not in the awareness set (model 2) as the base model. Models 3-6 are specified in eq. (6), allowing the visual and stated measures to affect the choice probabilities. Including dwell share (model 3) improves model fit significantly (LR-test: $p < 0.001$). We note that θ is statistically significant and positive, implying that a higher dwell share is associated with a higher probability of choosing a product. Model 4 reveals that including LET improves model fit (LR-test: $p < 0.001$), and the combined measure DwLET (model 5) also improves the model fit significantly (LR-test: $p < 0.001$) compared to the awareness set model. The BIC also supports the suitability of the combined measure. Models 6 includes stated consideration. This model provides an inferior model fit in the BIC value compared to the dwell share and DwLET models, but it does improve model fit compared to the global model (LR-test: $p < 0.001$).

Results for the behavioral CSF-models (eq. (7)) are presented in models 7-10. We see that 34% of the individuals are in the CSF-class (model 7) and the positive τ-parameter suggests that the dwell share affects the weight on the attributes for these individuals. The results for the corresponding model with LET measure (model 8) gives a higher CSF-share (40%) and the τ-parameter is positive. The combined measure (model 9) gives results similar to model 7, although the BIC is lower. Based on analysis of the first data set, in the pre-registered model specifications, the price parameter is not multiplied by the τ-expression in eq. (7). since this provided unstable results. This could be due to that price is always considered. The stated model (model 10) gives a share of 47% that display CSF behavior.

For robustness, we also estimated all models separately for the first and the second points of data collection. Results are presented in Appendix G (Tables G1 and G2). The θ parameters are similar across data sets, while the share of individuals that apply CSF behavior in the visual CSF models (models 7-9) is slightly higher in the second data collection. In addition, to account for preference heterogeneity across individuals, we estimate all models where we specify the alternative specific (meat type) parameters (α) and the attribute parameters (β) to take normal distributions, except price which takes a negative lognormal distribution. Results from these models are presented in Table G3. We note that the model fit improves significantly with the random parameter specifications. Overall, the conclusions for the MNL models in Table 3 hold for the RPL-specifications in Table G3, although the share of individuals that apply CSF behavior is higher in the non-random parameter specifications. We expect that this can be attributed to preference heterogeneity. Yet, random parameter specifications typically require large data sets, and the relatively small data set in this study suggests that we rely on non-random parameter specifications.

Motivated by the sharp decrease in fixations following the first two choice tasks, and in line with the recommendations in (Carlsson et al., 2012), the first two choice tasks were excluded from analysis. For robustness, we estimate all models reported in Table 3, while including these first two choice tasks (reported in Table G4). Results are robust to this specification.

We explore the model performance in the estimation sample and hold-out samples, respectively (Table 4) (Table G5 for model performance for RPL specifications). Overall, models 3, 7 and 9 provided the overall best predictions for both the estimation sample

Table 3
Discrete choice model overview (holdout sample excluded).

	# parameters	LL	θ (t)	% CSF[a]	τ (t)	BIC
1. Global model	12	−4096				8287
2. Awareness set model	12	−3999				8093
Eq. (6):						
3. γ = Dwell share	13	−3826	1.19 (16.5)			7755
4. γ = LET	13	−3924	0.82 (10.4)			7952
5. γ = DwLET	13	−3802	1.22 (18.2)			7706
6. γ = Stated	13	−3976	0.50 (3.2)			8855
Eq. (7):						
7. γ = Dwell share	15	−3742	1.10 (10.0)	34	1.20 (5.5)	7618
8. γ = LET	15	−3800	0.54 (5.6)	40	1.23 (8.2)	7735
9. γ = DwLET	15	−3717	1.16 (12.0)	34	1.19 (5.1)	7570
10. γ = Stated (1/0)	15	−3805	0.47 (2.9)	47	1.17 (8.7)	7745

Note: N = 2698 for all models (104 individuals). [a] Share of individuals that display CSF behavior.

and the hold-out sample.

5.4. Stated consideration set formation

In the previous section, we found that the visual CSF models outperformed the global base model and the awareness set model. They also outperformed the stated CSF model. In the following, we explore stated consideration, visual consideration, and the relationship between these measures. The stated consideration, as indicated by participants in the follow-up questions, displays large variation between the meat types. Beef was considered by all except one respondent, and the share of stated non-consideration is likewise low for the other meat types that are sold the most in supermarkets in Denmark (beef + pork, pork, and chicken). Meanwhile, only 72% of the respondents indicated to consider pork + soy, 53% for beef + soy, and 69% for lamb. The overall pattern follows closely the familiarity with the products; the products containing soy were not available on the market at the time of the study and lamb constitutes a very small market share.

We compare the consideration sets, as measured by stated and visual measures (Table 5). The first columns (# of fixations) show that individuals that reported that they did not consider certain meat types fixated more on those (veal, beef + soy, pork), while the opposite pattern holds for chicken. For the dwell and LET measures, there are few statistically significant differences between meat types that are reported considered and non-considered. Hence, there is low concordance between the stated and visual CSF measures.

