Journal of Choice Modelling 60 (2026) 100621

Contents lists available at ScienceDirect

Journal of Choice Modelling

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

The "dark" side of engagement in stated choice experiments: exploring the role of time and complexity with an example on food

Emilia Cubero Dudinskaya[a,*], Simona Naspetti[b], Raffaele Zanoli[a]

[a] Department of Agricultural, Food and Environmental Sciences (D3A), Università Politecnica delle Marche, Ancona, Italy
[b] Department of Materials, Environmental Sciences and Urban Planning (SIMAU), Università Politecnica delle Marche, Ancona, Italy

ARTICLE INFO

Keywords:
Survey engagement
Hybrid model
Task easiness
Latent variables
Cognitive burden

ABSTRACT

Online stated preference surveys have become increasingly common in recent years. However, concerns about respondents' engagement and data quality remain critical. Our study proposes a robust modelling framework that addresses the role of respondents' survey engagement while addressing key limitations in existing approaches. We implement a hybrid modelling framework incorporating engagement before and during the task as latent variables on data from a food choice experiment. The models consider engagement valence and temporal aspects while accounting for the order in which the task was displayed and for individual task easiness and complexity, based on respondents' preferences. Our results show the importance of distinguishing between the time respondents spend before and during the choice tasks, as each phase has unique implications for how respondents process the information. Moreover, the time respondents spent on the initial and later tasks has a different association with engagement, confirming the role of ordering effects, experience learning and changes in decision-making strategies. Finally, we highlight the key roles of easiness and task complexity in engagement. Such results offer insight into how task design can influence respondent scale heterogeneity and data quality.

1. Introduction

Stated preference surveys conducted online have become more widespread in recent years. Notwithstanding their known advantages (Byun et al., 2018; Schlereth et al., 2012; Telser and Zweifel, 2009), significant disadvantages have also been highlighted (Lindhjem and Navrud, 2011). Specifically, the use of pre-recruited online panels composed of semi-professional, recurrent respondents often results in strategic time-saving behaviour, where these participants rush through the questionnaire without carefully considering their choices (Börger, 2016; Campbell et al., 2018; Schwappach and Strasmann, 2006). Such behaviour compromises the collected data's quality and validity (Malhotra et al., 2008).

Given the increasing reliance on data collected through online surveys, where few controls are available to guarantee respondents' attention and engagement, it is important to guarantee that respondents actively engage with the survey, as the lack of understanding the task or not taking it seriously could potentially result in scale heterogeneity (Hess and Stathopoulos, 2013). Engagement refers to the individual's emotional, cognitive and physical investment in task performance (Hernandez and Guarana, 2016). In this context, response quality depends on how thoroughly a respondent executes the process of understanding the question, retrieving the relevant

This article is part of a special issue entitled: ICMC 2024 JOCM published in Journal of Choice Modelling.

* Corresponding author.
E-mail address: e.cuberod@agrecon.univpm.it (E. Cubero Dudinskaya).

https://doi.org/10.1016/j.jocm.2026.100621
Received 13 September 2024; Received in revised form 6 May 2026; Accepted 6 July 2026
Available online 13 July 2026

information in their mind, integrating it to form a judgement and formulating a response (Tourangeau et al., 2000).

Engagement is conceptualised as having temporal dimensions (Li et al., 2018). Individuals tend to perceive their job - answering a survey - as an ongoing narrative rather than a discrete instance (Hernandez and Guarana, 2016; Shipp and Jansen, 2011). Whereas previous research has proposed different scales to measure respondents' engagement (O'Brien and Toms, 2010; Webster and Ho, 1997), self-reported measures are not objective and require additional questions, generating a more extended survey and higher response fatigue. Moreover, such measures cannot capture the temporal dimension of engagement and the changes in its valence. Respondents can switch between positive and negative engagement during the survey completion, so the survey engagement valence can vary over time (Li et al., 2018).

In low-involvement products, such as food products (Mohr and Kühl, 2021), respondents may have limited motivation to invest cognitive effort in the questionnaire, which increases the risk of survey satisficing—i.e., giving "good enough" answers rather than carefully optimising each response. As Krosnick (1991) puts it, "when optimally answering a survey question would require substantial cognitive effort, some respondents simply provide a satisfactory answer instead" (p. 213). This low-motivation mode can show up as low engagement or attentiveness (Read et al., 2021) and as shortcuts such as speeding, straightlining/nondifferentiation, choosing the first acceptable option, or selecting "don't know" (Zhang et al., 2014), which can add noise to stated-choice estimates.

While most studies have focused on the positive side of engagement (Brodie et al., 2019; O'Brien and Toms, 2010), limited scholarly attention has been given to the "dark" side of engagement (Rosado-Pinto and Loureiro, 2020). Positive engagement typically involves behaviours such as attention, approaching and retaining interest (Li et al., 2018). Such behaviours are enhanced by tasks requiring lower cognitive complexity levels, increasing the user's performance in completing a task (Reychav and Wu, 2016). On the other hand, lower engagement, or disengagement, is characterised by withdrawal, avoidance and refusal (Li et al., 2018). These behaviours are accentuated by task complexity, which decreases user's interaction and participation, placing a psychological burden on participants and influencing their disengagement (Zhang et al., 2020). Therefore, while positive survey engagement and easier tasks lead respondents to be more cognitively, emotionally, and behaviorally invested in the survey, resulting in higher-quality data, lower engagement and more complex tasks can lead to refusal and strategic time-saving behaviours, where respondents aim to complete the task as quickly as possible without much thought.

Measuring survey engagement is challenging. Previous research has proposed using response time as a proxy for respondents' cognitive effort and engagement, as longer response times indicate that processing is ongoing (Börjesson and Fosgerau, 2015; Rose and Black, 2006). This approach seems especially useful as respondents' incentives to participate in online studies are frequently directly linked to the time required to complete the surveys (Campbell et al., 2016). However, while previous studies have incorporated response time for the entire survey or the whole choice experiment (Hess and Stathopoulos, 2013), this approach still presents a key limitation, as it ignores the individual time taken in each choice task and any prior informative tasks. It does not consider the temporal context of survey engagement, which is particularly concerning as temporal perceptions can significantly influence the attentional process (Hernandez and Guarana, 2016).

Distinguishing the engagement – and the time taken-in the initial informative tasks from the engagement in the development of subsequent choice tasks is the fundamental novelty of this paper. Engagement can vary across tasks, meaning that pre-experiment engagement and in-experiment engagement capture distinct phases of the respondents' engagement process (Newton et al., 2019). Different cognitive processes drive these phases. Pre-engagement reflects information acquisition, interest and comprehension of the task, while engagement during the experiment reflects deliberation, consideration of alternatives, and decision-making.

In the stages before the experiment, the respondents become informed and familiar with the choice scenario (the context, the choice task, the attributes and levels), as well as the concept of choice-making (Pearce et al., 2020). This stage is fundamental, as a limited understanding of the subsequent tasks can lead to biases that affect the consistency of choices (Genie et al., 2024). In fact, initial engagement can also influence subsequent task engagement, although it is not guaranteed that initial positive engagement will automatically lead to greater engagement in the subsequent tasks. There is a second, simultaneous mechanism, cognitive load, which might mitigate the initial positive engagement (Newton et al., 2019). As high engagement reflects deep thinking, it may make the transition to the subsequent task more difficult or result in a higher cognitive burden for the respondent in the longer term. Over time, respondents' attention to and engagement with the survey may decrease. This decline tends to be more pronounced in repetitive tasks (Langner and Eickhoff, 2013). Therefore, engagement at the initial stages might differ from engagement during the choice tasks, and both may have different effects on the consistency or randomness of choices.

Given the temporal context of survey engagement, it is also important to consider the order in which each choice task is displayed to a respondent. Previous research suggests that respondents exhibit relatively unstable preferences over the sequence of choice tasks (Nguyen et al., 2021). According to Swait and Adamowicz (2001), for a number of tasks, a respondent will learn about the task and the necessary effort they require; then, the application of the learned behaviour will be implemented during another number of tasks to finally succumb to fatigue and boredom, leading to the use of heuristics. For these reasons, it is important to consider the order in which each choice task was displayed.

Moreover, different choice tasks might vary in easiness or complexity, requiring less or more time. In fact, previous research has shown a positive relationship between decision time and the number of attributes (Jacoby et al., 1974) – more attributes to process will require more time. In this sense, task complexity is defined as the degree of difficulty in processing information in a decision-making situation (Ursic and Helgeson, 1990). However, the difficulty in processing information depends not only on the quantity of information but also on its structure – for example, the variability of attributes within and across alternatives (DeShazo and Fermo, 2002). The same logic applies to easiness. Tasks with dominant alternatives or with alternatives that share similar features, will be easier to compare (Shubatt et al., 2024). However, these measures alone do not include information on respondents' preferences. Alternatives that are perceived as similar in terms of desirability will increase choice difficulty (Best and Ursic, 1987), while alternatives perceived as clearly superior will increase choice easiness (Shubatt et al., 2024). Therefore, including respondent preferences is key to constructing a meaningful measure of complexity and easiness (Swait and Adamowicz, 2001).

While using the time for each task as a proxy for engagement -while controlling for order and complexity-might overcome some of the recently presented limitations, it remains the fact that even researcher-captured proxies can lead to endogeneity bias, as either type of indicator is not a measure of engagement but a function thereof (Hess and Stathopoulos, 2013).

The current study provides a robust modelling framework for researchers focused on analysing scale heterogeneity in respondents' choices within online DCE. Although the link between response time and data quality might seem obvious, several methodological concerns arise when incorporating such measures without generating endogeneity bias (Hess and Stathopoulos, 2013). Our contribution is to propose an approach that includes the effects of consumers' survey engagement in DCE estimations while jointly addressing several methodological issues. First, following Hess and Stathopoulos (2013), we implemented hybrid model structures (Ben-Akiva et al., 2002) in which respondents' level of engagement is treated as two separate latent variables to capture the temporal context of engagement and address the endogeneity bias. In this case, one latent variables represents engagement before the choice tasks and the second one during the choice tasks. Second, we implement two additional hybrid models to account for engagement, with task easiness and complexity specified linearly and quadratically, in order to study potential nonlinear effects on engagement. Third, we include a personalised measure of task complexity and easiness for each choice task and respondent based on their individual preferences. Fourth, all latent variables representing engagement during the choice tasks are specified, taking into account each respondent's response time for each choice task and the order in which the choice tasks were presented.

The remainder of this paper is organised as follows. The next section presents the methodology, followed by the empirical results section and their discussion. The final section summarises the key findings of the paper.

2. Survey work

The survey was launched in September 2020 across 11 countries: Denmark, France, Germany, Hungary, Italy, Latvia, the Netherlands, Slovenia, Spain, Switzerland and the United Kingdom. The respondents were selected by a third party (Cint International) using a quota sampling approach by age and occupation by gender. Quotas were defined according to the population distribution between 18 and 64 years old in each country (Eurostat, 2018). All participants provided informed consent before taking part in the study.

