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An integrated modelling approach examining the influence of goals, habit and learning on choice using visual attention data

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ABSTRACT

Previous economics literature has explored the role of visual attention on choice in isolation without accounting for other influences such as habits and goals or learning effects, nor their interrelationship. In this paper, we: (i) develop a novel joint framework to explore the relationship between visual attention, observed heterogeneity from stated habits and goals, and choice outcomes while accounting for shorter- and longer-term learning effects; and (ii) investigate whether accounting for these relationships improves model predictive power and behavioral insights. The empirical analysis used an eye-tracked discrete choice experiment on sugar-sweetened beverage purchasing (n = 152 adults with 20 choice tasks). Results suggest that habits, goals, and shorter-term learning are key drivers of information acquisition whereas cumulative choices (longer-term learning) affect subsequent choice outcome. Importantly, ignoring the joint relationship between habits, visual attention and choice may exaggerate the role of visual attention, leading to incorrect behavioral insights and reduced prediction accuracy.

1. Introduction

A better understanding of human decision-making behavior is fundamental to successful prediction and understanding the drivers of economic choices. Cognitive process tracing methods, such as eye-tracking, are well-established methods of seeking insight into the complex processes occurring within the 'black box' of consumer decision-making (Schulte-Mecklenbeck, Kuehberger, & Johnson, 2019). In the last decade, eye-tracking data have been used increasingly in the fields of psychology, neuroscience, marketing, health economics and food and agricultural economics to penetrate this 'black box' to explore (i) how 'bottom-up' influences in the visual environment (e.g., Orquin,

Abbreviations: AOI, area of interest; AR, auto-regressive; DCE, discrete choice experiment; MNP, multinomial probit; SSB, sugar-sweetened beverages

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Bagger, Lahm, Grunert, & Scholderer, 2019) and experimental constraints (e.g., Fenko, Nicolaas, & Galetzka, 2018; Ryan, Krucien, & Hermens, 2018) affect visual attention and thereby affect choices; (ii) how 'top-down' habits and goals guide visual attention and thereby affect choices (e.g., Reutskaja, Nagel, Camerer, & Rangel, 2011; Büttner et al., 2014; Balcombe, Fraser, & McSorley, 2015; Meißner, Musalem, & Huber, 2016; van der Laan, Papies, Hooge, & Smeets, 2016); and (iii) the potential improvement in the predictive power of choice models using visual attention data (Balcombe et al., 2015; Krucien, Ryan, & Hermens, 2017; Meyerding, 2018; Mullett & Stewart, 2016; Orquin & Loose, 2013; Spinks & Mortimer, 2015; Towal, Mormann, & Koch, 2013; van der Laan, Hooge, De Ridder, Viergever, & Smeets, 2015; Van Loo, Nayga, Campbell, Seo, & Verbeke, 2018; Vass, Rigby, Tate, Stewart, & Payne, 2018; Yegoryan, Guhl, & Klapper, 2019).

The first of the three sets of above studies focus on how choice experiments should be designed to minimize the influence of lexicographical biases. The second set of studies focus on explaining the underlying decision-making process through the use of visual attention data. The third set of studies focus on improving predictions by utilizing information about attribute attendance through eye-tracking data. In the latter studies, few explicit assumptions are made about the relationships between visual attention, information acquisition and decision processes. However, the implicit assumption is that visual attention has a down-stream effect on choice. For a detailed review of eye-tracking measurement and factors affecting visual attention in choice experiments see Orquin and Loose (2013) and Yegoryan et al. (2019), and in the food preferences literature, see Van Loo, Grebitus, Nayga, Verbeke, and Roosen (2018).

The literature to date has therefore mainly explored the role of eye-tracking data for different decision-making strategies in isolation without accounting for top-down influences such as habit. Failure to control for unobserved heterogeneity across different model components (e.g., habit and goals, visual attention and choice), and the feedback effect due to learning in repeated choices over time, may lead to a spurious effect of visual attention on choice; it may also worsen model predictive power. For example, Camerer, Ho, and Chong (2004) and Gabaix, Laibson, Moloche, and Weinberg (2006) have reported that accounting for the effect of previous choices on subsequent choices improves model prediction. Our proposed model extends the previous literature which has mainly considered the influences of 'top-down' and 'bottom-up' process pathways, heuristic processing, and the influence of previous choice on subsequent choice in isolation, and allows us to account for the interactions between these processes.

The potential interaction of 'top-down' and 'bottom-up' processing pathways in consumer decision-making has significant implications for business, including in the design of product packaging (Orquin et al., 2019) and store layout and product positioning (Valenzuela, Raghubir, & Mitakakis, 2013; Orquin et al., 2019). For example, there is emerging literature to suggest that weight-consciousness is associated with both increased visual attention to nutritional information on food products and increased willingness to pay for nutritional information (Ran, Yue, & Rihn, 2015). Further understanding of these interactions may help guide retail practices. For example, in order to promote sales for products that promote healthy weight, but are often not perceived as such by consumers, like nuts, manufacturers could consider displaying nutrition information more prominently to engage weight-conscious customers while keeping prices the same so as not to discourage purchases by customers who are not weight conscious.

In the current study, we address this gap and add to the health economics and business literature by developing a joint model to account for the influence of top-down factors on visual attention pathways. This paper advances the previous literature by accounting for the effects of 'top-down' influences on choice, as well as the interrelationships and feedback loops between these 'top-down' influences, visual attention and choice. We focus on improving predictions and quantifying the effect of visual attention on choices, after controlling for potential confounds. We assume top-down goal-driven control of visual attention (also referred to as the "endogenous effect") (Corbetta & Shulman, 2002; Theeuwes, 2010). The current study is motivated by the apparent paucity of consideration of the endogenous effect in previous prediction studies on the effects of goal, habits, visual attention and choice (i.e., goals and habits may direct visual attention, which subsequently has a down-stream effect on choice) (Van Loo, Grebitus et al., 2018). This endogenous effect is our principal focus. We formulate a comprehensive econometric framework and provide a computationally feasible estimation process. Although controlling for unobserved factors in a multilevel model is not difficult, the estimation of such models becomes near impossible using the usual full information likelihood or Bayesian approaches (see Bhat & Dubey, 2014 for a detailed discussion on issues related to estimation of multilevel models). Our proposed estimation method circumvents these difficulties.

In this study, we use eye-tracking data from a discrete choice experiment (DCE) on the effect of changing volume and price on non-alcoholic beverage purchases (n = 152) to investigate the effect of factors influencing inherent preferences (including habits and health goals) on choice and examine the mediating effect of visual attention using an integrated modelling approach. This is the largest eye-tracking sample size we are aware of to date in the health economics and food marketing literature. We address the above-highlighted research gaps and develop a comprehensive framework for analysing multilevel choice data with supplementary eye-tracking information to answer the following questions: Does accounting for the endogenous relationship between goals and habits, visual attention, and choice improve the predictive power of and insights drawn from choice models? To what extent is modifying visual stimuli of beverage alternatives predicted to change preferences and behaviour?

More generally, we add to the advancement of multilevel choice data analysis by developing a comprehensive framework that connects various components (visual attention, habits and goals, and choice) of models using a fully-specified covariance structure. We incorporate feedback loops in both visual attention and choice components in a parsimonious fashion through the use of a first-order lag structure.

The rest of the paper is organized as follows: in the next section we summarise the existing literature on visual attention, and existing models of the effects of habit and learning on choice, as well as highlight relevant literature gaps; we then outline our empirical example, followed by a detailed description of the methodology. We report and compare the model results and out-of-sample prediction statistics followed by discussion and concluding remarks.

