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Can decision field theory enhance our understanding of health-based choices? Evidence from risky health behaviors

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Abstract

Discrete choice models are almost exclusively estimated assuming random utility maximization (RUM) is the decision rule applied by individuals. Recent studies indicate alternative behavioral assumptions may be more appropriate in health. Decision field theory (DFT) is a psychological theory of decision-making, which has shown promise in transport research. This study introduces DFT to health economics, empirically comparing it to RUM and random regret minimization (RRM) in risky health settings, namely tobacco and vaccine choices. Model fit, parameter ratios, choice shares, and elasticities are compared between RUM, RRM and DFT. Test statistics for model differences are derived using bootstrap methods. Decision rule heterogeneity is investigated using latent class models, including novel latent class DFT models. Tobacco and vaccine choice data are better explained with DFT than with RUM or RRM. Parameter ratios, choice shares and elasticities differ significantly between models. Mixed results are found for the presence of decision rule heterogeneity. We conclude that DFT shows promise as a behavioral assumption that underpins the estimation of discrete choice models in health economics. The significant differences demonstrate that care should be taken when choosing a decision rule, but further evidence is needed for generalizability beyond risky health choices.

KEYWORDS

behavioral economics, decision field theory, decision rule heterogeneity, regret minimization, utility maximization

JEL CLASSIFICATION

C35, I12, I18

1 | INTRODUCTION

Discrete choice models are widely applied in health economics, overwhelmingly using stated preference (SP) data generated from discrete choice experiments (DCEs) (de Bekker-Grob, Ryan, & Gerard, 2012; Soekhai, de Bekker-Grob, Ellis, & Vass, 2019). These models provide policy-relevant outputs such as willingness-to-pay (WTP) and have been advocated for by

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several institutions, such as the US Food and Drug Administration, and the UK National Institute for Health and Care Excellence (U.S. Food and Drug Administration, 2016; Vass & Payne, 2017; National Institute for Health and Care Excellence, 2019).

Any choice model requires a behavioral assumption on the underlying decision process. The typical assumption in choice modeling studies using stated preference data (also referred to as DCEs) is random utility maximization (RUM) (Soekhai et al., 2019), due to its basis in economic consumer theory and ease of estimation (Boeri et al., 2013; Soekhai et al., 2019). Random utility maximization has also been used with revealed preference (RP) data (e.g., Buckell et al., 2021; Buckell & Hess, 2019; De Corte et al., 2021). In health sciences, nearly 99% of studies make the RUM assumption.[1] It is unlikely, however, that any single model can perfectly capture the way that different, unique individuals behave - all models are models - and so alternative approaches may expand researchers' understanding of behavior and contribute to policy evidence.

Indeed, previous studies have suggested alternative behavioral assumptions may be more realistic in some health behaviors (Araña, León & Hanemann, 2008, 2008; de Bekker-Grob et al., 2012; Djulbegovic et al., 1999; Ryan et al., 2018; Vass & Payne, 2017). For example, strong emotions are related to deviance from utility maximizing behavior (Araña et al., 2008), which may lead to biased results if RUM is used (Johnson et al., 1997). Further, behavioral heuristics such as satisficing are exhibited by individuals (Erdem et al., 2014; Genie et al., 2021; Swait et al., 2002). These studies show that psychological assumptions may have a substantial influence on decision-making and behavioral models in health economics. If health-based decisions are better described by alternative decision rules, policy evidence generated from DCEs may be improved.

Previous studies introduced random regret minimization (RRM) to health economics (Boeri et al., 2013; Buckell et al., 2021; de Bekker-Grob & Chorus, 2013; de Bekker-Grob, Donkers, Bliemer, Veldwijk, & Swait, 2020; Dennis et al., 2020; Paul et al., 2018; Ryan et al., 2018). These studies indicate that whilst RUM is a good general assumption, allowing for RRM behaviors can offer improved model performance in some cases. In addition, RRM may generate different, policy-relevant explanations of behavior, and may uncover that different individuals are best described by different decision rules (Boeri et al., 2013; Buckell et al., 2021; de Bekker-Grob & Chorus, 2013). Random regret minimization model outputs differed, such as predicted choice shares (Dennis et al., 2020).