6. Discussion

In the presence of many choice options, unfamiliar options, or time pressure, individuals may simplify the decision process by screening out alternatives and only carefully evaluating a reduced set of alternatives. This decision process, where the CSF involves non-compensatory decision rules, violates assumptions in discrete choice models. CSF has been investigated in different research fields that apply discrete choice analysis, typically using observational data and survey data. However, there are to the best of our knowledge no studies on visual CSF using implicit measures obtained by eye-tracking. The process of CSF is interesting to investigate from a behavioral insights perspective; should consideration be accounted for in discrete choice models for increased understanding of consumer behavior? We contribute to the literature by exploring visual awareness and consideration stages of the decision process and evaluate how they compare to stated CSF methods.

Consumers may use heuristics, due to an overwhelming number of products to choose from in the purchase situation. Perhaps a consumer with strong preferences for convenience only considers familiar brands. However, it might be that some of the less known brands have much higher levels of convenience. In this case, the consumer may be worse off, since he/she did not even consider the alternative that he/she preferred the most. A standard RUM will in such a case give relatively low preferences for convenience, implying that ignorance of CSF in the model may bias estimates. Still, accounting for consideration sets in discrete choice models is not without concern. Non-considered products are commonly excluded from the data, and this may in itself cause biased estimates from sample selection bias. For example, a consumer may only consider products below a certain price constraint. Estimating models on "cleaned" data, without products above the price constraint, will result in less significant price parameters since there will be little variation in the price among the remaining products.

CSF can be incorporated in discrete choice models using different data sources and model specifications. We explore visual awareness sets and consideration sets and evaluate how they compare to the commonly used deterministic methods, which rely on the individual's self-reported (stated) consideration. We do this in an experimental set-up, allowing us to collect visual attention data and in addition, we collect stated consideration data. Each of the methods (stated and visual CSF) have their advantages and limitations. An important advantage of the stated method is the simplicity of collecting self-reported consideration data. It is, however, associated with limitations, as respondents may not recall correctly which alternatives they considered, or may not be aware of their true consideration set. The combination of visual and stated data sources in this study enables us insights regarding stated consideration data.

Table 4
Performance statistics for discrete choice models.

	Estimation sample		Holdout sample	
	$P(i)_{median}$	$P(i)_{mean}$	$P(i)_{median}$	$P(i)_{mean}$
1. Global model	0.28	0.27	0.27	0.27
2. Awareness set model	0.29	0.29	0.28	0.28
Eq. (6):				
3. γ = Dwell share	**0.30**	**0.32**	**0.28**	**0.31**
4. γ = LET	0.29	0.30	0.27	0.29
5. γ = DwLET	0.29	0.32	0.28	0.31
6. γ = Stated (1/0)	0.29	0.29	0.28	0.28
Eq. (7):				
7. γ = Dwell share	**0.30**	**0.32**	**0.28**	**0.31**
8. γ = LET	0.29	0.30	0.27	0.29
9. γ = DwLET	**0.30**	**0.32**	**0.28**	**0.31**
10. γ = Stated (1/0)	0.28	0.29	0.27	0.29

Note: Bold indicates bets model fit. P(i) = choice probability of chosen alternative. N = 2698 for estimation sample, N = 1004 for holdout sample.

Table 5
Visual measures by stated consideration (SC) and stated non-consideration (S-nC).

	# fixations			Dwell share			**LET**			**DwLET**		
	SC	S-nC	|*t-value*|	SC	S-nC	|*t-value*|	SC	S-nC	|*t-value*|	SC	S-nC	|*t-value*|
Beef	7.03	7.53	0.40	0.113	0.121	0.50	0.537	0.442	1.60	0.081	0.086	0.25
Lamb	6.70	7.00	1.17	0.111	0.103	2.03	0.520	0.508	1.02	0.080	0.073	1.95
Veal	6.67	7.76	3.07	0.109	0.106	0.73	0.527	0.547	1.17	0.079	0.079	0.12
Beef + pork 70/30	7.43	7.10	0.62	0.118	0.097	2.84	0.539	0.510	1.21	0.087	0.066	2.96
Beef + pork 30/70	7.25	7.34	0.27	0.113	0.115	0.23	0.534	0.537	0.21	0.083	0.083	0.04
Beef + soy	6.32	6.85	2.27	0.104	0.105	0.32	0.508	0.520	0.97	0.072	0.074	0.65
Pork	7.11	8.01	2.65	0.115	0.125	2.12	0.536	0.577	2.59	0.083	0.094	2.20
Pork + soy	7.27	7.28	0.06	0.115	0.110	1.56	0.540	0.540	0.04	0.086	0.079	1.89
Chicken	6.88	5.87	2.79	0.107	0.099	1.60	0.517	0.533	0.91	0.076	0.072	0.86

Note: H0: mean(SC) - mean(S-nC) = 0.