2. Literature review

2.1. The relationship between visual attention and choice

There are two main ways in which visual attention is posited to affect choice: the 'top-down' goal-driven pathway, and the 'bottom-up' stimulus-driven pathway. In the former cognitive process, individuals focus their attention on relevant cues based on goals and pre-defined preferences (Land, Mennie, & Rusted, 1999; Hayhoe, 2000; Hayhoe, Shrivastava, Mruczek, & Pelz, 2003). Previous research by van der Laan et al. (2016) and Orquin and Scholderer (2011) found increased attention on food options that correspond to respondents' intended health goals. It is plausible that pre-defined goals and habits direct visual attention towards relevant products, for inclusion or exclusion from the choice consideration set (Souza, 2015), according to 'Choice Set Formation' theory (Swait, 1984; Ben-Akiva & Boccara, 1995).

The second, or 'bottom-up' process considers choice as stimulus-driven. The bottom-up process assumes that by making an alternative more salient, one can affect the choice. The stimulus-driven process presents an opportunity to change health behaviours through modifying the stimulus. Recent research has demonstrated the importance of salience of product packaging elements (Chandon, Hutchinson, Bradlow, & Young, 2009; Orquin et al., 2019) on consumer attention, independent of consumer health goals (Orquin et al., 2019). Eye-tracking provides a useful opportunity to examine the influence of goals and habits on choice, mediated through visual attention.

Further, decision-making heuristics may drive visual attention and thereby choice. For example, sequential visual attention movement across the 'row' in a traditional tabular choice task layout may suggest an 'elimination by aspects' strategy whereby a given attribute is compared to a threshold or compared across alternatives (Tversky, 1972). Alternatively, visual attention that moves sequentially down a column may suggest an 'additive compensatory-model' approach in which all attributes for a given alternative are considered before moving on to the next alternative (Keeney & Raiffa, 1993). For example, Ares, Mawad, Giménez, and Maiche (2014) found in an eye-tracked choice experiment that consumers who reported more 'analytical' thinking styles had longer attention on nutritional information in order to differentiate between yoghurt alternatives. Those who reported more 'intuitive' thinking styles spent relatively more time looking at the label background. It is possible that there is a causal relationship between consumer health goals and the use of heuristics, but this needs to be established by future research. Nonetheless, the conjecture that goals may cause heuristics adoption is a plausible one.

Improved understanding of the cognitive processes that lead to choice decisions may enhance the real-world applicability of data from experimental studies, and potentially identify levers for intervention when the goal is to change choices through altering preferences. This paper examines the effects of neglecting the endogenous relationship between goals and habits, visual attention and choice may introduce bias in the parameter estimates and exaggerate the effect of habits, goals and visual attention on choices.

2.2. The effect of learning on visual attention and choice

Over time, individuals learn to separate relevant and irrelevant cues through practice and experience (Haider & Frensch, 1999). Previous studies have established that decision-makers become more efficient over time when making repeated or similar choices, potentially due to learning (Meißner & Decker, 2010; Meißner et al., 2016; Payne, Bettman, & Johnson, 1988). The availability of eye-tracking along with choice data opens an avenue to disentangle the effect of shorter-term choices (choices made in the last one or two choice occasions) and longer-term choices (cumulative count of various choices made until the last choice occasion in a stated preference (SP) study).

In this study, we refer to the effect of past choices on subsequent choices as "learning". However, we acknowledge that there are several potential explanations for this effect. The 'drift diffusion model' in psychology (Krajbich & Rangel, 2011) describes the accumulation of information over time in favour of a particular alternative, until evidence in favour of that alternative exceeds a threshold. Similarly, the 'choice perseveration model' (Senftleben et al., 2019) posits that previous choices of an alternative cumulatively bias a respondent towards that alternative.

One way to capture the learning effect is to regress the exogenous variables of the previous time periods (e.g., experimental constraints such as previous price levels) on the current choice (see Erdem et al., 1999 for further discussion). Although this approach is easy to incorporate, it may cause explosion of parameters for a moderate to high number of alternatives and attributes. An alternative could be regression of the past utility value on the current utility in order to reduce the number of parameters. However, a simple utility regression approach may induce bias in parameter estimation due to the need to regress both observed and unobserved utility portions (Bhat, 2015).

In order to obtain unbiased estimates, a 'lag structure' on utility (both observed and unobserved) is used widely in spatial econometrics and time series analysis (LeSage & Pace, 2009). The use of a lag structure is elegant but challenging due to estimation of high dimensional integrals (see Anselin, 2001 for a detailed discussion of pertinent issues). Instead, eye-tracking researchers outside of health (this issue has been ignored to date in the health literature) have used simple regression by either incorporating previous choices (e.g., Meißner et al., 2016) or previous attribute values as explanatory variables (e.g., Ben-Elia & Shiftan, 2010). These approaches may cause bias in parameter estimates if an auto-regressive component is present in the data generation process.

On the other hand, incorporating learning effects requires capturing the effect of past choices and contexts on present choices. Abstracting the potential availability of data, the econometric challenge in representing learning models lies in accounting for unobserved factors across choice occasions, which imply that choices (utilities) are not independent over time. In this paper, we incorporate a first-order autocorrelation process in our econometric framework to quantify the impact of full (systematic and stochastic) prior preferences. To our knowledge, this is the first such specification in the eye-tracking literature. We develop a parsimonious model with improved predictive power compared to extant practice. Below, we apply our model to decision-making in a beverage choice task with health policy and retail practice implications.

3. Material and methods

3.1. Empirical application

There is increasing consumer and government interest in reducing the consumption of sugar-sweetened beverages (SSBs), which are a major cause of excess energy consumption and contribute significantly to the global burden of chronic disease, including obesity (Singh et al., 2015). Understanding the mechanisms for consumer beverage choices may help guide retail changes or policy development to decrease the purchase and consumption of less healthy beverages and to increase the consumption of healthier beverages.

The relationship between visual attendance and participant demographics, beverage preference and choice characteristics was explored using an eye-tracked DCE. Details of the DCE without the addition of eye-tracking data have been published (Blake et al., 2018; 2019) which report on the DCE applied to different, larger samples than used in the eye tracking dataset used in this current study. Briefly, the primary purpose of the DCE was to explore heterogeneity in consumer beverage preferences and price responsiveness over key socioeconomic characteristics including income levels and usual SSB consumption frequency. This eye-tracked dataset provides the opportunity to investigate the effect of factors influencing inherent preferences (self-reported habits, goals and experimental constraints) on choice, and to then examine the mediating effect of visual attention and to do so accounting for learning effects.

3.1.1. Participants

Participants completed the DCE while being monitored at an eye-tracking laboratory in Melbourne, Australia. Participants were Australian residents 18 years or older. Recruitment targets were set for this sample so as to reflect the Australian adult population in age and gender. A minimum of 70% of participants who had consumed a SSB purchased from a convenience store at least "a few times" in the past month was set. Participants were recruited from a database of past participants at the research center, through the university staff newsletter, social media, local newspaper advertising, and direct recruitment through local community organisations. Participants provided written informed consent and were given an AU$30 supermarket gift card for their time. Ethical approval was received from Monash University Human Research Ethics Committee (approval number CF15/4153-2015001760).

3.1.2. Experimental design

In the labelled DCE, participants selected a beverage within a hypothetical convenience store setting. Each participant completed 20 choice tasks involving three SSB alternatives (energy drink, flavored milk, regular soft drink (i.e., "soda")), four non-sugar-sweetened alternatives (non-SSBs: plain low-fat milk, fruit juice, diet soft drink, bottled water), and a "no drink" alternative (meaning that they would "consume no drink on this occasion"). Each beverage was described by alternative-specific prices and generic volume attributes which each varied over four levels. An orthogonal design was generated using Ngene software (Rose, Collins, Bliemer, & Hensher, 2009). Prior to completing the choice tasks, half of participants were randomly exposed to a real-world educational message designed to discourage selection of SSBs. See Web Appendix A for further detail on experimental design and an example choice task and list of attribute levels for each alternative.