This study extends this literature by introducing decision field theory (DFT) (Busemeyer & Townsend, 1993) to health economics as an alternative decision rule, and compares DFT to both RUM and RRM. Studies call for further experimental models in health (de Bekker-Grob & Chorus, 2013), including DFT models (Vass & Payne, 2017). Evidence from behavioral economics and eye-tracking data in health-based DCEs shows the presence of behavioral anomalies and context effects (Ryan et al., 2018), which DFT may better explain (Roe et al., 2001). In transport economics, comparisons showed DFT outperformed RUM and RRM in traditional DCEs (Hancock et al., 2018; Hancock et al., 2021). Thus, in some cases, DFT may better explain health choice behaviors than existing paradigms. It should be noted that should a modeler specifically be using choice models to derive policy and practice relevant measures, such as marginal rates of substitution (MRS) and WTP, then a move toward any model that is not a RUM model is inadvisable. The work in this article is more relevant to an analyst specifically interested in providing a better account of behavior. However, certain key outputs (e.g., elasticities) can be derived, thus DFT is not merely just for model-fitting exercises. If one is willing to sacrifice some of the key benefits of RUM, then a move toward DFT models becomes possible.

In the next section, we set out DFT and motivate our modeling. In Section 3 we describe the data and models. Section 4 presents the results. Section 5 discusses, and Section 6 concludes.

2 | DECISION FIELD THEORY FOR HEALTH ECONOMICS

Decision field theory models (Busemeyer & Townsend, 1993), from the class of sequential sampling models (Busemeyer et al., 2019), are designed as cognitive models of decision making. Decision field theory is based on psychological principles (Busemeyer & Diederich, 2002), and explicitly attempts to capture the choice deliberation process. It is assumed that decision-makers update preferences for alternatives over time. By attending to a single attribute (across alternatives) of the choice task at each moment in time, decision-makers update their previous preferences with an additional "valence" toward each alternative, derived from the set of values for that attribute. Preferences accumulate through repeated updates over time with different attributes. A choice is made when the preference for one of the alternatives reaches an internal preference threshold, or when an external factor is reached, such as a time step limit.

Decision field theory is a probabilistic-dynamic model of decision-making (Busemeyer & Townsend, 1993) in which preferences accumulate over time, unlike RRM and RUM models (probabilistic-static). This model was initially applied to binary decision-making under uncertainty, such as gambles (Townsend & Busemeyer, 1995), and is frequently applied to controlled laboratory settings, such as eye-tracking experiments (e.g., Noguchi & Stewart, 2014), to understand the comparison of alternatives.

Extensions to multi-attribute (Diederich, 1997), and multi-alternative choice scenarios (Roe et al., 2001), allow for further applications.[2] These advances, together with the psychological approaches adopted by DFT, allow cognitive phenomena unexplained by RUM to be modeled (Berkowitsch et al., 2014), such as context effects (similarity, attraction, and compromise) (Roe et al., 2001). Moreover, this allows violations of standard RUM assumptions to be overcome, such as the independence of irrelevant alternatives (IIA) assumption[3] (Berkowitsch et al., 2014). Applications therefore frequently include the study of context effects (e.g., Trueblood et al., 2013), aimed at understanding the cognitive decision-making process in survey tasks.

However, DFT is not frequently used to understand riskless choice (Hancock et al., 2018) or decision-making in discrete choice experiments, despite its flexibility in modeling context effects. Recent applications of DFT have successfully introduced this model to general decision-making tasks, with a larger number of attributes,[4] but maintain a focus on the modeling of psychological context effects, consumer choice behavior, or transport economics.

Some of DFT's advantages are also demonstrated by RRM models, such as the compromise effect (Chorus, 2012b) and relaxation of the IIA assumption (Chorus, 2012a), but DFT models still differ from RRM models. First, due to their dynamic nature. Random regret minimization models are characterized by a *static* valuation of regret. Further, DFT models depart from the mathematical logit framework, while RRM models remain within this framework.

Comparisons of DFT models to traditional decision-making models are limited, partly due to the perceived computational complexity of the model (Otter et al., 2008). In consumer choice, DFT performed well for out-of-sample prediction and when context effects were deliberately introduced, compared to RUM (Berkowitsch et al., 2014). For apartment choice, DFT was also shown to outperform RUM (Cohen et al., 2017).

Recent methodological extensions enable further comparisons of DFT to other decision rules in surveys or DCEs. For example, the derivation of choice probabilities at any response time allows for a finite response time (external threshold) to be estimated. Other extensions include alternative-specific constants (ASCs) and deterministic heterogeneity (Hancock et al., 2018). In a comparison of DFT to RUM and RRM for a DCE of transport mode choice, DFT improved model fit and out-of-sample forecasts (Hancock et al., 2018). Further, a scale-invariant DFT allows for better incorporation of deterministic interactions, and outperformed RUM models (Hancock et al., 2021).