Selected respondents were fully or partly responsible for their household grocery shopping, consciously bought organic food products at least a few times a year and resided in one of the countries under study. The target population included only consumers of the selected product, as survey engagement might be lower by default among non-consumers. Respondents employed in or having a close relative working in food-related industries were excluded, as they might have more knowledge on the topic than an average consumer.

The questionnaire was developed in English, translated into the relevant national languages, and uploaded to the Qualtrics platform. The questionnaire included a hypothetical choice experiment. Incomplete and low-quality responses were dropped (i.e., those that did not pass attention checks – instructed response and straightlining), with a final dataset of 2 366 responses obtained.

The selected product was tomato puree, as it is widely consumed and available in all 11 countries in the study (Xue et al., 2021). Moreover, demand for it is expected to grow in the EU (European Comission, 2017). The product attributes were selected from previous literature (Bernard et al., 2009; Edenbrandt, 2018; Mandolesi et al., 2022): seed type, natural vitamin C content, origin, and price (Table 1).

Non-hybrid seeds refer to a crop variety that is allowed to inter-pollinate freely through natural mechanisms (e.g., wind, insects, animals, and other natural means) (FAO, 2016), in accordance with the cycles and ecological balance of Nature (IFOAM, 2020). Moreover, farmers can save open-pollinated seeds for use in subsequent seasons, as the characteristics of the crop variety will remain relatively stable (Fajardo Vizcayno et al., 2014). On the other hand, hybrid seeds are produced by cross-pollination of unlike parents to

Table 1
Attribute levels.

Attribute	Level
Seed type	Non-hybrid seeds (NH) Hybrid seeds (H) New genomic techniques seeds (NGT)[a]
Vitamin-C natural content label	+ vitamin C No label
Origin	National EU Out of EU[a]
Price	−50% of average price −25% of average price +25% of average price +50% of average price

[a] Reference category.

combine the best traits of each chosen variety, resulting in more robust, more resistant plants with higher yields (FAO, 2016). However, this means that farmers cannot use seeds from a hybrid plant the next season to produce the same crop (Osman et al., 2008). New Genomic techniques (NGTs) are a set of methods -such as CRISPR-based gene editing-that enable the development of new plant varieties and seeds with desired traits by making targeted changes to the plant's genome, often without introducing DNA from unrelated species (Lusser et al., 2011; Madre and Agostino, 2017).

Regarding price, respondents were asked to report the price they usually pay for a 500-g bottle of organic tomato puree. The prices were requested and were expressed in the local currency. If the respondent was unaware of the price, the survey provided a mean price averaged across the main outlets (e.g., supermarkets, online) and across diverse quality levels (e.g., premium vs discounted).

Respondents were presented with 12 choice sets of two alternatives of tomato puree in a bottle of 500 g and an opt-out. Using the Ngene software, a fractional design based on priors from a pilot survey was obtained through a D-efficient approach (D-error = 0.57). The choice tasks and the alternatives were shown randomly to avoid ordering effects. The time and order in which each respondent went through each choice task were accounted for.

Before the choice experiment, the participants were provided with three introductory screens. The first one introduced the choice experiment and presented a table describing all available attributes and levels (Table 1). The second screen included an example of how the choice task would look (Fig. 1) with a "cheap talk" to reduce the hypothetical bias (Carlsson et al., 2005; Cummings and Taylor, 1999). The third screen included information about the key aspects that differentiate the different types of seeds and their labels in the choice experiment. The time each respondent spent on each of these screens was also measured.

3. Methodology

In the present paper, we adopt the approach presented by Hess and Stathopoulos (2013) to investigate respondents' survey engagement/disengagement impact on scale heterogeneity, implementing three hybrid model structures (Ben-Akiva et al., 2002). This section presents the econometric approach and the model specification.

3.1. Econometric approach

The hybrid model expands the discrete choice framework by including explicit modelling of latent factors that are usually difficult to measure on population heterogeneity, providing a richer behavioural representation of the choice process while improving the model's explanatory power (Ben-Akiva et al., 2002). This means that reasonably measurable characteristics (such as sociodemographics) can be combined with characteristics that are more difficult to measure (for example, psychological indicators).

The hybrid model includes a discrete choice structure and a latent variable model. Each of them consists of structural and measurement components (Márquez et al., 2020). While structural components explain utility functions and latent variables in terms of observable variables, the measurement equations link the latent variables to their indicators (Mariel et al., 2015).

The discrete choice model structure is based on the random utility theory (McFadden, 1974), in which its structural components explain typical utility functions in terms of observable attributes. In this case, the utility for respondent n of an alternative j is:

$$U_{nj} = V_{nj} + \varepsilon_{nj} \tag{1}$$

where ε_{nj} is a random variable following an extreme value distribution and V_{nj} depends on the scale parameter for respondent n (θ_n), the attributes (X_{nj}) and a vector of estimated attribute parameters β_n' that vary between individuals:.

$$V_{nj} = \theta_n \beta_n' X_{nj} \tag{2}$$

Following Hess and Stathopoulos (2013), we hypothesise that scale varies among respondents as a function of their engagement. The present paper includes two latent variables (α_{1n}, α_{2n}). The latent variables are defined in the structural models by measurable

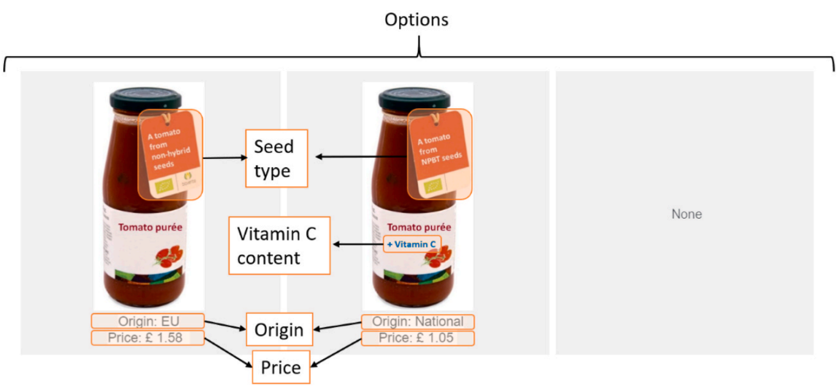

Fig. 1. Example of a choice.

sociodemographic characteristics (Schmid and Axhausen, 2019), which are specified as:

$$\alpha_{ln} = l(z_{ln}, \Upsilon_l) + \eta_{ln} \tag{3}$$

where $l(z_{ln}, \Upsilon_l)$ represents the deterministic part of the latent variable α_{ln}, in which $l = 1, 2$. Specifically, z_{ln} is a vector of sociodemographic variables of respondent n for the latent variable l, while Υ_l is the vector of estimated parameters for each latent variable. The random component of the latent variables is specified to follow a normal distribution, i.e. $\eta_l \sim N(0,1)$.

Then, we specify V_{nj} in the utility function in Eq. (1) as:

$$V_{nj} = e^{\left(\tau_1 \alpha_{1n} + \tau_2 \alpha_{2n}\right)} \beta_n' X_{nj} \tag{4}$$

That is, we define $\theta_n = e^{(\tau_1 \alpha_{1n} + \tau_2 \alpha_{2n})}$, where τ_l is a vector of parameters that explain the impact of the latent variable α_{ln} on the scale of utility.

The final component of the model is determined by the measurement equations for the indicator variables. A set of indicator measures assumed to be determined by the latent variable is used to approximate the latent variable (Grilli and Notaro, 2019). The set of measurement equations links the latent variable to the indicator (Mariel et al., 2015). The aim is to explain the observed variables for I_{lkn} based on α_{ln} (Hess and Stathopoulos, 2013). Therefore, the kth indicator for respondent n is defined as:

$$I_{lkn} = m\left(\alpha_{ln}, \zeta_{I_{l_k}}\right) + \nu_n \tag{5}$$

where the indicator I_{lkn} is a function of the latent variable α_{ln} and a vector of parameters $\zeta_{I_{l_k}}$. The specification of the error term ν_n determines the behaviour of the measurement model and depends on the assumptions regarding the indicators.

While indicators can be specified as continuous or ordered responses, in the present paper, we include only continuous indicators in the hybrid model. In this case:

$$I_{lkn} = \delta_{I_{l_k}} + \zeta_{I_{l_k}} * \alpha_{ln} + \nu_{kn} \tag{6}$$

where $\delta_{I_{l_k}}$ is a constant for the kth indicator, $\zeta_{I_{l_k}}$ is the estimated effect of the latent variable α_{ln} on this indicator and ν_{kn} is a normally distributed disturbance with a mean of zero and a standard deviation of $\sigma_{I_{l_k}}$. By centring the indicator on zero, there is no need to estimate $\delta_{I_{l_k}}$:

$$I_{kn}^{*} = I_{kn} - \overline{I_{kn}} \tag{7}$$

where $\overline{I_{kn}}$ is the indicators' mean. Then, using a normal density, we estimate $\sigma_{I_{l_k}}$ and $\zeta_{I_{l_k}}$.

Based on the assumption that the latent variable influences the value of indicators and the choice process, both are modelled together. Thus, there is a full integration of the choice model with the latent variable. Moreover, this approach overcomes the bias of directly incorporating the indicators into the utility function (Hess and Stathopoulos, 2013).

The log-likelihood (LL) function is composed of the likelihood of the observed sequence of choices (y_n) for respondent n and the likelihood of observed indicators. Thus, in combination, the LL function is integrated over the distribution of the random component in the latent variable (η) and the randomly distributed vector of taste coefficients (β_n):

$$LL\left(\Omega, \Upsilon_l, \tau_l, \zeta_{I_l}, \sigma_{I_l}\right) = \sum_{n=1}^{N} \ln \int_{\beta} \int_{\eta} L(y_n | \cdot)\, L\left(I_{l_n} | \cdot\right) g(\eta)\, m(\beta | \Omega)\, d\beta d\eta \tag{8}$$

with $\beta_n \sim m(\beta_n | \Omega)$, where Ω is a vector of parameters to be estimated. Since the integral does not have a closed-form solution, it is approximated through simulation (Vij and Walker, 2016). We used maximum simulated likelihood estimation using 250 MLHS draws.[1]

3.2. Model specification and estimation

In this specific case, the hybrid model framework allows us to describe how survey engagement affects the randomness (or consistency) of choices, treating engagement proxy measures as latent dependent variables rather than explanatory variables. This is an important step, as survey engagement proxies may present a correlation with other unobserved effects, leading to endogeneity bias (Hess and Stathopoulos, 2013).

Three hybrid models were estimated. In each, all model components were estimated simultaneously using the Apollo package (Hess and Palma, 2019) in R. While model specification details will be presented in the following sections, we introduce the three models and their main differences here. The structure of the first model is introduced in Fig. 2 and is considered the base model. Rectangles represent the observable components of the model, while the ellipses represent the unobservable (latent) components. Specifically, α_{1n} represented the engagement before the choice task and α_{2n} referred to the engagement during the choice task. ρ_l represents the

[1] Higher number of draws was not possible to estimate given the 28.392 choices, the number of random variables and the accessible RAM.