Following the DCE, participants completed questions on stated attendance to attributes and alternatives as well as strength of SSB consumption habit. This included an 11-point scale of readiness to consider reducing SSB intake based on a validated tool to assess readiness to quit smoking (Biener & Abrams, 1991) and the Self-Report Behavioral Automaticity Index, a 4-item measure of habit strength measured on a 5-point Likert scale with higher scores signifying a stronger habit (Gardner, Abraham, Lally, & de Bruijn, 2012).

3.1.3. Eye-tracking data

A discrete, web-cam like device tracked eye movements (Tobii Pro, 2011, Tobii TX300; Stockholm, Sweden). Participant visual attention to Areas of Interest (AOIs) was defined using a continuous measure (fixation duration) (Krucien et al., 2017). AOIs were defined for each attribute 'row', each alternative 'column' and for each individual choice task table cell. For each participant, choice tasks with less than two fixations were excluded from the analysis to reduce data noise from random eye-movements.

3.2. Model overview

We describe the model here with further detail including relevant estimation approach provided in Web Appendix B.

3.2.1. Econometric details

Let $j = 1,\ldots,8$ be labelled alternatives, where $j = 8$ represents the "no drink" option. Each respondent completes T tasks, each task t having a choice set $C_t = \{1,2,\ldots,8\}$ of all beverages. A beverage is presented as a constant label (e.g., fruit juice, flavored milk, see Web Appendix A- Fig. A.1), a generic size for all beverage types S_j (varying across four levels) in milliliters, and a varying alternative specific price (p_{jt}) in Australian dollars (see Web Appendix A- Table A.1 for price levels). With this preamble, the model specified in Fig. 1 can be defined econometrically.

Let the utility U_{jt} (subscript for person n is omitted for clarity, but should be assumed throughout) be given as

$$U_{jt} = \alpha_j + \beta_j(S_j/p_{jt}) + \gamma_j d_{j,t-1} + \delta_j D_{j,t} + \varphi_j ln(Y_{jt}) + \varepsilon_{jt}, j = 1, \cdots, 8, t = 1, \cdots, T, \tag{1}$$

where

α_j is the alternative-specific constant for beverage j;
β_j is the marginal impact of the volume to price ratio for beverage j, expected to be positive;
$d_{j,t-1} = 1$ if beverage j chosen in the prior task $(t-1)$, $=0$ otherwise, used to proxy for shorter-term learning within the task;
γ_j is the utility impact of $d_{j,t-1}$;
$D_{j,t} = \Sigma_{t=1,\ldots,t-1} d_{j,t}$ is the cumulative choice of beverage j in all prior tasks to t, which proxies for longer-term learning within the task;
δ_j is the utility impact of $D_{j,t}$;
Y_{jt} is the visual attention the respondent gave to beverage j during task t, which is defined as the total time (msec) spent on the label, volume and price, used in the model with a natural log transform to reflect the assumption of diminishing marginal impact of visual attention on utility (see Orquin & Loose, 2013);
φ_j is the utility impact of $\ln(Y_{jt})$;
ε_{jt} is the additive stochastic utility for j at task t.

As we noted earlier, we assume that ε_{jt} is auto-regressive AR(1). An AR(1) process allows for the possibility that time previously spent on an alternative partly determines how much time will be spent on it currently, combining the possibility that both present and past conditions help to establish present behaviour.:

$$\varepsilon_{jt} = \lambda_j \varepsilon_{j,t-1} + \eta_{jt}, j = 1, \cdots, 8, t = 1, \cdots, T, \tag{2}$$

λ_j is the one-period autoregression coefficient, with a range from -1 to $+1$;
η_{jt} is a contemporaneous stochastic utility that has no time dependence to it.

This assumption allows stochastic sources of utility for a beverage to be correlated over trials. The link between utilities U_{jt}, for all j, and observed choice d_{jt} is given through the relationship

$$d_{jt} = 1 \text{if} U_{jt} \geq \max(U_{kt}, k \neq j), =0 \text{ otherwise}, \quad \text{for} j = 1, \cdots, 8, t = 1, \cdots, T, \tag{3}$$

implying that choice is made on the basis of utility maximization. Since the utilities are stochastic, it is necessary that we specify the distributional law followed by errors η_{jt} to specify the link between utilities and observed choices. We assume that

$$\eta_t \ MVN(0_\eta | \Omega_\eta), t = 1, \cdots, T, \tag{4}$$

where MVN(a|B) is the multivariate normal distribution with mean a and covariance matrix B;

η_t is a 8x1 vector of stochastic utilities;
0_η is a 8x1 vector of zeroes;
Ω_η is the contemporaneous covariance matrix for the stochastic utilities (note that there is no temporal component to this matrix).

We estimate the visual attention (continuous) model which is later integrated into the choice model. The visual attention model is given by the following equation:

$$Y_{jt} = a_j + \rho_j Y_{j,t-1} + \sum\nolimits_{l=1..3} \kappa_{jl} H_l + \sum\nolimits_{k=1..6} \pi_{jk} \psi_k + \theta_j d_{j,t-1} + \xi_{jt}, j = 1, \cdots, 8, t = 1, \cdots, T, \tag{5}$$

where

a_j is the intercept of visual attention time for beverage j;
ρ_j is the AR(1) coefficient for the previous time spent on beverage j, ranging in the interval $[-1, +1]$;
H_l is the individual's habit, a count of l={strongly disagree, disagree, neutral, agree and strongly agree} across four scale items (see definition in note for Table 1);
κ_{jl} is the marginal time impact of scale value H_l on visual attention given to j;
Ψ_k is equal to 1 if the individual's score or response on an item measuring the intention to drink less SSBs on a 10-point scale (1 = no thought of drinking less to 10 = taking action to drink less) is equal to k, $k = 1,\ldots,6$, and $\Psi_k = 0$ if $k = 7,\ldots,10$;
π_{jk} is the marginal time impact of the k-th dummy variable Ψ_k on beverage j;
θ_j is the time impact of $d_{j,t-1}$;

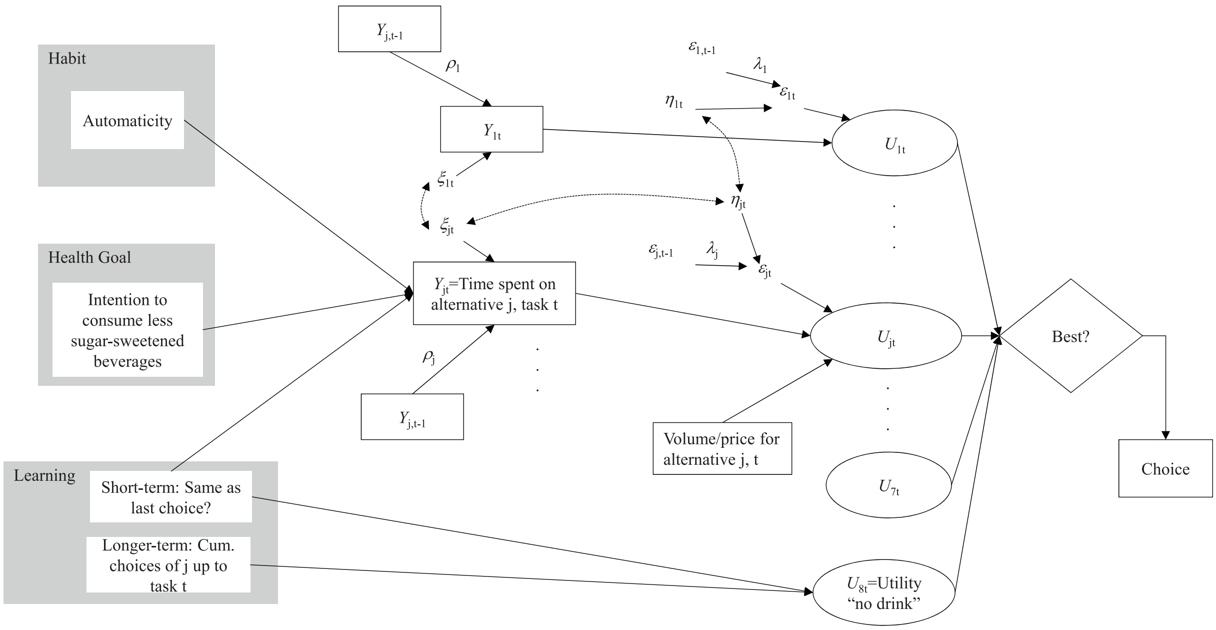

Fig. 1. Econometric model schematic.