We find that the visual CSF models including the visual measures dwell share and DwLET respectively provide the best model fit. The results suggest that a share of individuals (~34% in a sample of 104 individuals) use CSF behavior, while the remaining individuals do not. The CSF behavior described in the model implies that the product characteristics of an alternative that is screened out are given less importance in the decision process. Our finding that a subset of individuals apply a simplifying decision rule is in line with results from the ANA literature (Caputo et al., 2018; Dudinskaya et al., 2020; Scarpa et al., 2009), and it is also consistent with (Campbell et al., 2014, 2018), which infers CSF probabilistically and show that a subset of individuals screen out alternatives. The stated consideration measure reveals that products that are reported to be considered are more likely to be chosen and that a large share of individuals applies CSF behavior (47%).

We further explore the concordance between stated and visual consideration. There are studies in the ANA literature that use eye-tracking data in choice experiments to compare stated and visual (Balcombe et al., 2017) or inferred and visual (Chavez et al., 2018; Van Loo et al., 2018) attribute non-attendance. Yet, this remains to be examined in the CSF context. We find that for some product types, there is no systematic relation between the stated consideration and visual attention (fixations), while for other product types the stated non-considered product types receive more visual attention than those that are stated to be considered. If a product is reported as non-considered but is examined carefully, this suggests that the individual might be willing to choose that product should the utility from the attributes be sufficiently high. Our findings suggest that the stated consideration is at least to some extent a measure of low preferences rather than non-consideration, where some individuals have very low levels of utility from certain products, but they do not per se violate compensatory behavior by screening out products. We suggest that the interpretation of stated CSF models should be done with care; if stated CSF rather measures preferences, the inclusion of such data directly in the utility function will be a source of endogeneity. Similar concerns can arise when including stated attitude measures in the utility functions (Johnston et al., 2017). Possibly, stated consideration data could become a more valued measure of consideration, rather than preferences if complemented with additional questions that more precisely distinguish consideration from low utility.

One of the limitations of this study is that while eye-tracking data provides rich information about visual attention, visual consideration requires that we make certain assumptions. We have tested different measures, but these are based on individuals' eye movements, not their underlying thought processes. We emphasize that eye-tracking data does not yield a clear-cut measure of CSF, since eye movements are not necessarily a perfect index of the underlying decision process. Other processes influence eye movements simultaneously with the decision process such as stimulus characteristics or aspects of the motor control system itself (Orquin and Wedel, 2020).

Another limitation of the study is related to the sample size. While this is common in eye-tracking studies, larger samples would be beneficial to enable estimation of more complex choice models, which can provide additional insights regarding the heterogeneity between individuals in the decision process.

We find little support for the awareness set stage in the context of this study. The rate of visually ignored products is very low. In choice experiments, which are commonly conducted online, the number of alternatives presented in each choice task is typically relatively low, often in the range of two to four alternatives. Moreover, the number of choice tasks is commonly in the range of 4–12, although more than twelve is not unusual. The limited number of alternatives and choice tasks is motivated by a concern that respondents are unable or unwilling to process more information. In this experiment, the laboratory setting is different from typical choice experiments, which likely affects respondents' attention and behavior. Participants are recruited from a panel that is frequently invited to participate in eye-tracking experiments, and they are likely familiar with the experimental setting, which might affect their behavior. The conclusions should therefore not be transferred directly to online panel data collections. Still, this study finds that visual attention is very high despite a high number of alternatives (nine) and choice tasks (40), suggesting that respondents are capable of attending more alternatives and tasks than is usually used. These findings corroborate previous conclusions (Carlsson and Martinsson, 2008; Hess et al., 2012; Louviere, 2003).

In conclusion, we find heterogeneity among individuals in the CSF behavior in the models based on visual measures. While the majority of the participants did not use CSF as defined in this setting, 34% out of 104 participants did screen out certain alternatives and thus put less importance on the aspects of these alternatives when making the final decision. This implies that accounting for CSF has the potential to increase our understanding of the decision process, and it can target concerns with biases in estimates when decision-makers are applying two-stage decision processes.

An important advantage of the stated CSF method is the simplicity of collecting self-reported consideration data. However, there is low concordance between visual and stated measures, and our findings suggest that a stated measure is associated with endogeneity concerns, as our results indicate that such data to some degree measures preference strength rather than consideration. This may be due to respondents not recalling correctly which alternatives they considered, or that they are not aware of their true consideration set. We emphasize the need for further analysis of the stages of the decision process, using eye-tracking data, as this is of importance for applied CSF analysis. Moreover, this study is limited to visual and stated CSF. A broad field of research applies stochastic methods (inferred CSF) to accommodate CSF behavior (Habib et al., 2013; Thiene et al., 2017; Truong et al., 2018). We suggest that more work on the concordance between CSF methods, including inferred methods, is important.

Funding

The first author acknowledges support from the Swedish Retail and Wholesale Council (Post doc scholarship 2018).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jocm.2022.100375.

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