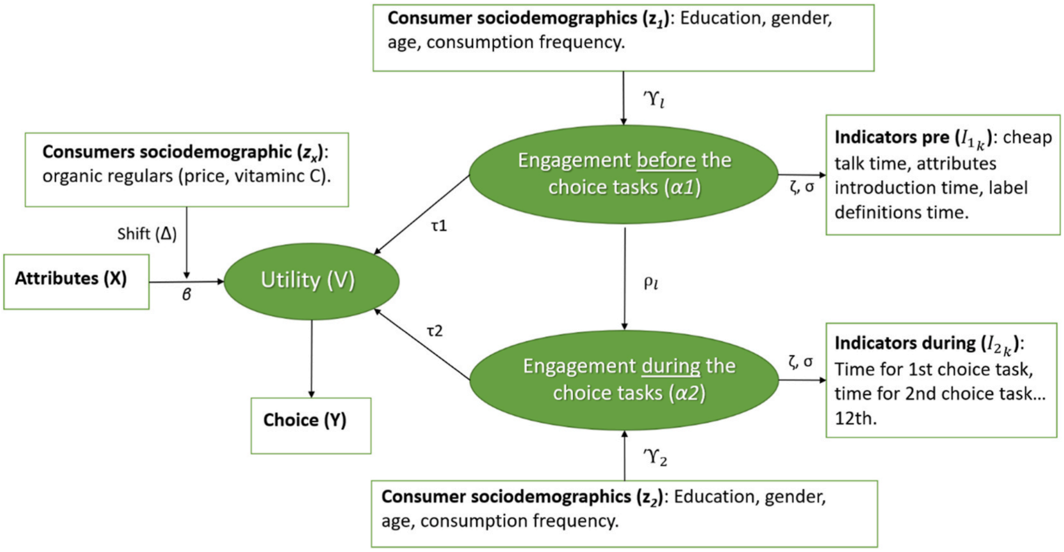

Fig. 2. Base model graphical representation.

influence of the engagement before the choice task on the engagement during the choice task.

Consumers' sociodemographic characteristics affect both consumers' survey engagement latent variables (α_{1n}, α_{2n}) and the utility function (V). Utility is a function of observed attributes X_n. A latent engagement factor (captured by α_{1n}, α_{2n}) rescales utility, and the latent factor also explains the indicators I_{1kn} and I_{2kn}.

The second model (Fig. 3) is based on the first model, with the addition of including the ease of completing each choice task for each respondent as an explanatory variable in α_{2n}. The ease of completing each choice task was modelled using both linear and quadratic terms to explore the possibility of a non-linear relationship.

In the third model (Fig. 4), as in the previous models, α_{1n} represented the latent engagement before the choice task and α_{2n} refers to the latent engagement during the choice task. Then, instead of including task easiness as an explanatory variable, the third model includes task complexity, as previous research shows that increasing task complexity may induce changes in information processing (Spinks and Mortimer, 2016). Complexity is operationalized following Swait and Adamowicz (2001), including both linear and quadratic terms. The discrete choice model specification was the same for all three models.

3.2.1. Specification of the utility function for choice model

Based on Eqs. (2) and (4), in our specific case, V_{nj} is defined as:

$$V_{nj} = \theta_n {*} \Big(\alpha_{None} + \left(\beta_{Price} + \Delta \text{ Organic }_{Price_n}\right) {*} Price_{nj} + \mu_{\ National_n} {*}\ National_{nj} + \mu_{\ EU_n} {*}\ EU_{nj} + \mu_{\ Non-hybrid_n} {*}\ Non-hybrid_{nj} + \mu_{\ Hybrid_n} {*}\ Hybrid_{nj} + \left(\mu_{Vitamin\ C_n} + \Delta \text{ Organic }_{Vitamin\ C_n}\right) {*}\ Vitamin\ C_{nj}\Big) \tag{9}$$

where α_{None} is the alternative specific constant for the "none" alternative, and Price, Origin, Seeds and Vitamin C, are the choice attributes described in Table 1. The price parameter was assumed to be non-random for simplicity and was entered into the utility function in Euros. The dummy-coded variable $National_{\ nj}$ equals 1 when the tomato puree comes from a national origin and 0 otherwise. The remaining attribute variables were coded following the same logic. The random parameters $\mu_{\ National_n}$, $\mu_{\ EU_n}$, $\mu_{\ Non-hybrid_n}$, $\mu_{\ Hybrid_n}$ and $\mu_{Vitamin\ C_n}$, were assumed to be normally distributed to allow both positive and negative preferences for each attribute, as well as heterogeneity among respondents' marginal utilities.

Two additional sociodemographic interactions were introduced as shifts in the means. Specifically, a shift in the price sensitivity (Δ Organic $_{Price_n}$) and Vitamin C preference (Δ Organic $_{Vitamin\ C_n}$) for regular organic consumers, which are defined as those respondents who buy at least 50% of their food as organic. This decision was made since regular organic consumers might be more willing to pay for organic products than occasional consumers and prefer less processing and more "natural" or "untouched" products than those with any alterations or additives (Aertsens et al., 2009; Mandolesi et al., 2022; Zander et al., 2015; Zanoli and Naspetti, 2002).

3.2.2. Specification of the latent variables

All three hybrid models presented two latent variables. In all three hybrid models, the first latent variable (α_{1n}) corresponded to engagement before the choice experiment, when instructions and key information about the choice experiment were provided to the respondents. The second latent variable (α_{2n}) refers to the respondent's survey engagement during the choice experiment when repetitive tasks are faced.

We carried out an extensive specification search for possible sociodemographic variable interactions for the latent variables. As a

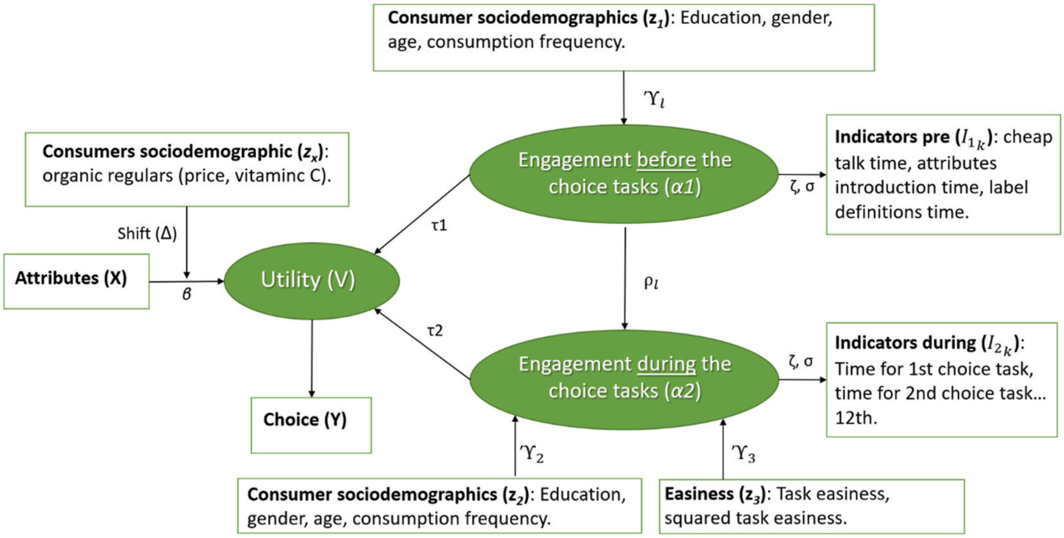

Fig. 3. Second model graphical representation – including ease to complete each c**hoice task**.

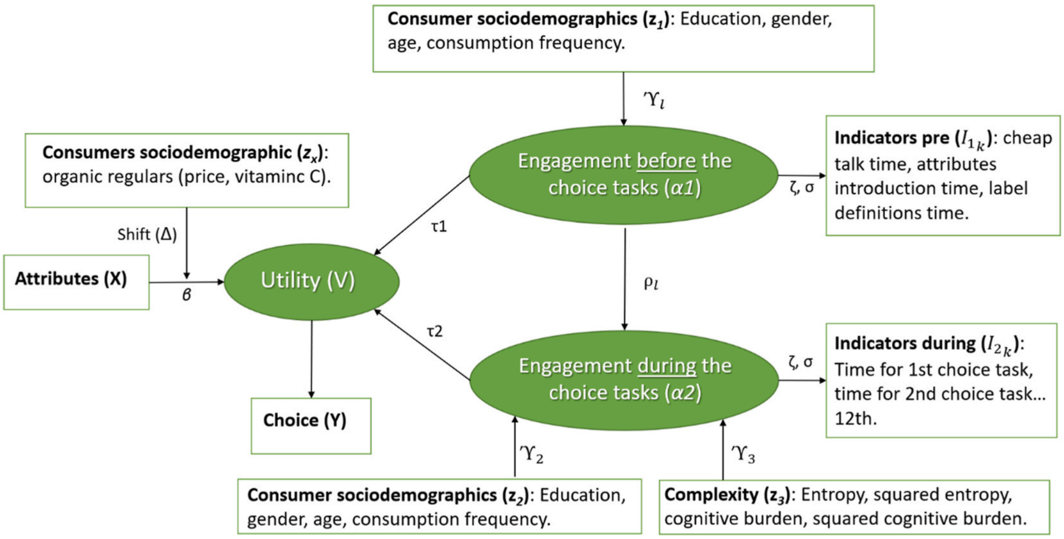

Fig. 4. Third model graphical representation – including task complexity **indicators**.

result, the following sociodemographic variables were included: whether a respondent has a university degree ($\Upsilon_{1_{Education}}$; $\Upsilon_{2_{Education}}$), female gender ($\Upsilon_{1_{Female}}$; $\Upsilon_{2_{Female}}$), age between 18 and 24 years old ($\Upsilon_{1_{Age\ 18-24}}$; $\Upsilon_{2_{Age\ 18-24}}$), age between 25 and 34 years old ($\Upsilon_{1_{Age\ 25-34}}$; $\Upsilon_{2_{Age\ 25-34}}$), age between 35 and 44 years old ($\Upsilon_{1_{Age\ 35-44}}$; $\Upsilon_{2_{Age\ 35-44}}$) and whether a respondent purchases processed food products ($\Upsilon_{1_{Frequency}}$; $\Upsilon_{2_{Frequency}}$). Additionally, we included the influence of initial engagement (α_{1_n}) on the engagement during the choice task (α_{2_n}) through ρ_l. Therefore, in the base model, the structural equations for each the latent variables are:

$$\alpha_{1_n} = \Upsilon_{1_{Education}} * Education_n + \Upsilon_{1_{Female}} * Female_n + \Upsilon_{1_{Age\ 18-24}} * Age\ 18-24_n + \Upsilon_{1_{Age\ 25-34}} * Age\ 25-34_n + \Upsilon_{1_{Age\ 35-44}} * Age\ 35-44_n + \Upsilon_{1_{Frequency}} * Frequency_n + \eta_1 \tag{10}$$

$$\alpha_{2_n} = \Upsilon_{2_{Education}} * Education_n + \Upsilon_{2_{Female}} * Female_n + \Upsilon_{2_{Age\ 18-24}} * Age\ 18-24_n + \Upsilon_{2_{Age\ 25-34}} * Age\ 25-34_n + \Upsilon_{2_{Age\ 35-44}} * Age\ 35-44_n + \Upsilon_{2_{Frequency}} * Frequency_n + \rho_l * \alpha_{1_n} + \eta_2 \tag{11}$$