ξ_{jt} is a stochastic source of visual attention time arising from other sources than those enumerated in (5).

To complete the specification of model (5), we need to stipulate the density for

$$\xi_t \; MVN(0_\xi|\Omega_\xi),\ t = 1, \cdots, \mathrm{T}, \tag{6}$$

which has an analogous interpretation to the terms defined for expression (4). Finally, we specify that error terms (η_t,ξ_t) may covary across beverages in the same task. Since both stochastic vectors are MVN, we can specify this as follows:

$$\begin{pmatrix}\eta_t\\ \xi_t\end{pmatrix} MVN\begin{pmatrix}0_\eta \, | & \Omega_\eta & \\ 0_\xi \, | & \Omega_{\eta\xi} & \Omega_\xi\end{pmatrix},\quad t = 1, \cdots, \mathrm{T}, \tag{7}$$

where $\Omega_{\eta\xi}$ is the covariance matrix for stochastic covariation between (η_t,ξ_t); other quantities as previously defined.

To summarize, the model system depicted in Fig. 1 has the following characteristics which together significantly advance the current approach to visual attention data and choice model analysis:

a) The choice component is a Multinomial Probit (MNP) model with contemporaneous covariation given through the covariance matrix Ω_η, which is 8*x*8, thus allowing beverage utilities to be correlated positively or negatively for the same task, and for utility variances to differ across beverages. In addition, the MNP model allows for an AR (1) error at the beverage level.
b) The visual attention time, Y_{jt}, is a nonlinear predictor (through the natural logarithm transformation) of the attractiveness/utility of a beverage. The natural logarithm reflects the *a priori* conjecture that the marginal impact of visual attention on utility of beverage j diminishes with increasing time.
c) Y_{jt} is influenced by past visual attention to beverage j through an AR (1) specification, in addition to which habit, health goal and learning can impact the attention given to a beverage during any task.
d) Visual attention is correlated across beverages, through the covariance matrix Ω_ξ, which is 8*x*8, making it possible that consistent patterns of time allocations to beverage pairs (whether increasing or decreasing) be captured within a task.
e) Finally, contemporaneous stochastic utilities η_{jt} and stochastic visual attentions ξ_{jt} for a given beverage j during task t can covary, through covariance matrix $\Omega_{\eta\xi}$, also 8*x*8.

We tested the following models where attention/AOI time is modelled as a driver of preference, where V represents the observed part of utility and E is the unobserved part of utility. A 'Joint' model refers to models where the habit, visual attention and choice outcomes are linked by the covariance structure and has the properties a) to e) as described above. An 'Independent' model refers to a model which does not assume a correlation between visual attention time and choice through an error structure:

- Joint-AR(1)VE: Joint model with AR(1) structure on both observed and unobserved parts of utility.
- Joint-AR(1)V: Joint model with AR(1) structure on observed part of utility.
- Joint-AR(1)E: Joint model with AR(1) structure on unobserved part of utility.
- Independent-AR(1)E: Independent model with AR(1) structure on unobserved part of utility.

We also tested the following models where time is used to capture screening behavior through a penalty function (P), to be detailed later:

- Joint-AR(1)VEP: Joint model with AR(1) structure on both observed and unobserved parts of utility and penalty function.
- Joint-AR(1)EP: Joint model with AR(1) structure on unobserved part of utility and penalty function.

Please note that for all the models, the continuous (visual attention) component has AR(1) structure on both observed and unobserved portions of propensity.

Identification of this model system requires that a number of restrictions be imposed. With respect to the choice model, it is necessary that one of the Alternative Specific Constants (ASCs) be normalized, so we set $\alpha_1 = 0$ (for j = 1, bottled water). Additionally, it is necessary to restrict elements of covariance matrix Ω_η since at most 7*8/2 = 28 of its 8*9/2 = 36 elements can be identified (Bunch, 1991), with at least one of the 28 elements being normalized to unity (in this case, the variances of the differences of stochastic utility of energy drink and bottled water, j = 1,2); accordingly, the cell (1,1) is set to 1.

The joint model described above is used to test whether visual attention is a driver of choice. To test whether habits, goals, and constraints work as *screening mechanisms*, we still use visual attention Y as an explanatory variable in expression (1), but with a different functional form that lets it serve as a penalty to utility. Specifically, we rewrite the utility function of beverage j as follows. Note that the penalty function of each alternative differs:

$$U_{jt} = \alpha_j + \beta_j(S_j/p_{jt}) + \gamma_j d_{j,t-1} + \delta_j D_{j,t} + ln\tau_{jt} + \varepsilon_{jt},\ j = 1,\ \cdots,8,\ t = 1,\ \cdots,T, \tag{8}$$

where

$\tau_{jt}\ (1 + \exp(Y_{jt}))^{-1}$ is the penalty term associated with beverage j in task t.

The logistic parameterization of the penalty τ ensures that its value is bounded between 0 and 1, so in expression (8) the penalty is bounded between $-\infty$ (Y_{jt} small, near zero) and 0 (Y_{jt} large). Thus, an alternative is *screened* out (i.e., becomes unavailable) because its utility grows very negative as visual attention decreases. Note that there is no further stochastic component in the penalty function other than that implied through the logistic functional form.

While we assume the direction of causality to be from goals and habits to visual attention, which subsequently informs preferences through choice, it is plausible that other causal relationships may coexist. For a model with three dependent variables, a total of six different causality directions may co-exist. For example, goals and habits may affect choices which can then direct visual attention. In this paper, we do not model all possible causality directions. Researchers can simultaneously model multiple causality directions by embedding the proposed multilevel framework in a latent class framework where each class represent a causality direction.

3.2.2. *Parameter estimation by composite maximum likelihood*

The full vector of parameters to be estimated is quite extensive due to the dimensionality of the three covariance matrices, even after accounting for identification restrictions that must be imposed:

$$\begin{aligned}\Gamma_C &= \{(\alpha_1,\cdots,\alpha_8)', (\beta_1,\cdots,\beta_8)', (\gamma_1,\cdots,\gamma_8)', (\delta_1,\cdots,\delta_8)', (\varphi_1,\cdots,\varphi_8)', (\lambda_1,\cdots,\lambda_8)'\}\\ \Gamma_Y &= \{(a_1,\cdots,a_8)', (\rho_1,\cdots,\rho_8)', (\kappa_{11},\cdots,\kappa_{83})', (\pi_{11},\cdots,\pi_{86})', (\theta_1,\cdots,\theta_8)'\}\\ \Gamma_\Omega &= \{\Omega_\eta, \Omega_\xi, \Omega_{\eta\xi}\},\end{aligned} \tag{9}$$

This dimensionality imposes a significant computational burden in using traditional likelihood-based estimation methods, reflecting the complication of a first-order auto-regressive MNP choice model, plus the lagged, linear visual attention models. This causes difficulties both theoretical and computational in nature (e.g., choice probabilities near zero). By itself, the MNP choice probability is a well-known challenge in the literature (Connors, Hess, & Daly, 2014). Simulated maximum likelihood methods (e.g., Geweke- Hajivassiliou-Keane (GHK) simulator, Hajivassiliou, McFadden, & Ruud, 1996) can calculate MNP probabilities accurately only up to a limited number of dimensions (Sándor & András, 2004) and suffer from long computational times (Train, 2000; Craig, 2008). Therefore, it is challenging to estimate the full set of parameters using maximum likelihood.

A competing method is to use a Bayesian approach to evaluate the complex likelihood function, which would involve sampling from a complex series of conditional distributions. A review of literature involving the MNP kernel shows that the Bayesian approach has often not performed as expected in terms of recovering parameters and their standard errors (Franzese, Hays, & Schaffer, 2010; Patil et al., 2017), though some studies have found the performance of Bayesian approach to be quite good (Daziano, 2015). Faced with these polarized results, we opted not to pursue this path.

Instead, we use the composite marginal likelihood (CML) approach. This has been established in the last decade as a powerful approach for parameter estimation involving likelihood functions with high dimensional integrals. A comprehensive discussion on the CML approach is outside the scope of this paper and readers are referred to the literature for background (Varin & Vidoni, 2005; Varin, 2008; Varin, Reid, & Firth, 2011), and to Bhat and colleagues (Bhat & Dubey, 2014; Bhat, Pinjari, Dubey, & Hamdi, 2016) for its application in the context of discrete choice models. Bhat and colleagues have performed extensive simulation testing using the CML approach for complex econometric models and have observed highly accurate results.

One of the practical advantages of the CML method for our problem is that it reduces the dimensionality of integration of likelihood function terms to calculations based on pairs of random variables. To our knowledge, this is the first time CML has been applied in the eye-tracking literature. The details of the CML likelihood function and our estimation method are provided in Web Appendix B.

4. Results

4.1. *Sample description*

Between November 2015 and March 2016, 160 eligible adults completed the eye-tracked DCE (see Web Appendix C Fig. C.1 for participant flow diagram). Eye movements were recorded on every choice task for 139 participants (used for main analysis) and during at least one choice task for 13 participants. These 13 individuals were excluded from the main analysis but used to test out-of-sample prediction. Mean duration of the study (DCE and post-DCE questions) was 24.6 mins (SD 7.8), and the DCE alone 4.4 mins (SD 2.2).

Participant demographics are summarized in Web Appendix D, Table D.1. The convenience sample by design approximately reflected the Australian population based on age and gender. There was a higher proportion of those in the lowest income quintile compared to the Australian population income distribution. Sixteen percent reported that they never drink SSBs. Participants scored a mean 9.6/20 (SD 4.3) on the Self-Report Behavioral Automaticity Index habit measure, meaning that on average participants had a moderately strong SSB consumption habit (Gardner et al., 2012). Forty-eight percent of participants reported currently taking action or considering how to drink fewer SSBs.

4.2. *Description of visual attendance*

While total fixation duration per choice task nearly halved from mean 18.2 secs (SD 10.0) in the first choice task to 10.3 secs (SD 8.0) in the final choice task, the proportion of time spent looking at *relevant information* (choice set task), increased from mean 71% fixation duration (SD 16%) to 82% fixation duration (SD 17%) in the final choice task.

Visual non-attendance of beverage types was highest for energy drink, and lowest for bottled water. Non-attendance on all beverage types increased through subsequent choice tasks, although non-attendance was temporarily decreased after the 10th choice scenario when participants were presented with a message reminding them to "consider their options carefully". Most people attended to volume and price in every choice task. Further descriptive results of visual attendance data are found in Web Appendix E.

4.3. *Model estimation results*

In this section, we first present fixation duration results (Table 1), followed by choice component results (Table 2). As noted in Web Appendix A, we tested the effects of the educational message using the model of best fit (Joint-AR(1)E, fully compensatory AR-1 Error model, described later) and found no significant effect on beverage choice,

Table 1
Parameter estimates for visual attention (total fixation duration on) beverage j, task t, j = 1,…,8, t = 1,…,T.

Theoretical construct [a]	Explanatory variables	Visual attention (fixation duration) on beverage j during task t (Y_{jt}) (t-statistic)						
		Bottled water	Energy drink	Plain low-fat milk	Flavored milk	Soft drink (regular)	Soft drink (diet)	Fruit juice
Alternative Specific Constant (ASC) (α_j)	Alternative Specific Constant (ASC)	0.024 (4.5)	-0.170 (-7.7)	-0.117 (-9.8)	-0.113 (-10.5)	-0.198 (-11.3)	-0.298 (-16.9)	-0.319 (-11.66)
Habit (H_l) [b] (measured by automaticity, base = strongly disagree)	Disagree	-0.022 (-2.2)	0.084 (2.6)	0.090 (3.6)	0.084 (6.9)	0.123 (2.3)	0.096 (3.0)	0.068 (2.6)
	Neutral	-0.211 (-2.1)	0.070 (4.1)	0.013 (2.3)	-0.021 (-3.0)	0.070 (3.4)	-0.046 (-2.1)	-0.098 (-4.2)
	Agree and strongly agree	-0.150 (-5.9)	-0.036 (-5.5)	0.013 (2.3)	0.050 (2.7)	0.070 (3.4)	-0.046 (-2.1)	-0.098 (-4.2)
Health goals (Ψ_k) (Intention to drink less SSBs; 1-10 ordinal scale, 1 = no thought of drinking less, 10 = taking action to drink less (base: score 7–10))	Score 1	0.114 (3.9)	0.012 (2.0)	-0.026 (-4.4)	-0.037 (-5.5)	-0.049 (-6.5)	NS	-0.034 (-4.8)
	Score 2	0.114 (3.9)	0.012 (2.0)	-0.026 (-4.4)	-0.037 (-5.5)	-0.049 (-6.5)	NS	-0.034 (-4.8)
	Score 3	0.114 (3.9)	0.012 (2.0)	-0.026 (-4.4)	-0.037 (-5.5)	-0.049 (-6.5)	NS	-0.034 (-4.8)
	Score 4	0.114 (3.9)	0.012 (2.0)	-0.026 (-4.4)	-0.037 (-5.5)	-0.049 (-6.5)	NS	-0.034 (-4.8)
	Score 5	0.114 (3.9)	0.012 (2.0)	0.098 (7.2)	0.055 (4.8)	-0.049 (-6.5)	0.097 (7.9)	0.118 (8.9)
	Score 6	0.114 (3.9)	0.012 (2.0)	0.098 (7.2)	0.055 (4.8)	-0.049 (-6.5)	0.097 (7.9)	NS
Learning [c]	Shorter-term ($d_{j,t-1}$): Same alternative chosen in the last choice task (Yes = 1, No = 0)	0.309 (14.7)	0.384 (6.4)	0.453 (7.9)	0.510 (9.4)	0.364 (7.9)	0.505 (9.5)	0.552 (9.8)
Learning (ρ_j, autoregressive parameter)	Time spent on beverage j in previous task (t-1)	0.586 (9.5)	0.569 (8.0)	0.686 (9.8)	0.725 (7.3)	0.679 (8.7)	0.597 (10.8)	0.642 (5.1)

NS, not significant.
[a] Results for cognitive analysis time (visual attention time on choice experiment, excluding visual attention to alternative and attribute information) were not significant were therefore omitted from the final model and are not reported here.
[b] Habit (automaticity): This variable was constructed to measure the automaticity in habit towards drinking SSBs (sugar-sweetened beverages) by taking the average of scores reported for following statements: I consume non-diet cordial, non-diet soft drinks, sports drinks, energy drinks, flavored milk and fruit drink… (i) Automatically, (ii) Without having to consciously remember, (iii) Without thinking, and (iv) Before I realise I'm drinking it. Four questions on five-point Likert scales from strongly disagree (1) to strongly agree (5). Means were constructed from responses to each of the four items for analysis.
[c] Longer-term learning ($D_{j,t}$) results not displayed as all findings non-significant.

Table 2
Parameter estimates for Multinomial Probit (MNP) choice model.