3.2.2.1. Inclusion of task easiness as an explanatory variable and its empirical calculation. Although across all models α_{1_n} and α_{2_n}

correspond to the same concept, the specification of α_{2_n} varied between the models. Specifically, in the second model (Fig. 3), a linear and quadratic specification of the ease of performing a task is included as an explanatory variable of α_{2_n}:

$$\alpha_{2_n} = \acute{\Upsilon}_{2_{Education}} * \ Education_n + \acute{\Upsilon}_{2_{Female}} * \ Female_n + \acute{\Upsilon}_{2_{Age\ 18-24}} * Age\ 18 - 24_n + \acute{\Upsilon}_{2_{Age\ 25-34}} * Age\ 25 - 34_n + \acute{\Upsilon}_{2_{Age\ 35-44}} * Age\ 35 - 44_n + \acute{\Upsilon}_{2_{Frequency}} * \ Frequency_n + \rho_l * \alpha_{1_n} + \acute{\Upsilon}_{2_{Ease}} * Ease_{\ n} + \acute{\Upsilon}_{2_{Ease\hat{}2}} * Ease_n^2 + \eta_2 \tag{12}$$

The construct of easiness is based on Shubatt et al. (2024), in which options are easier to compare in two situations: 1) when they are closer to dominance and 2) when they have similar features. The idea behind this is that comparisons of alternatives require aggregating trade-offs across attributes; more similar options will require fewer trade-offs, as the respondent can divert their attention from similar features, making it easier to compare the differences between alternatives (Rubinstein, 1988; Tversky and Edward Russo, 1969). As a result, Shubatt et al. (2024) proposed the ease of comparison as an increasing transformation H of the value dissimilarity ratio:

$$\lambda_{xy} = H\left(\frac{|U(x) - U(y)|}{d(x, y)}\right) \tag{13}$$

where $d(x,y) = \sum_k |\beta_k (x_k - y_k)|$ is the L_1 distance between x and y in value-transformed attribute space, $U(x) = \sum_k \beta_k x_k$, and $U(y) = \sum_k \beta_k y_k$.

In other words, the numerator represents the value difference between the two alternatives, while the denominator is a distance metric measuring their dissimilarity. Note that the utility functions in the numerator include β_k, which is a vector of unknown attribute weights. Several approaches could be used to specify β_k, such as assigning equal weights to all attributes or using priors from other studies. However, implementing equal weights is unrealistic, as not all attributes are valued in the same way. Moreover, using priors from other studies or precedent estimations results in mean values, ignoring respondent's heterogeneity. For this reason, innovating from previous studies, we used the conditionals estimates obtained for each respondent from a mixed logit estimation on the same dataset and assigned to each respondent their correspondent β_k. This approach allows us to approximate the different weights that diverse respondents gave to the different attributes.

3.2.2.2. Inclusion the complexity as an explanatory variable and its empirical calculation. The third model (Fig. 4) includes the same explanatory variables from the base model for α_{1_n}, while for engagement during the choice tasks (α_{2_n}), complexity is also included as a explanatory variable. Following Swait and Adamowicz (2001) and based on information theory (Soofi, 1994; Soofi and Retzer, 2002), task complexity can be approximated through a measure of information content or uncertainty in the decision-making process. Thus, the resulting approximate uncertainty (or entropy) measure, in a C_n set of alternatives i, in the r^{th} replication - or, as in our case, the number of the choice task-is:

$$\widetilde{H^r} = -\sum_{i \in C_n} \widetilde{\pi_i^r}(X^r) \ln\left[\widetilde{\pi_i^r}\ (X^r)\right] \tag{14}$$

where, X^r is a vector of product attributes in each r^{th} choice task and $\widetilde{\pi_i^r}$ is the probability of choice with the following form:

$$\widetilde{\pi_i^r}\ (X) = \frac{\exp(\beta X_i^r)}{\sum_{j = C^r} \exp\left(\beta X_j^r\right)} \tag{15}$$

where β is a vector of unknown attribute weights. Following the same approach for estimating task easiness, we used the conditionals estimates obtained for each respondent from a mixed logit estimation on the same dataset and assigned to each respondent their correspondent β.

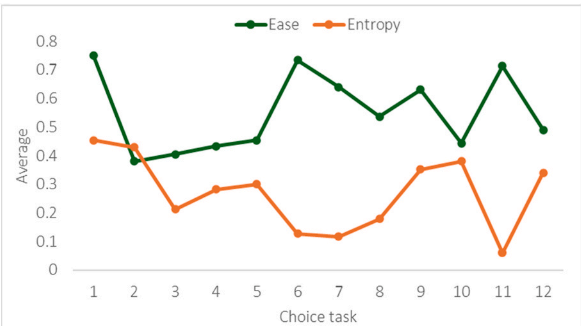

Fig. 5. Average easiness and entropy for each choice task.

The average easiness and entropy per choice task were calculated and presented in Fig. 5. Besides the second choice task, in which both measures are close to 0.5, easiness and entropy mirror each other. When easiness is high (for example, choice task number 6 or 11), entropy is low, and vice versa.

According to Swait and Adamowicz (2001), based on this entropy approximation, it is also possible to define a proxy for cumulative cognitive burden:

$$\widetilde{\psi^r} = \begin{cases} 0 \; for \; r = 1 \\ \sum_{r'=1}^{r-1} \widetilde{H^{r'}} \; for \; r = 2, \ldots, R \end{cases} \tag{16}$$

where r represents the number of the choice task, R is the total number of choice tasks seen by each respondent, and $H^{r'}$ is the entropy of the r^{th} choice task.

Therefore, the structural equation for the second latent variable in the third model specification is:

$$\alpha_{2_n} = \Upsilon_{2_{Education}} * Education_n + \Upsilon_{2_{Female}} * Female_n + \Upsilon_{2_{Age\ 18-24}} * Age\ 18-24_n + \Upsilon_{2_{Age\ 25-34}} * Age\ 25-34_n + \Upsilon_{2_{Age\ 35-44}} * Age\ 35-44_n + \Upsilon_{2_{Frequency}} * Frequency_n + \rho_l * \alpha_{1_n} + \Upsilon_{2_{Entropy}} * \widetilde{H^r}_n + \Upsilon_{2_{Entropy^2}} * \widetilde{H^r}^2_n + \Upsilon_{2_{Cumulative\ cognitive\ burden}} * \widetilde{\psi^r}_n + \Upsilon_{2_{Cumulative\ Cognitive\ Burden^2}} * \widetilde{\psi^r}^2_n + \eta_2 \tag{17}$$

3.2.3. Specification of the measurement model

For the measurement model of the base hybrid structure, three indicators were explained based on α_{1_n}. Each indicator corresponded to the time each respondent took for each of the following tasks before starting the choice tasks: 1) familiarising with the list of attributes, 2) reading the cheap talk and 3) reviewing the definition of the labels included in the choice experiment. The latent variable during the choice tasks (α_{2_n}) is specified considering the time each respondent spent for each choice task, according to the order in which they were displayed.

Following Hess and Stathopoulos (2013), all the time measures were transformed into their natural logarithm to obtain superior performance compared to the not transformed value. The time indicators follow a continuous specification with ζ as the estimated parameter that measures the impact of the latent variable on the time indicators. The random component was specified to follow a normal distribution. This approach allows us to measure the scale heterogeneity simultaneously for all time-related issues and order.

Table 2
Estimation results – for the choice model component (part I).

	Engagement base model		Engagement + Easiness		Engagement + Complexity	
Respondents	2366		2366		2366	
Observed choices	28392		28392		28392	
Log-likelihood (full model)	−53801.2		−53516.30		−53351.57	
Log-likelihood (choice)	−24140.62		−23885.71		−23700.65	
Adjusted Rho2 (choice)	0.226		0.234		0.240	
AIC	107720.4		107154.6		106829.1	
BIC	108060.8		107506.5		107192.6	
Variable	**Estimate**	**Rob.t-ratio**	**Estimate**	**Rob.t-ratio**	**Estimate**	**Rob.t-ratio**
α_{None} [a]	−1.155	−9.889	−1.148	−8.919	−3.060	−7.241
β_{Price}	−0.581	−16.290	−0.588	−12.567	−1.157	−9.542
$\mu_{National}$ [b]	1.141	18.618	1.133	9.364	1.930	12.138
μ_{EU} [b]	0.958	18.122	1.006	10.419	1.667	11.426
$\mu_{Non\text{-}hybrid}$ [c]	0.711	12.385	0.671	7.693	1.157	8.934
μ_{Hybrid} [c]	−0.053	−1.104	−0.018	−0.371	−0.214	−2.083
$\mu_{Vitamin\ C}$	0.496	10.904	0.535	9.470	0.981	8.372
$s_{National}$ [b]	1.426	20.100	−1.389	−9.607	2.699	12.796
s_{EU} [b]	1.107	18.644	1.005	8.920	1.758	9.668
$s_{Non\text{-}hybrid}$ [c]	1.451	20.933	1.360	10.465	2.748	12.948
s_{Hybrid} [c]	−1.326	−20.585	−1.207	−8.780	−2.501	−11.825
$s_{Vitamin\ C}$	−1.257	−22.293	−1.309	−11.519	−2.307	−13.078
$\Delta_{Organic\ Price}$	0.110	2.555	0.124	2.499	0.266	2.229
$\Delta_{Organic\ Vitamin\ C}$	−0.520	−4.539	−0.371	−2.392	−1.089	−4.144
τ_1	0.767	4.540	−9.415	−3.950	17.026	2.859
τ_2	−0.308	−7.732	−0.451	−7.372	−0.508	−8.290
ρ_l	2.087	4.012	−20.806	−3.537	33.489	2.859

[a] Reference category: Alternative constant.
[b] Reference category: Outside Europe.
[c] Reference category: NPBT seeds.

4. Results

The hybrid choice model components and the model fit are presented in Table 2. The first model is considered the base model of engagement. The second model (Engagement + Easiness) builds on the first model, including task easiness as an explanatory variable of the engagement during the choice task. The third model (Engagement + Complexity) also builds on the base model, including a set of proxy measures of complexity as explanatory variables for engagement during the choice task. The likelihood ratio test indicates that the model fit significantly improves when adding easiness (LR(2) = 569.8, $p = 1.86e^{-124}$) or the complexity indicators (LR (4) = 899.26, $p = 2.41e^{-193}$) compared to the engagement base model.

Results from the hybrid choice model components show that most parameters (except the hybrid seeds) were statistically significant for all three models' attributes. As expected, the price coefficient was significant and negative. The national and EU origin coefficients were statistically significant and positive, indicating a clear preference for national and EU origin over non-EU products. The coefficient for non-hybrid seeds was significant and positive, indicating that respondents derived greater utility from non-hybrid seeds than from New Genomic techniques seeds. These results align with previous studies showing that organic consumers are generally against genetically modified products (Andersen et al., 2015; Edenbrandt, 2018).