Theoretical Construct	Explanatory Variables	Utility of beverage j, task t (U_{jt}) (t-statistic)							
		Bottled water	Energy drink	Plain low-fat milk	Flavored milk	Soft drink (regular)	Soft drink (diet)	Fruit juice	No drink
Alternative Specific Constant (ASC) α_j	Alternative Specific Constant (ASC)	NS	−0.170 (−1.88)	−0.169 (−2.66)	−0.198 (−1.89)	0.068 (2.34)	−0.048 (−2.42)	0.718 (4.51)	0.696 (6.46)
Design variable (β_j)	Volume/Price Ratio (ml/AU$)	0.523 (20.52)	0.403 (12.75)	0.220 (6.99)	0.782 (8.14)	0.598 (10.63)	0.680 (12.02)	0.713 (14.83)	NS
Shorter-term choice effect ($d_{j,t-1}$)	Same alternative chosen in the last choice task (Yes = 1, No = 0)	NS	NS	NS	NS	NS	NS	NS	0.513 (8.88)
Longer-term choice effect ($D_{j,t}$)	Cumulative sum of choice of the same alternative until last choice task	0.080 (13.20)	0.221 (14.20)	0.193 (12.75)	0.121 (3.50)	0.118 (4.98)	0.159 (8.34)	0.043 (2.10)	0.243 (15.15)
Visual attention (Y_{jt})	Natural logarithm of time spent on beverage j, task t	1.374 (15.37)	1.482 (9.83)	1.435 (10.99)	1.199 (11.80)	1.288 (13.85)	1.298 (11.05)	1.155 (13.01)	NS
	Autoregressive parameter value (on unobserved utility)[a]	0.573 (7.01)							

NS, not significant.
Results for habit and goal parameters (direct effect of habit and goals on utility) were not statistically significant and were therefore omitted from the final model and are not reported here.
[a] Bottled water has the highest choice share, therefore we take this as the reference alternative.

hence sub-samples were pooled and we used the full sample (n = 139) in the estimation (n = 13 used in out-of-sample predictions below).

We found evidence for the AR(1) structure on both observed and unobserved components of the fixation duration (continuous) model, combined with AR(1) structure on the unobserved portion of the choice component, as in the Joint-AR(1)E model. This implies that respondents do exercise their experience from previous tasks when acquiring information on alternatives and thus past fixation behavior guides current information acquisition strategy. Therefore, the results described below correspond to the Joint-AR(1)E model.

As shown in Table 1 and as anticipated, stronger SSB habits (H_l) are generally associated with positive (increased) visual attendance time on SSBs and negative (decreased) visual attendance time on non-SSB alternatives. For example, people with a moderate to strong habit of drinking SSBs are likely to spend less time looking at the attributes of bottled water as compared to attributes of regular soft drink. Some parameter estimates for visual attention are the same for different health goal categories (Ψ_k). For example, mild to moderate health goals with scores in the range of 1 to 6 out of 11 had the same association with visual attention to bottled water. Participants who reported a high intention to drink less SSBs spent more time looking at the attributes of SSBs compared to people who have a lower intention to change SSB consumption. Intuitively, it may suggest that a conscious decision to reduce consumption of SSBs leads to careful evaluation of various aspects of such beverages prior to choice. This could be a demonstration of ‘regret regulation’ (Pieters & Zeelenberg, 2007), which posits that choices are made to minimize future regret, leading to a careful examination of products which they are trying to avoid.

We also observed that shorter-term learning results ($d_{j,t-1}$) suggested that respondents tended to spend more time on an alternative if it was chosen in the previous task occasion. Finally, the positive autoregressive coefficients (ρ_j) for all beverages (last row of Table 1) suggest that respondents do exercise their experience (reinforcing or discouraging from previous tasks) when acquiring information on alternatives, and thus past fixation behavior guides current information acquisition strategy. The AR structure parsimoniously captures the effect of past information (represented through habit, goal, past choices and other unobserved characteristics) on current information acquisition (visual attention time spent on attributes), and therefore operates as a feedback link between past and current tasks.

In Table 2 (MNP choice model results), the volume and price attributes are included in the model as a volume/price ratio to accommodate the trade-off between them. As per *a priori* expectations, the volume/price ratio (β_j) was significant and positive for all beverages, suggesting participants preferred beverages with higher volume per dollar ratios. We observed non-significant coefficients for the direct effect of shorter-term choices ($d_{j,t-1}$) indicated by last chosen beverage on the subsequent beverage selection, suggesting that shorter-term choices are an indirect driver of information acquisition through visual attention time to attribute and alternative information. However, we found a significant and positive effect of longer-term preference on the choice of all beverages including the “no drink” option (indicated by the cumulative sum of chosen alternatives until the last choice occasion, $D_{j,t}$).

In addition to these findings from the Joint-AR(1)E model, both shorter and longer-term learning effects were found to be significant in both visual attention and choice components in the independent model (Independent-AR(1)E, the model which does not assume a correlation between visual attention time and choice through error structure).[1] The AR coefficient is positive and statistically significant, suggesting the presence of feedback loops between past and current choice occasions. Finally, time spent on beverage information has a positive effect on the

[1] The detailed estimation result for the independent model is available from the authors on request.

Table 3
Covariance matrix (Ω) parameter estimates.

Utility of beverage j, task t (U_{jt})	Correlation of visual attention across beverage alternatives (Ω_ξ)							Correlation of stochastic utilities across beverage alternatives Ω_η						
	Bottled water	Energy drink	Plain low-fat milk	Flavored milk	Soft drink (regular)	Soft drink (diet)	Fruit juice	Energy drink	Plain low-fat milk	Flavored milk	Soft drink (regular)	Soft drink (diet)	Fruit juice	No drink
Bottled water	0.597 (8.51)													
Energy drink	NS	0.560 (8.33)												
Plain low-fat milk	0.277 (2.11)	0.294 (2.95)	0.471 (6.96)											
Flavored milk	NS	NS	0.174 (7.16)	0.477 (8.53)										
Soft drink (regular)	NS	0.321 (10.99)	0.169	NS	0.650 (8.59)									
Soft drink (diet)	0.352 (11.47)	NS	0.034	−0.121	0.353 (4.58)	0.721 (6.94)								
Fruit juice	0.253 (9.78)	NS	0.205 (9.43)	0.158 (4.40)	NS	0.209 (6.41)	0.762 (3.92)							
Energy drink	NS	NS	0.025	0.016 (1.85)	NS	0.014	0.222 (4.30)	1.000						
Plain low-fat milk	NS	NS	NS	−0.020	NS	0.031	0242 (4.53)	0.580	0.775 (8.22)					
Flavored milk	NS	NS	0.070 (2.35)	0.128 (2.96)	−0.040 (−2.25)	−0.021 (−1.15)	0.409	0.760 (3.32)	0.634 (11.83)	1.087 (11.62)				
Soft drink (regular)	0.029 (2.54)	NS	−0.001	−0.047 (−4.77)	0.036 (2.13)	0.071 (2.10)	0.103 (3.56)	0.547	0.486	0.570 (9.49)	0.839 (9.28)			
Soft drink (diet)	NS	NS	NS	NS	0.052 (2.89)	0.040 (2.42)	0.006	0.504	0.219 (2.15)	0.425	0.391	0.805 (8.28)		
Fruit juice	−0.008	NS	0.013	0.018	NS	0.023	0.228 (6.41)	0.723 (8.52)	0.597	0.727	0.588	0.332 (5.86)	1.084 (11.33)	
No drink	0.398 (13.38)	0.135 (6.26)	0.308 (7.64)	0.112 (9.03)	0.248 (10.61)	0.418 (12.08)	0.527 (12.22)	0.619	0.589	0.641	0.572	0.441	0.526	1.563

NS, not significant.

likelihood of choice of a beverage. Thus, importantly, with the help of the joint model, we are able to disentangle the effect of shorter- and longer-term preferences on information acquisition and alternative selection (choice). Results for habit and goal parameters (direct effect of habit and goals on utility) were not significant.

Although this broad directional effect finding is in line with Balcombe et al. (2015), in Table 3 we estimate the joint covariance matrix (Ω), along with inclusion of the autoregressive structure, which allows us to obtain the 'true effect' of structural endogenous factors such as fixation duration, short and longer-term choices, while allowing for better model fit. Estimates greater than zero indicate positive correlation between visual attention and choice, while estimates less than zero indicate negative correlation. For example, utility of healthier alternatives like bottled water, plain low-fat milk, diet soft drink and fruit juice are positively correlated with visual attention to bottled water. Our assumption that there exists a significant correlation between information gathering as observed through fixation duration (continuous model), habit and final decision-making (choice model) is reinforced by the covariance matrix. In addition, characterization of unobserved sources of dependence in information gathering across SSBs implies that we control for the bias in the model that would otherwise be created in the observed sources of dependence, and is generally ignored in the prior literature.

4.4. Data-fit statistics

Table 4 displays the model fit statistics. We explored two decision-making mechanisms using eye-tracking data: (1) fully compensatory, and (2) two-step decision-making process where screening precedes the fully compensatory decision step. The fully compensatory behavior is captured by the model where fixation duration is used as an explanatory variable in the choice model. The second decision-making behavior is captured by introducing a penalty function in the choice model as a function of fixation time (as discussed in the Methodology Section 3.1.3). The estimation results for the penalty models are similar to the fully compensatory models, including direction of signs of parameter coefficients, together with positive fixation duration parameters. The penalty value for a beverage alternative approaches a large negative number as the fixation duration increases. This suggests that participants may spend more time analyzing an option before eliminating it from the final consideration set in order to minimize choice regret (Pieters & Zeelenberg, 2007).

Table 4 also provides the model fit measures for these two competing models and other tested models. Since the models were estimated using a CML approach, the non-nested models can be compared by the Composite Likelihood Information Criterion (CLIC), which is similar to the familiar AIC and BIC criteria (Varin & Vidoni, 2005). The model with *higher* CLIC is preferred. Based on CLIC statistics, the current dataset is best represented by the fully compensatory model (Joint-AR(1)E) with CLIC of −4942922.25, compared to a CLIC of −4958377.42 for the screening model Joint-AR(1)EP, and CLIC of −4961982.10 for screening model Joint-AR(1)VEP. This suggests that the fully compensatory decision behavior is preferred in the current dataset, an eminently reasonable result given the low complexity of the choice task (eight alternatives with two varying attributes).

We then tested the performance of Joint-AR(1)E against the nested models using adjusted composite likelihood ratio test (ADCLRT) (equivalent to the likelihood ratio test in the CML approach; see Varin et al., 2011). The Joint-AR(1)E model is superior to its competitors with the same compensatory behavior mechanism but with AR structure on observed utility (Joint-AR(1)VE and Joint-AR(1)V), and to the Independent-AR(1)E, in which the correlation in the unobserved part of utility between fixation duration and choice is zero (p-value 0.010).

Differences in model fit may be exaggerated due to the difference in log-likelihood values while in fact performing equally well in terms of in-sample or out-of-sample prediction. Table 5 demonstrates that the

Table 4
Model fit statistics.

Role of Visual Attention (Y_{jt})	Model	Number of parameters	Composite Marginal Likelihood Value	AR(1) parameter value (t-statistic)	Adjusted composite likelihood ratio (p-value comparison with AR(1)EJ model)[a]	Composite likelihood information criteria (CLIC)
Used as a preference driver (fully compensatory model)	Joint-AR(1)VE	139	−4943689.19	0.016 (2.25)	0.446	N/A
	Joint-AR(1)V	139	−4943351.02	−0.052 (−2.13)	0.475	N/A
	Joint-AR(1)E	137	−4942782.99	0.573 (7.01)	N/A	−4942922.25
	Independent-AR(1) VE	135	−4945495.05	0.112 (1.84)	0.010	N/A
Used to capture screening behavior through penalty function [b] (two step approach)	Joint-AR(1)VEP	138	−4961851.03	0.431 (5.42)	N/A	−4961982.10
	Joint-AR(1)EP	138	−4958239.42	0.594 (13.13)	N/A	−4958377.42

[a] p-value calculation is based on 100 bootstrap samples.
[b] Beta values for all penalty function times were positive- results available on request from authors.

Table 5
Model fit for in- and out-of- sample prediction.

Model	Predicted Share								Mean absolute error (MAE)
	Bottled water	Energy drink	Plain low-fat milk	Flavored milk	Soft drink (regular)	Soft drink (diet)	Fruit juice	No drink	
In-Sample[a]									
Observed share	0.27	0.07	0.06	0.10	0.11	0.09	0.20	0.09	
Joint-AR(1)VE	0.18	0.12	0.16	0.11	0.11	0.07	0.18	0.07	0.039
Joint-AR(1)V	0.27	0.10	0.15	0.08	0.10	0.13	0.15	0.03	0.038
Joint-AR(1)E	0.24	0.09	0.12	0.15	0.10	0.09	0.16	0.05	0.031
Independent-AR(1)E	0.58	0.06	0.06	0.05	0.05	0.07	0.10	0.04	0.075
Joint-AR(1)VEP	0.15	0.04	0.23	0.18	0.13	0.10	0.16	0.01	0.069
Joint-AR(1)EP	0.21	0.05	0.11	0.17	0.11	0.12	0.21	0.03	0.038
Out-of-sample [b]									
Observed share	0.20	0.08	0.13	0.13	0.11	0.12	0.20	0.04	
Joint-AR(1)VE	0.19	0.12	0.17	0.11	0.11	0.07	0.17	0.08	0.029
Joint-AR(1)V	0.28	0.09	0.16	0.08	0.10	0.12	0.14	0.03	0.031
Joint-AR(1)E	0.20	0.05	0.12	0.16	0.10	0.12	0.21	0.03	0.013
Independent-AR(1)E	0.59	0.06	0.06	0.05	0.05	0.07	0.09	0.04	0.098
Joint-AR(1)VEP	0.14	0.04	0.24	0.18	0.14	0.10	0.16	0.01	0.048
Joint-AR(1)EP	0.25	0.09	0.13	0.15	0.10	0.09	0.14	0.05	0.024

[a] Sample size = 2780 (139 individuals with 20 choice tasks)
[b] Sample size = 206 (13 individuals with varying number of choice tasks)

fully compensatory behavior model Joint-AR(1)E has better prediction accuracy for both in-sample (mean absolute error (MAE) of 0.031) and out-of-sample (MAE of 0.013) data compared to all other models. Interestingly, while there is a large discrepancy in data fit statistics, predictions are very similar for the fully compensatory behavior model Joint-AR(1)VE (0.039 and 0.029 for in- and out-of-sample predictions, respectively) and Joint-AR(1)V (0.038 and 0.031 for in- and out-of-sample predictions, respectively). Among all tested models, the Independent-AR(1)E model has the worst in- and out-of-sample prediction accuracy. These results support the need to capture screening processes to enhance the predictive power of eye-tracking models.

4.5. Elasticity effects

To quantify the true magnitude of difference in discrete choice model estimations accounting for the possibility of screening during the decision-making process with those models that do not, we calculate the elasticity effects for fixation time with respect to beverage choice. For brevity, we only calculate and compare the elasticity effect of fixation for the fully compensatory model Joint-AR(1)E (preferred model) and its corresponding independent version (Independent-AR(1)E).

For the elasticity calculation, we increase the fixation time by 10% and calculate the implied change in share for each beverage. Since the model is based on a Probit kernel, the expression for elasticity effects does not take a closed form. Table 6 shows that elasticity values obtained from the two models are indeed statistically different (for all beverages, the *p*-value < 0.05). As expected, the implied shares are higher for the independent model than the joint model. Finally, the true effect of visual attention on choice (share from the joint model divided by share from the independent model) is around 56% to 65% for all beverages. This implies that if an analyst fails to consider the interrelationship between information gathering (visual attention) and information processing (decision-making), the result may be an overestimation of the impact of visual attention on actual choice.