The hybrid seed type is only significant and negative in the model including complexity, showing that, while in the base model and the one including easiness, respondents are indifferent between hybrid seeds and New Genomic Techniques seeds, when task complexity is included, respondents prefer New Genomic Techniques seeds over hybrid seeds. Such a result might hint that the seed type attribute added complexity to the task, as the preferences for other attributes remain stable. More complex tasks lead to more random choices (Mattmann et al., 2019). So, respondents probably had difficulty distinguishing between the two seed types (hybrid vs. New Genomic techniques), even though their differences were initially introduced. For this reason, in the initial models, there are no significant differences between the two seed types. However, when accounting for task complexity and cognitive burden, the true preferences emerge.

While the preference for New Genomic Techniques seeds over hybrid seeds is a surprising result, the reason might be that hybrid seeds were introduced to the respondents as seeds that cannot be resown. This might have influenced their responses. On one hand, making the distinction between the two seeds types more complex. On the other hand, highlighting the importance for consumers of the organic Fairness principle, given the potential limited access to smaller commercial seed companies and producers, also threatens food security (Adhikari, 2014; Bonina and Cantliffe, 2004). Moreover, previous studies have shown that consumers do not always see the crops from New Genomic Techniques as the worst alternative (Tanaka, 2017), as 'hybrid' appears more "manipulated" than genomic techniques that promise to "mimic naturally occurring processes".

The coefficient for the natural presence of vitamin C was significant and positive. However, the significant standard deviations for all the attributes revealed that the preferences for origin, seed type and vitamin C content varied among respondents.

Looking at the role of sociodemographic variables, regular organic consumers are less sensitive to price (Δ Organic $_{\text{Price}}$) in all three models and present a lower preference for additional Vitamin C (Δ Organic $_{\text{Vitamin C}}$). While previous studies concluded that consumers value additional nutritional content positively (Bernard et al., 2009), especially when labelled as natural, organic consumers are quite attached to naturalness, perceiving it as 'sacred' (Scott et al., 2018; Siegrist et al., 2016). In this view, if Nature is minimally altered, it is seen to be polluted or contaminated. For these consumers, "organic" is linked to the idea of "natural" and "not manipulated" products (Aerni, 2009; Zanoli and Naspetti, 2002).

The parameter τ_1 measures the impact of the latent variable α_1 (initial engagement) on the scalar of the utility function. In the base model and the model including complexity, the estimate is positive and significant at the 1% level, implying that increases in latent engagement before the choice task positively affect the scalar, leading to more consistent choices. However, in the second model specification, including task easiness, τ_1 remains significant but negative. This outcome, combined with the negative parameters of α_1

Table 3
Estimation results – for the structural equation for the latent variable $\boldsymbol{\alpha_1}$ (part II).

Variable	Engagement base model		Engagement + Easiness		Engagement + Complexity	
	Estimate	Rob.t-ratio	Estimate	Rob.t-ratio	Estimate	Rob.t-ratio
$\gamma_{\text{Education Before}}$	−0.032	−0.457	0.064	0.939	−0.082	−1.372
$\gamma_{\text{Gender Before}}$	0.150	2.012	−0.103	−1.488	0.166	2.205
$\gamma_{\text{Age 18-24 Before}}$ [a]	−0.356	−3.221	0.222	2.833	−0.364	−3.823
$\gamma_{\text{Age 25-34 Before}}$ [a]	−0.218	−2.240	0.191	2.094	−0.203	−2.081
$\gamma_{\text{Age 35-44 Before}}$ [a]	−0.121	−1.273	0.164	2.763	−0.272	−3.623
$\gamma_{\text{Frequency Before}}$	0.011	0.117	−0.085	−0.973	0.019	0.249
$\zeta_{\text{Intro-attributes}}$	0.126	5.945	−0.108	−5.368	0.112	5.940
$\zeta_{\text{Intro cheap talk}}$	0.084	4.878	−0.076	−4.489	0.071	4.473
$\zeta_{\text{Intro definitions}}$	0.101	6.041	−0.103	−6.082	0.095	5.719
$\sigma_{\text{Intro-attributes}}$	0.589	25.681	0.592	25.936	0.591	25.895
$\sigma_{\text{Intro cheap talk}}$	0.507	20.710	0.508	20.892	0.508	20.872
$\sigma_{\text{Intro definitions}}$	0.545	27.733	0.545	27.848	0.546	27.725

[a] Reference category: Above 45 years old.

(Table 3), indicate that the estimated orientation of α_1 and its related estimators (τ_1 and ρ_l) in this model is reverse in compared to models 1 and 3. For consistency purposes, we still refer to α_1 as initial engagement, keeping in mind its reverse orientation compared to the other two models. This means that for all models, lower initial engagement is associated with more random choices. Such results are in line with expectations (Hess and Stathopoulos, 2013).

On the other hand, the parameter τ_2 measures the impact of the latent variable α_2 on the scalar of the utility function. The estimate is negative and significant for all models, indicating that increases in engagement during the choice experiment negatively affect the scale of the utility function, making choices more random. While such a result might seem counterintuitive, it is important to consider that, because engagement is measured by the time spent on each choice task, the latent variable might capture not only engagement but also aspects related to uncertainty and cognitive effort, which could lead to more random choices.

The influence of the initial engagement on the engagement during the task (ρ_l) is significant at 1% and positive in the base model and the model including complexity, while negative in the model specification including task easiness. These results indicate that initial engagement can influence engagement during the task. Specifically, in models 1 and 3, higher initial engagement positively influences engagement during the task. In the second model (including task easiness), the negative ρ_l has to be interpreted taking into consideration the reverse orientation of α_1, meaning that lower levels of initial engagement negatively influence engagement during the task.

Table 3 presents the parameters of the structural equation and the measurement component for the latent variable α_1 for all three models. In the base model and the model including complexity, we observed a higher value for survey engagement before the choice tasks for female respondents compared to their male counterparts. Moreover, in all model specifications, younger respondents, between 18 and 34 years old ($\acute{\Upsilon}1_{Age\ 18-24}$, $\acute{\Upsilon}1_{Age\ 25-34}$), presented a lower initial engagement, in this base model, compared to respondents older than 35 years old, while in the second (Engagement + Easiness) and third model (Engagement + Complexity), also respondents between 35 and 44 years old ($\acute{\Upsilon}1_{Age\ 35-44}$) present lower initial engagement compared to respondents above 45 years old.

Table 4
Estimation results – for the structural equation for the latent variable α_2 (part III).

Variable	Engagement base model		Engagement + Easiness		Engagement + Complexity	
	Estimate	Rob.t-ratio	Estimate	Rob.t-ratio	Estimate	Rob.t-ratio
$\gamma_{\text{Education During}}$	0.053	0.499	0.098	0.913	0.048	0.478
$\gamma_{\text{Gender During}}$	0.062	0.580	0.129	1.201	0.041	0.402
$\gamma_{\text{Age 18-24 During}}$ [a]	−0.002	−0.015	−0.155	−0.944	−0.046	−0.306
$\gamma_{\text{Age 25-34 During}}$ [a]	−0.058	−0.414	−0.038	−0.268	−0.061	−0.467
$\gamma_{\text{Age 35-44 During}}$ [a]	−0.158	−1.143	−0.114	−0.845	−0.034	−0.257
$\gamma_{\text{Frequency During}}$	−0.029	−0.262	0.153	1.403	−0.039	−0.378
γ_{Easiness}	-	-	3.587	4.373	-	-
$\gamma_{\text{Easiness squared}}$	-	-	−5.258	−6.121	-	-
γ_{entropy}	-	-	-	-	9.472	9.503
$\gamma_{\text{entropy squared}}$	-	-	-	-	−9.082	−7.677
$\gamma_{\text{Cognitive Burden}}$	-	-	-	-	−0.183	−1.884
$\gamma_{\text{Cognitive Burden squared}}$	-	-	-	-	0.091	3.755
$\zeta_{\text{Time cset1}}$	0.162	4.356	0.018	3.531	0.011	2.917
$\zeta_{\text{Time cset2}}$	0.183	4.403	0.020	3.561	0.012	2.913
$\zeta_{\text{Time cset3}}$	0.204	4.400	0.022	3.536	0.014	2.940
$\zeta_{\text{Time cset4}}$	0.195	4.363	0.022	3.507	0.013	2.958
$\zeta_{\text{Time cset5}}$	0.190	4.425	0.021	3.533	0.013	2.945
$\zeta_{\text{Time cset6}}$	0.196	4.473	0.022	3.520	0.013	2.951
$\zeta_{\text{Time cset7}}$	0.197	4.413	0.022	3.480	0.013	2.934
$\zeta_{\text{Time cset8}}$	0.196	4.326	0.022	3.540	0.013	2.975
$\zeta_{\text{Time cset9}}$	0.208	4.449	0.023	3.524	0.014	2.955
$\zeta_{\text{Time cset10}}$	0.206	4.487	0.022	3.482	0.014	2.946
$\zeta_{\text{Time cset11}}$	0.195	4.397	0.021	3.471	0.013	2.937
$\zeta_{\text{Time cset12}}$	0.197	4.512	0.022	3.464	0.014	2.954
$\sigma_{\text{Time cset1}}$	0.615	27.821	0.612	27.887	0.614	27.999
$\sigma_{\text{Time cset2}}$	0.549	26.584	0.547	26.487	0.548	25.907
$\sigma_{\text{Time cset3}}$	0.514	23.634	0.517	24.146	0.514	23.644
$\sigma_{\text{Time cset4}}$	0.517	24.397	0.516	23.749	0.517	23.425
$\sigma_{\text{Time cset5}}$	0.499	19.244	0.497	19.498	0.499	19.264
$\sigma_{\text{Time cset6}}$	0.486	20.178	0.483	20.510	0.488	20.348
$\sigma_{\text{Time cset7}}$	0.478	23.195	0.477	22.986	0.477	22.894
$\sigma_{\text{Time cset8}}$	0.438	23.806	0.433	24.797	0.438	23.751
$\sigma_{\text{Time cset9}}$	0.548	18.487	0.545	19.037	0.547	18.636
$\sigma_{\text{Time cset10}}$	0.466	27.888	0.471	27.190	0.467	27.654
$\sigma_{\text{Time cset11}}$	0.497	28.834	0.498	28.334	0.496	28.566
$\sigma_{\text{Time cset12}}$	0.513	20.942	0.508	20.398	0.508	21.672

[a] Reference category: Above 45 years old.

Two possible explanations arise for why, in all models younger respondents exhibit lower engagement before starting the choice tasks. On the one hand, younger generations have a shorter attention span (Serbanescu, 2022), paying little attention to instructions or skipping them entirely (Brosnan et al., 2019). On the other hand, as the latent variable indicators are based on the time spent reviewing the information before the choice task, these results might actually indicate that younger people require less time, given their familiarity with online surveys (Wu et al., 2022; Yan and Tourangeau, 2008). Having a university degree ($\Upsilon 1_{Education}$) and consuming frequently processed food products ($\Upsilon 1_{Frequency}$) were not significant in any of the models.

Results from the measurement model for the latent variable α_1 show in all models that increases/decreases in initial engagement are associated with increases/decreases in the time respondents spent in familiarising themselves with the attributes included in the choice experiment ($\zeta 1_{Intro-attributes}$), the "cheap talk" screen with the instructions ($\zeta 1_{Intro-cheap\ talk}$) and reading the definitions of the labels used in the discrete choice experiment ($\zeta 1_{Intro-definitions}$). Meanwhile, the parameters $\sigma 1_{Intro-attributes}, \sigma 1_{Intro-cheap\ talk}, \sigma 1_{Intro-definitions}$ capture the variance of their respective indicators.

Table 4 shows the parameters of the structural equation and the measurement component for the latent variable α_2 (engagement during the choice tasks) for all three models. Neither sociodemographic characteristic was significant in any of the models. However, the proxies included in the Easiness and Complexity model were highly significant and present interesting results.

Regarding the second model with the easiness indicators, the results indicate that easier tasks generate more engagement during the choice experiment ($\zeta 2_{Easiness}$). However, the relationship between engagement and task easiness is not linear. As the task easiness increases, so does the engagement, but only until a certain point, at which too easy tasks decrease the engagement ($\zeta 2_{Easiness\ squared}$) (Fig. 6). While initially such a result might not seem intuitive, it is important to remember that choice tasks are repetitive tasks, which, according to previous research, tend to lead to less engagement when their complexity is low or too cognitively demanding (Langner and Eickhoff, 2013).

Concerning the third model and the complexity indicators, the results indicate two distinct yet simultaneous processes. On one hand, tasks with higher levels of information entropy (uncertainty) increase the latent engagement during the choice tasks ($\zeta 2_{Entropy}$). However, also in this case, the relationship between latent engagement and entropy is not linear. Higher levels of information entropy might actually lead to a decrease in the engagement($\zeta 2_{Entropy\ squared}$). These results are consistent with Streufert et al. (1967), who concluded that as information load increases, strategic integrated decision-making initially increases until a point, then decreases. In other words, as a task gets more complicated, respondents can become engaged by making trade-offs and evaluating attributes; however, at some point, the greater focus and effort required to perform the task leads to a decrease in their engagement (Fig. 7).

On the other hand, we have cognitive burden ($\zeta 2_{Cognitive\ burden}$), indicating that higher cognitive burden is associated with lower latent engagement. However, as the cognitive burden rises, the engagement increases ($\zeta 2_{Cognitive\ burden\ squared}$). As cognitive burden is operationalized as the cumulative entropy of the tasks, this means that as respondents go through the choice tasks, they accumulate cognitive burden, which will also be associated with higher engagement. While this might initially seem counterintuitive, the result follows the same pattern identified by Streufert et al. (1967) for general unintegrated decision-making, which first decreases and then increases with increasing information load. Such results may indicate that, in the absence of initial knowledge about the task, respondents engage in mental search processes to select appropriate strategies to perform the task, which increases their cognitive burden but decreases their engagement, as cognitive capabilities are focused on the search for these processes (Kalyuga, 2010). However, as respondent moves ahead across the tasks and with the increase in cumulative cognitive burden, respondents explore shifts in their decision-making strategies – potentially relying on heuristics to simplify choices - which leads to a marginal reduction of effort in each task but allows respondents to stay engagement(Czajkowski et al., 2014; Swait and Adamowicz, 2001).

Regarding the measurement model for the latent variable α_2, all models show that increases in latent engagement during the choice tasks are associated with increases in the time taken in each choice task. Moreover, the time estimates for the choice tasks exhibit a steady trend after the third task. The estimates for the first two tasks are lower than the trend of the remaining estimates, indicating that spending more time on the later tasks has a greater impact on consumer engagement compared to spending more time on the initial tasks.

These results partially support the role of ordering effects in which respondents exhibit relatively unstable preferences over the

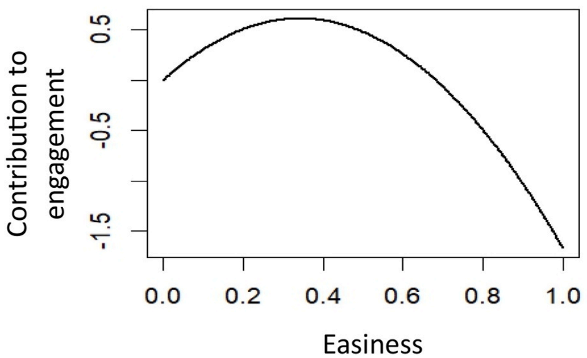

Fig. 6. Non-linear relationship between easiness and engagement during the t**ask choice**.

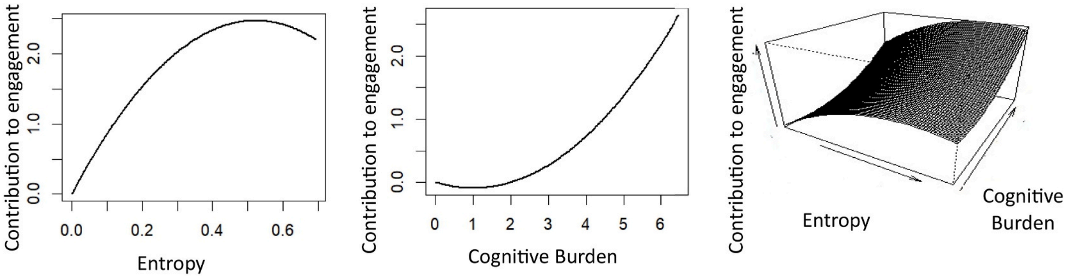

Fig. 7. Non-linear relationship between complexity and engagement during the t*ask choice*.

sequence of choice tasks (Nguyen et al., 2021). Specifically, higher response times for the initial choice sets displayed to any respondent will be associated with learning effects, given that these are the most difficult ones for the respondents (Carlsson et al., 2012; Hess et al., 2012). Then, a respondents understand the task, the time they take to complete it could decrease (Spinks and Mortimer, 2016). However, according to our results, spending more time on the following choice tasks indicates that the respondent is more likely to be engaged in the survey. In this case, time can be perceived as a proxy for cognitive effort (Börger, 2016; Börjesson and Fosgerau, 2015; Yan and Tourangeau, 2008), which means that a respondent invests more time and effort to understand or read and make the necessary trade-offs to achieve their decision, increasing also their engagement.

It is important to highlight that the estimators for the choice task indicators in the second (Easiness) and third (Complexity) models are lower than the same estimators in the base model. Such a result might indicate the key role that task easiness and complexity have on respondents' engagement and choice consistency (Shubatt et al., 2024; Swait and Adamowicz, 2001).

5. Conclusions

The findings of this study offer valuable insights into understanding the role of respondents' engagement in online discrete choice experiments while addressing key limitations in existing approaches. We implement a hybrid modelling framework that incorporates engagement as latent variables, while accounting for valence and temporal aspects of engagement, task order, ease and complexity.

Our results highlight engagement as a dynamic process, which can be distinguished between the phases before and during the choice tasks, as each phase has unique implications for how respondents process information and, subsequently, the consistency of their decisions. Such distinction aligns with previous research (Hernandez and Guarana, 2016; Langner and Eickhoff, 2013; Li et al., 2018) on how engagement fluctuates across different tasks developed over time and the effect of repetitive tasks. Our study extends these findings to the area of online discrete choice experiments and their impact on choice randomness. Specifically, our results show that while higher positive values of latent engagement are associated with taking more time before and during the survey, latent engagement before the choice task has a different effect on the randomness of choices than latent engagement during the task.

Respondents with a more positive value for latent engagement before the survey make more consistent choices and are more likely to take more time to familiarise themselves with the cheap talk and the description of the labels used in the choice experiment. Such results highlight the importance of the introductory section of the discrete choice experiment, indicating that introductory information (e.g., cheap talk) should be clear and concise to avoid overwhelming the respondent. Moreover, when dealing with food choice, because staple food products (even organic) are often relatively low-involvement, respondents may enter the experiment with weaker intrinsic motivation, making engagement management (especially in the introductory materials) particularly important to limit satisficing and preserve decision consistency throughout repeated choice tasks (Krosnick, 1991; Mohr and Kühl, 2021).

Engaged respondents during the choice experiment, on the other hand, make less consistent choices, even if they are also more likely to take more time to complete the choice tasks. Such results were also observed by Fraser et al. (2021), who found evidence of preference instability not necessarily related to low levels of respondents engagement, but uncertainty. In our case, as engagement during the choice task is measured by the time spent on each choice task, the latent variable might capture not only engagement but also aspects related to uncertainty and cognitive effort. Such effect is incorporated into our analysis through the two hybrid model structures that measure task easiness and complexity.

The resulting estimates for task easiness (Shubatt et al., 2024) show that too easy a choice task or too difficult might decrease engagement as well. This means that, during repetitive tasks, respondents need some challenge or might risk losing engagement. However, such challenges should be contained according to the capabilities of the selected respondents, as tasks that are too hard might also generate lower engagement.The same notion is supported by the entropy of information, as too little or too much entropy is also associated with lower engagement.

The incorporation of the complexity measures (Swait and Adamowicz, 2001) allow us to demonstrate that the decision-making processes changes during the development of the choice experiment. Specifically, the estimates related to the cumulative cognitive burden show that, initially, increases in cognitive burden are associated with lower engagement during the survey. When respondents are exposed to the initial tasks, in the absence of knowledge and familiarity with the task, respondents must develop their own metal processes to identify the best strategies to perform the task (Kalyuga, 2010). This process requires high cognitive effort, but direct mental resources to the search of such strategies instead of the choice, initially reducing the engagement. In fact, by separating the full time spent to complete the choice experiment into the time taken to complete the different choice tasks, it is possible to identify that the time taken to complete the initial choice tasks have a lower weight on engagement and the increased randomness of choices, probably linked to the learning effects. As the way decisions are made at this stage might differ from the following tasks, it might be wise to include one or two additional practice choice tasks at the beginning of the choice experiments so that consumers can familiarise themselves with the task without decreasing the data quality.

As respondents progress through choice tasks, they collect more information on the possible trade-offs in each choice task, increasing their engagement. However, due to the perceived higher complexity of choice tasks and accumulated cognitive burden, respondents experience fatigue, which may prompt changes in information processing and decision making (Czajkowski et al., 2014; Spinks and Mortimer, 2016; Swait and Adamowicz, 2001). In order to simplify their choices, respondents switch from strategic integrated decision-making to general unintegrated decision-making – relying on alternative strategies as heuristics (Lee and Lee, 2004; Streufert et al., 1967). While this change allows the respondents to keep engaged with the choice task, moving to more heuristic choices leads to more inconsistent choices (DeShazo and Fermo, 2002; Fraser et al., 2021; Swait and Adamowicz, 2001).

Although these results seem to indicate that higher engagement during the task may lead to more random choices, such outcome should be interpreted with caution. A respondent engagement should not be limited to their investment in the task (Hernandez and Guarana, 2016), but should also take into account additional factors that might influence it, such as the easiness of the task, information entropy and cognitive burden (DeShazo and Fermo, 2002; Swait and Adamowicz, 2001). Moreover, it is important to keep in mind that these factors are specific to each individual, so in our case, they have been integrated into the respondents' preferences through the conditionals of a previously estimated model, allowing us to capture the individual variation in their perception of task easiness and complexity, enhancing the precision of our model. Such results offer novel insights into how task design can influence respondent choices and data quality, especially when dealing with food choices.