5. Discussion

In this study, we developed a model to analyze the relationship between habits and goals, visual attention and choice outcomes in a joint framework. We found habit, goal and longer-term learning effects to be significant drivers of decision-making processes independent of the effects of visual attention. We also found unobserved factors to be significant drivers of choice. Most importantly, we found that ignoring potential unobserved heterogeneity between habits, visual attention and choice outcomes may exaggerate the role of visual attention as a driver of choice leading to low prediction accuracy.

Taking account of each variable separately, we found that time spent on beverage alternative information was positively correlated with the likelihood of choice of that alternative, similar to findings of

Table 6
Average treatment effect (ATE) on probability of choosing a particular option due to 10% increase in total time spent looking at that option including attribute values (standard errors): comparison of independent and joint model performance.

Alterative	Baseline observed choice share	ATE for 10% increase in fixation time Independent-AR(1)E	ATE for 10% increase in fixation time Joint-AR(1)E model [a]	*p*-value	True effect [b]	Spurious effect [c]
Bottled water	0.27	0.031 (0.003)	0.020 (0.003)	0.005	65%	35%
Energy drink	0.07	0.018 (0.002)	0.010 (0.002)	0.002	56%	44%
Plain low-fat milk	0.06	0.019 (0.002)	0.010 (0.002)	0.001	53%	47%
Flavored milk	0.10	0.018 (0.002)	0.011 (0.002)	0.007	61%	39%
Soft drink (regular)	0.11	0.018 (0.002)	0.011 (0.002)	0.007	61%	39%
Soft drink (diet)	0.09	0.016 (0.002)	0.010 (0.002)	0.017	63%	37%
Fruit juice	0.20	0.023 (0.003)	0.015 (0.002)	0.013	65%	35%
None	0.09					

[a] ATE values are based on 500 model estimation repetitions.
[b] The true effect is the ratio of share estimations from the joint model/ independent model estimations.
[c] Additional percentage of share not accounted for by true effect.

Balcombe et al. (2015) and others (e.g., Henderson, Williams, Castelhano, & Falk, 2003), who did not simultaneously account for multiple drivers of choice, potentially masking unobserved heterogeneity.

Other authors outside of the eye-tracking literature (Camerer et al., 2004; Gabaix et al., 2006) have reported that Markov-like decision models, which consider the influence of previous information acquired on respondent information acquisition behaviours in subsequent choices, provide better data-fit than models which ignore such information acquisition behaviours. This improved predictive power is possibly due to accounting for the endogeneity inherent in such decision-making behaviours. Unlike prior modelling approaches, our more comprehensive approach allows both prior preferences and goal and constraint-based screening to co-exist simultaneously as drivers of choice within a probabilistic approach. While we did not find a significant direct effect of habit and goals on utility, our model allows for this mechanism to be explored in future studies. These advances could be used to identify the mechanism of effect of different cognitive and environmental influences on health or non-health behaviour and purchasing decisions, and thus identify targets for effective intervention. The high predictive power demonstrated by out-of-sample predictions further highlights the need for joint modelling of influences on decision-making, to better identify the potential effect of interventions and the influence of different goals and influences for targeting.

The superior fit of the joint model with AR(1) structure on the unobserved part of utility using time as a preference driver suggests that a significant portion of utility explanatory power is in the unobserved factors affecting choice. Of course, there are a number of decision-making heuristics that our model could be adapted to account for, while harnessing the strength of our model of also accounting for other competing influences on choice rather than considering eye tracking data in isolation. These include the influence of 'row-based' visual attention or 'elimination by aspects' strategy whereby a given attribute is compared to a threshold or between alternatives (Tversky, 1972), and 'column-based' visual attention strategies suggesting an 'additive compensatory-model' approach in which all attributes for a given alternative are considered before moving on to the next alternative (Keeney & Raiffa, 1993). Visual attention data could be used following our suggested approach to provide evidence for 'row' and 'column' behavioral processes jointly, while accounting for other influences on choice as we have done, aiding decision-making in health and non-health DCEs.

Our model provides evidence of several pathways whereby previous choices and attention may influence subsequent choice and attention. We observed that respondents tended to spend more time on an alternative if it was chosen in the previous task occasion. This may suggest that the previously chosen alternative works as an anchor in the shorter-term, and other options are then evaluated in comparison to the anchor in a binary fashion. This is similar to the 'drift diffusion model' in psychology (Krajbich & Rangel, 2011). Independently, we found that the cumulative sum of choice of an alternative in previous choice tasks increased the probability of choice in subsequent tasks ($D_{j,t,}$). This is consistent with the choice perseveration model (Senftleben et al., 2019) whereby previous choices cumulatively bias a respondent such that the likelihood of choosing an alternative increases with subsequent choices.

As discussed in our review of the literature, choice set formation theory proposes that such heuristics may be preceded by an initial screening step in which the set of alternatives to be further considered is narrowed (e.g., Swait, 1984; Ben-Akiva & Boccara, 1995). Pre-determined or 'inherent' preferences, habits and goals (Tversky & Thaler, 1990; Simonson, 2008) may drive this screening behavior. Variation in choice set formation behavior could be further explored using visual attention data by parameterizing the constraints as a function of visual attention as done in our penalty approach. Future comprehensive models should ideally extend our framework to accommodate multiple decision-making strategies simultaneously. Similarly, interactions with non-health goals could be explored, for example cost-saving. Further work should test the causal relationships between decision-making variables we have proposed using exogenous source of variation.

Finally, our findings suggest that visual attention time does influence choice in complex ways and our model provides a means of exploring the effect of intentionally varying visual attention duration on choice. Marketers or policy makers who wish to influence choice should consider the potential influence that shortening or lengthening consideration time may have on choice, or the influence of factors that may affect visual attention on choice, which in our case study might affect the healthiness of beverage purchases. For example, the removal of SSBs from display has been found to reduce sales of these beverages and increase sales of healthier alternatives in a real-world café setting (Huse, Blake, Brooks, Corben, & Peeters, 2016).

The interaction of 'top-down' and 'bottom-up' processing pathways in consumer decision-making has significant implications for business, including in the design of product packaging (Orquin et al., 2019) and store layout and product positioning (Valenzuela et al., 2013). For example, observed retail practice of product positioning and consumers perceptions of product positioning strategies have been shown to interact to influence purchasing behaviour (Valenzuela et al., 2013). Not accounting for these interactions may cause poor predictions of consumer behaviour and sub-optimal category management. On the other hand, product positioning strategies could be optimised by better understanding this interaction. For example, Valenzuela et al. (2013) suggest initial positioning of products during an introductory period could be aligned with consumer expectations about the position of popular or cheaper products, which may later persist in future purchases due to learning effects, even after products have been moved to less salient (expensive) positions.

6. Conclusions

In this study, we developed an integrated model to analyze the relationship between information acquisition, inferred from visual attention and choice outcome while accounting for stated participant goals and habits. We observed that the frequent practice in previous literature of ignoring the effect of these top-down influences on both visual attention and choice may exaggerate the role of visual attention as a driver of choice. Most notably, we have added to the literature by developing a model that incorporates both observed characteristics (goals and habits) and unobserved characteristics and observed choice history. The model developed here enables researchers to test the guiding effect of observed and unobserved characteristics on visual attention thus providing insight into decision-making strategies and interventions to modify visual stimuli in health, business, and beyond. We hope that the current study will provide a framework to help health and non-health researchers establish the practical validity of eye-tracking data in the context of choice modelling while accounting for other competing influences on choice.

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.

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Appendix A. Supplementary material

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