Despite the contributions of the present paper, several limitations arise. First, as the response time is measured on a click-by-click basis, there is no way to ensure that the consumer is not exposed to distractions or multitasking when compiling the choice experiment (Zwarun and Hall, 2014). As all response times are included as a continuous variable, it is not possible to warrant respondents who require significantly more time because of being faced with other distractions (Campbell et al., 2018). We believe the study can be extended by including additional controls for response times that are too prolonged, as they might be a sign of less engaged respondents.

Second, although this study includes different national settings, it is important to highlight that it examined only one empirical context: a specific product's food choice. We believe the impact of response time, ordering effects, easiness and complexity introduced in this study should be of wider interest also for other research areas, as well as the separation of engagement before and during the choice tasks. However, there is no certainty that respondents' decision processes won't change among diverse products (Fraser et al., 2021), so future research should inspect various settings and choice contexts. For example, could considering response time have a different effect on models related to transport or health contexts? Health contexts might face more complex decisional processes, for example. Further research is necessary to analyse possible diverse outcomes and address the role of extreme response times, cognitive effort and their effect on the parameter estimates.

CRediT authorship contribution statement

Emilia Cubero Dudinskaya: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing – original draft. **Simona Naspetti:** Validation, Writing – review & editing. **Raffaele Zanoli:** Conceptualization, Formal analysis, Funding acquisition, Supervision, Writing – review & editing.

Funding

The research leading to these results has received funding from the European Union's Horizon 2020 program under grant agreement No 727230 - LIVESEED (https://liveseed.eu/). Responsibility for the information and views set out in this study lies entirely with the authors.

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.2026.100621.

References

Adhikari, J., 2014. Seed sovereignty: analysing the debate on hybrid seeds and GMOs and bringing about sustainability in agricultural development. J. For. Livelihood 12, 33–46.

Aerni, P., 2009. What is sustainable agriculture? Empirical evidence of diverging views in Switzerland and New Zealand. Ecol. Econ. 68, 1872–1882. https://doi.org/10.1016/J.ECOLECON.2008.12.016.

Aertsens, J., Verbeke, W., Mondelaers, K., van Huylenbroeck, G., 2009. Personal determinants of organic food consumption: a review. Br. Food J. 111, 1140–1167. https://doi.org/10.1108/00070700910992961.

Andersen, M.M., Landes, X., Xiang, W., Anyshchenko, A., Falhof, J., Østerberg, J.T., Olsen, L.I., Edenbrandt, A.K., Vedel, S.E., Thorsen, B.J., Sandøe, P., Gamborg, C., Kappel, K., Palmgren, M.G., 2015. Feasibility of new Breeding Techniques for organic farming. Trends Plant Sci. 20, 426–434. https://doi.org/10.1016/j.tplants.2015.04.011.

Ben-Akiva, M., Mcfadden, D., Train, K., Walker, J., Bhat, C., Bierlaire, M., Bolduc, D., Boersch-Supan, A., Brownstone, D., Bunch, D.S., Daly, A., De Palma, A., Gopinath, D., Karlstrom, A., Munizaga, M.A., 2002. Hybrid choice models: progress and challenges. Mark. (Lond.) 13 (3 13), 163–175. https://doi.org/10.1023/A:1020254301302, 2002.

Bernard, J.C., Gifford, K., Santora, K., Bernard, D.J., 2009. Willingness to pay for foods with varying production traits and levels of genetically modified content. J. Food Distrib. Res. 40, 1–11. https://doi.org/10.22004/AG.ECON.99780.

Best, R., Ursic, M., 1987. The impact of information load and variability on choice accuracy. Adv. Consum. Res. 14, 106.

Bonina, J., Cantliffe, D.J., 2004. Seed production and seed sources of organic vegetables. In: UF/IFAS Ext. https://doi.org/10.32473/edis-hs227-2004.

Börger, T., 2016. Are fast responses more random? Testing the effect of response time on scale in an online choice experiment. Environ. Resour. Econ. 65, 389–413. https://doi.org/10.1007/S10640-015-9905-1/TABLES/8.

Börjesson, M., Fosgerau, M., 2015. Response time patterns in a stated choice experiment. J. Choice Model. 14, 48–58. https://doi.org/10.1016/J.JOCM.2015.02.001.

Brodie, R.J., Fehrer, J.A., Jaakkola, E., Conduit, J., 2019. Actor engagement in networks: defining the conceptual domain. J. Service Res. https://doi.org/10.1177/1094670519827385.

Brosnan, K., Babakhani, N., Dolnicar, S., 2019. "I know what you're going to ask me" why respondents don't read survey questions. Int. J. Mark. Res. 61, 366–379. https://doi.org/10.1177/1470785318821025. PAGE:STRING:ARTICLE/CHAPTER.

Byun, H., Shin, J., Lee, C.Y., 2018. Using a discrete choice experiment to predict the penetration possibility of environmentally friendly vehicles. Energy 144, 312–321. https://doi.org/10.1016/J.ENERGY.2017.12.035.

Campbell, D., Mørkbak, M.R., Olsen, S.B., 2016. Response time in online stated choice experiments: the non-triviality of identifying fast and slow respondents. J. Environ. Economics Policy. https://doi.org/10.1080/21606544.2016.1167632.

Campbell, D., Mørkbak, M.R., Olsen, S.B., 2018. The link between response time and preference, variance and processing heterogeneity in stated choice experiments. J. Environ. Econ. Manag. 88, 18–34. https://doi.org/10.1016/J.JEEM.2017.10.003.

Carlsson, F., Frykblom, P., Johan Lagerkvist, C., 2005. Using cheap talk as a test of validity in choice experiments. Econ. Lett. 89, 147–152. https://doi.org/10.1016/J.ECONLET.2005.03.010.

Carlsson, F., Mørkbak, M.R., Olsen, S.B., 2012. The first time is the hardest: a test of ordering effects in choice experiments. J. Choice Model. 5, 19–37. https://doi.org/10.1016/S1755-5345(13)70051-4.

Cummings, R.G., Taylor, L.O., 1999. Unbiased value estimates for environmental goods: a cheap talk design for the contingent valuation method. Am. Econ. Rev. 89, 649–665. https://doi.org/10.1257/aer.89.3.649.

Czajkowski, M., Giergiczny, M., Greene, W.H., 2014. Learning and fatigue effects revisited: investigating the effects of accounting for unobservable preference and scale heterogeneity. Land Econ. 90, 324–351. https://doi.org/10.3368/LE.90.2.324.

DeShazo, J.R., Fermo, G., 2002. Designing choice sets for stated preference methods: the effects of complexity on choice consistency. J. Environ. Econ. Manag. 44, 123–143. https://doi.org/10.1006/JEEM.2001.1199.

Edenbrandt, A.K., 2018. Demand for pesticide-free, cisgenic food? Exploring differences between consumers of organic and conventional food. Br. Food J. 120, 1666–1679. https://doi.org/10.1108/BFJ-09-2017-0527.

European Comission, 2017. EU agricultural outlook. For the Agricultural Markets and Income 2017-2030.

Eurostat, 2018. Database on Income and Living Conditions [WWW Document]. URL https://ec.europa.eu/eurostat/web/income-and-living-conditions/data/database (accessed 10.6.20).

Fajardo Vizcayno, J., Hugo, W., Sanz Alvarez, J., 2014. Appropriate Seed Varieties for small-scale Farmers: Key Practices for DRR Implementers. FAO.

FAO, 2016. Seed Security Assessment - a Practitioner's Guide. FAO, Rome.

Fraser, I., Balcombe, K., Williams, L., McSorley, E., 2021. Preference stability in discrete choice experiments. Some evidence using eye-tracking. J. Behav. Exp. Econ. 94, 101753. https://doi.org/10.1016/J.SOCEC.2021.101753.

Genie, M.G., Poudel, N., Paolucci, F., Ngorsuraches, S., 2024. Choice consistency in discrete choice experiments: does numeracy skill matter? Value Health 27, 1594–1604. https://doi.org/10.1016/J.JVAL.2024.07.001.

Grilli, G., Notaro, S., 2019. Exploring the influence of an extended theory of planned behaviour on preferences and willingness to pay for participatory natural resources management. J. Environ. Manag. 232, 902–909. https://doi.org/10.1016/J.JENVMAN.2018.11.103.

Hernandez, M., Guarana, C.L., 2016. An examination of the temporal intricacies of job engagement. https://doi.org/10.1177/0149206315622573.

Hess, S., Hensher, D.A., Daly, A., 2012. Not bored yet – revisiting respondent fatigue in stated choice experiments. Transp. Res. Part A Policy Pract. 46, 626–644. https://doi.org/10.1016/J.TRA.2011.11.008.

Hess, S., Palma, D., 2019. Apollo: a flexible, powerful and customisable freeware package for choice model estimation and application. J. Choice Model. 32, 100170. https://doi.org/10.1016/J.JOCM.2019.100170.

Hess, S., Stathopoulos, A., 2013. Linking response quality to survey engagement: a combined random scale and latent variable approach. J. Choice Model. 7, 1–12. https://doi.org/10.1016/J.JOCM.2013.03.005.

IFOAM, 2020. Principles of Organic Agriculture.

Jacoby, J., Speller, D.E., Kohn, C.A., 1974. Brand choice behavior as a function of information load. https://doi.org/10.1177/002224377401100106.

Kalyuga, S., 2010. Schema Acquisition and Sources of Cognitive Load. Cognitive Load Theory, pp. 48–64. https://doi.org/10.1017/CBO9780511844744.005.

Krosnick, J.A., 1991. Response strategies for coping with the cognitive demands of attitude measures in surveys. Appl. Cogn. Psychol. 5, 213–236. https://doi.org/10.1002/ACP.2350050305;REQUESTEDJOURNAL:JOURNAL:10990720;PAGEGROUP:STRING:PUBLICATION.

Langner, R., Eickhoff, S.B., 2013. Sustaining attention to simple tasks: a meta-analytic review of the neural mechanisms of vigilant attention. Psychol. Bull. 139, 870–900. https://doi.org/10.1037/A0030694.

Lee, B.K., Lee, W.N., 2004. The effect of information overload on consumer choice quality in an on-line environment. Psychol. Market. 21, 159–183. https://doi.org/10.1002/MAR.20000;JOURNAL:JOURNAL:15206793;WGROUP:STRING:PUBLICATION.

Li, L.P., Juric, B., Brodie, R.J., 2018. Actor engagement valence: conceptual foundations, propositions and research directions. J. Serv. Manag. 29, 491–516. https://doi.org/10.1108/JOSM-08-2016-0235.

Lindhjem, H., Navrud, S., 2011. Using internet in stated preference surveys: a review and comparison of survey modes. Inter. Rev. Environ. Res Economics 5, 309–351. https://doi.org/10.1561/101.00000045.

Joint Research Centre, Institute for Health and Consumer Protection, Institute for Prospective Technological Studies, Lusser, M., Parisi, C., Plan, D., Rodríguez-cerezo, E., 2011. New Plant Breeding Techniques: State-Of-The-Art and Prospects for Commercial Development. Publications Office. https://doi.org/10.2791/60346.

Madre, Y., Agostino, V.D., 2017. New Plant-Breeding Techniques: What are we Talking About? [WWW Document]. Farm Europe. URL https://www.farm-europe.eu/travaux/new-plant-breeding-techniques-what-are-we-talking-about/ (accessed 10.5.21).

Malhotra, N., Krosnick, J., Sniderman, P., Stiglitz, J., Schneider, D., Bullock, J., Levendusky, M., Popp, E., 2008. Completion time and response order effects in web surveys. Public Opin. Q. 72, 914–934. https://doi.org/10.1093/POQ/NFN050.

Mandolesi, S., Cubero Dudinskaya, E., Naspetti, S., Solfanelli, F., Zanoli, R., 2022. Freedom of choice - organic consumers' discourses on new plant breeding techniques. Sustainability 14, 8718. https://doi.org/10.3390/SU14148718.

Mariel, P., Meyerhoff, J., Hess, S., 2015. Heterogeneous preferences toward landscape externalities of wind turbines - combining choices and attitudes in a hybrid model. Renew. Sustain. Energy Rev. 41, 647–657. https://doi.org/10.1016/j.rser.2014.08.074.

Mattmann, M., Logar, I., Brouwer, R., 2019. Choice certainty, consistency, and monotonicity in discrete choice experiments. J. Environ. Economics. Policy 8, 109–127. https://doi.org/10.1080/21606544.2018.1515118. REQUESTEDJOURNAL:JOURNAL:TEEP20.

McFadden, D., 1974. Conditional logit analysis of qualitative choice behavior. In: Zarembka, P. (Ed.), Frontiers in Econometrics. Academic Press, New York, NY, NY, pp. 105–142.

Mohr, S., Kühl, R., 2021. Exploring persuasion knowledge in food advertising: an empirical analysis. SN Business & Economics 1 (8 1), 107. https://doi.org/10.1007/S43546-021-00108-Y, 2021.

Márquez, L., Cantillo, V., Arellana, J., 2020. Assessing the influence of indicators' complexity on hybrid discrete choice model estimates. Transportation 47, 373–396. https://doi.org/10.1007/s11116-018-9891-6.

Newton, D.W., LePine, J.A., Kim, J.K., Wellman, N., Bush, J.T., 2019. Taking engagement to task: the nature and functioning of task engagement across transitions. J. Appl. Psychol. 105, 1. https://doi.org/10.1037/APL0000428.

Nguyen, T.C., Le, H.T., Nguyen, H.D., Ngo, M.T., Nguyen, H.Q., 2021. Examining ordering effects and strategic behaviour in a discrete choice experiment. Econ. Anal. Pol. 70, 394–413. https://doi.org/10.1016/J.EAP.2021.03.005.

O'Brien, H.L., Toms, E.G., 2010. The development and evaluation of a survey to measure user engagement. J. Am. Soc. Inf. Sci. Technol. 61, 50–69. https://doi.org/10.1002/ASI.21229.

Osman, A.M., Almekinders, C.J.M., Struik, P.C., Lammerts van Bueren, E.T., 2008. Can conventional breeding programmes provide onion varieties that are suitable for organic farming in the Netherlands? Euphytica 163 (3 163), 511–522. https://doi.org/10.1007/S10681-008-9700-Y, 2008.

Pearce, A., Harrison, M., Watson, V., Street, D.J., Howard, K., Bansback, N., Bryan, S., 2020. Respondent understanding in discrete choice experiments: a scoping review. Patient 14, 17. https://doi.org/10.1007/S40271-020-00467-Y.

Read, B., Wolters, L., Berinsky, A.J., 2021. Racing the clock: using response time as a proxy for attentiveness on self-administered surveys. Polit. Anal. 1–20. https://doi.org/10.1017/PAN.2021.32.

Reychav, I., Wu, D., 2016. The interplay between cognitive task complexity and user interaction in mobile collaborative training. Comput. Hum. Behav. 62, 333–345. https://doi.org/10.1016/J.CHB.2016.04.007.

Rosado-Pinto, F., Loureiro, S.M.C., 2020. The growing complexity of customer engagement: a systematic review. EuroMed J. Bus. 15, 167–203. https://doi.org/10.1108/EMJB-10-2019-0126/FULL/PDF.

Rose, J.M., Black, I.R., 2006. Means matter, but variance matter too: decomposing response latency influences on variance heterogeneity in stated preference experiments. Mark. Lett. 17, 295–310. https://doi.org/10.1007/s11002-006-8632-3.

Rubinstein, A., 1988. Similarity and decision-making under risk (is there a utility theory resolution to the Allais paradox?). J. Econ. Theor. 46, 145–153. https://doi.org/10.1016/0022-0531(88)90154-8.

Schlereth, C., Eckert, C., Skiera, B., 2012. Using discrete choice experiments to estimate willingness-to-pay intervals. Mark. Lett. 23, 761–776. https://doi.org/10.1007/S11002-012-9177-2/TABLES/2.

Schmid, B., Axhausen, K.W., 2019. In-store or online shopping of search and experience goods: a hybrid choice approach. J. Choice Model. 31, 156–180. https://doi.org/10.1016/J.JOCM.2018.03.001.

Schwappach, D.L.B., Strasmann, T.J., 2006. "Quick and dirty numbers"?: the reliability of a stated-preference technique for the measurement of preferences for resource allocation. J. Health Econ. 25, 432–448. https://doi.org/10.1016/J.JHEALECO.2005.08.002.

Scott, S.E., Inbar, Y., Wirz, C.D., Brossard, D., Rozin, P., 2018. An overview of attitudes toward genetically engineered food. Annu. Rev. Nutr. 38, 459–479. https://doi.org/10.1146/annurev-nutr-071715.

Serbanescu, A., 2022. Millennials and the Gen Z in the era of social media. In: Ashlock, M.Z., Atay, A. (Eds.), Social Media, Technology, and New Generations: Digital Millennial Generation and Generation Z. Lexington Books, London, pp. 61–78.

Shipp, A., Jansen, K., 2011. Reinterpreting time in fit theory: crafting and recrafting narratives of fit in medias res. https://doi.org/10.5465/AMR.2009.0077.

Shubatt, C., Yang, J., Coffman, K., Conlon, J., Gabaix, X., Graeber, T., Gonczarowski, Y., Green, J., Laibson, D., Li, S., Natenzon, P., Rao, G., Rees-Jones, A., Shleifer, A., Phd, H., 2024. Tradeoffs and comparison complexity. SSRN Electron. J. https://doi.org/10.2139/ssrn.4694035.

Siegrist, M., Hartmann, C., Sütterlin, B., 2016. Biased perception about gene technology: how perceived naturalness and affect distort benefit perception. Appetite 96, 509–516. https://doi.org/10.1016/J.APPET.2015.10.021.

Soofi, E.S., 1994. Capturing the intangible concept of information. J. Am. Stat. Assoc. 89, 1243–1254. https://doi.org/10.1080/01621459.1994.10476865.

Soofi, E.S., Retzer, J.J., 2002. Information indices: unification and applications. J. Econom. 107, 17–40. https://doi.org/10.1016/S0304-4076(01)00111-7.

Spinks, J., Mortimer, D., 2016. Lost in the crowd? Using eye-tracking to investigate the effect of complexity on attribute non-attendance in discrete choice experiments. BMC Med. Inf. Decis. Making 16 (1 16), 14. https://doi.org/10.1186/S12911-016-0251-1, 2016.

Streufert, S., Driver, M.J., Haun, K.W., 1967. Components of response rate in complex decision-making. J. Exp. Soc. Psychol. 3, 286–295. https://doi.org/10.1016/0022-1031(67)90030-3.

Swait, J., Adamowicz, W., 2001. The influence of task complexity on consumer choice: a latent class model of decision strategy switching. J. Consum. Res. 28, 135–148. https://doi.org/10.1086/321952.

Tanaka, Y., 2017. Major psychological factors affecting acceptance of New Breeding Techniques for crops. J. Int. Food Agribus. Mark. 29, 366–382. https://doi.org/10.1080/08974438.2017.1382417.

Telser, H., Zweifel, P., 2009. Validity of discrete-choice experiments evidence for health risk reduction. https://doi.org/10.1080/00036840500427858.

Tourangeau, R., Rips, L.J., Rasinski, K., 2000. The Psychology of Survey Response. https://doi.org/10.1017/CBO9780511819322.

Tversky, A., Edward Russo, J., 1969. Substitutability and similarity in binary choices. J. Math. Psychol. 6, 1–12. https://doi.org/10.1016/0022-2496(69)90027-3.

Ursic, M.L., Helgeson, J.G., 1990. The impact of choice phase and task complexity on consumer decision making. J. Bus. Res. 21, 69–90. https://doi.org/10.1016/0148-2963(90)90006-Y.

Vij, A., Walker, J.L., 2016. How, when and why integrated choice and latent variable models are latently useful. Transp. Res. Part B Methodol. 90, 192–217. https://doi.org/10.1016/J.TRB.2016.04.021.

Webster, J., Ho, H., 1997. Audience engagement in multimedia presentations. Data Base 28, 63–77. https://doi.org/10.1145/264701.264706.

Wu, M.J., Zhao, K., Fils-Aime, F., 2022. Response rates of online surveys in published research: a meta-analysis. Computers in Human Behavior Reports 7, 100206. https://doi.org/10.1016/J.CHBR.2022.100206.

Xue, L., Cao, Z., Scherhaufer, S., Östergren, K., Cheng, S., Liu, G., 2021. Mapping the EU tomato supply chain from farm to fork for greenhouse gas emission mitigation strategies. J. Ind. Ecol. 25, 377–389. https://doi.org/10.1111/JIEC.13080.

Yan, T., Tourangeau, R., 2008. Fast times and easy questions: the effects of age, experience and question complexity on web survey response times. Appl. Cogn. Psychol. 22, 51–68. https://doi.org/10.1002/ACP.1331.

Zander, K., Padel, S., Zanoli, R., 2015. EU organic logo and its perception by consumers. Br. Food J. 117, 1506–1526. https://doi.org/10.1108/BFJ-08-2014-0298.

Zanoli, R., Naspetti, S., 2002. Consumer motivations in the purchase of organic food: a means-end approach. Br. Food J. 104, 643–653. https://doi.org/10.1108/00070700210425930.

Zhang, C., Arbor, A., Conrad, F.G., 2014. Speeding in web surveys: The tendency to answer very fast and its association with straightlining. Survey Research Methods 8 (2), 127–135. https://doi.org/10.18148/SRM/2014.V8I2.5453.

Zhang, X., Ding, X. yan, Wang, G. shan, Ma, L., 2020. Investigating the influences of social overload and task complexity on user engagement decrease. Total Qual. Manag. Bus. Excel. 31, 1774–1787. https://doi.org/10.1080/14783363.2018.1509698.

Zwarun, L., Hall, A., 2014. What's going on? Age, distraction, and multitasking during online survey taking. Comput. Hum. Behav. 41, 236–244. https://doi.org/10.1016/J.CHB.2014.09.041.