In this study, comparisons are made in the context of risky health behavior. Discrete choice experiments are frequently used to inform risky health behaviors such as tobacco, food choices, or alcohol (Biondi et al., 2019; Pechey et al., 2014; Regmi et al., 2018). Eye-tracking data in health-based DCEs motivates the use of DFT in health, showing the presence of behavioral anomalies and context effects (Ryan et al., 2018). Studies call for the introduction of DFT in health (Vass & Payne, 2017), or highlight the need for alternative decision-making models (de Bekker-Grob et al., 2012). Specifically, Busemeyer et al. (2007) illustrate how complex emotional-cognitive interactions in smoking behavior may allow for DFT to conceptually explain decisions. More generally, studies call for cognitive approaches allowing for context effects or time pressures to enhance choice models in economics (e.g., Otter et al., 2008). Departures from RUM are well-documented in risky health behaviors (Cawley & Ruhm, 2011). Further, modeling non-RUM choice behavior enhanced understanding of choices in tobacco, food choices, and human immunodeficiency virus prevention; and even changed policy recommendations in tobacco (cf. Biondi et al., 2019; Boeri et al., 2013; Buckell et al., 2021; Buckell & Sindelar, 2019). Alternative behavioral models may therefore be especially applicable to risky health choices and may further inform policy or public health interventions.

In addition, studies suggest that individuals apply different decision rules to choice making (decision rule heterogeneity), leading to different models best predicting different behavior (e.g., de Bekker-Grob & Chorus, 2013). Some individuals may minimize regret, for example, while others are more utility-minded (Smith, 1996). de Bekker-Grob & Chorus (2013) apply a hybrid RUM-RRM model, while Boeri et al. (2013) model decision rule heterogeneity based on observed sociodemographic characteristics. Both studies find evidence for improved behavioral understanding, and de Bekker-Grob & Chorus (2013) show improved model fit, but these applications do not allow for simultaneous modeling of multiple decision rules.

To incorporate multiple decision rules or heuristics, studies have previously proposed and implemented latent class models (Chorus, 2010; Hensher et al., 2010). In methodological applications, Hess et al. (2012) show that latent class models may incorporate decision rule heterogeneity, in addition to taste heterogeneity. More recently in health settings, Dennis et al. (2020) allow for a decision rule heterogeneous RUM-RRM model, improving model fit and behavioral understanding. Buckell et al. (2021) take a similar approach using multiple datasets, finding roughly equal proportions of individuals demonstrating RUM and RRM behavior. By introducing DFT to decision rule heterogeneous models, the potential for finding decision rule heterogeneity increases, as does the prospect of improved behavioral understanding.

Therefore, this study aims to empirically compare DFT to RUM and RRM in the context of risky health choices, specifically in tobacco and vaccination. Further, latent class, decision rule heterogeneous models are applied to extend understanding of decision rule heterogeneity in health-based choices.

3 | METHODS

3.1 | Data

This was a secondary analysis of two DCEs. The first is of cigarettes and e-cigarettes conducted in 2017 in the United States (Buckell et al., 2019). Eligible participants were current smokers and recent quitters, aged 18–64, residing in the US. The choice experiment was a best-best DCE, designed using a Bayesian D-optimal design, in which respondents chose their first and second preference out of a six-alternative choice set: two cigarette products, two e-cigarette products, and two opt-outs. For this study, only respondents' first preference was analyzed as methods investigating ranked alternatives were not available for DFT. Respondents made 12 choices each. 2031 participants were recruited online, and were matched to the population on age, gender, and region using data from the 2014 Behavioral Risk Factor Surveillance System, a nationally representative survey collecting data on behavioral risk factors (Centers for Disease Control and Prevention, 2020). Descriptive characteristics are presented in Table 1. Cigarettes and e-cigarettes were described by four attributes selected to represent prices/flavors in the US

TABLE 1 Descriptive characteristics of participants.

Variable	Tobacco data	Vaccine data
Number of participants (*N*)	2031	2147
Sex:		
Female	1101 (54.2%)	810 (37.7%)
Male	930 (45.8%)	1321 (61.5%)
Other		16 (0.7%)
Age (years)	38 (30–52)	55 (27–65)
Age categories:		
Middle-aged	1199 (59.0%)	775 (36.1%)
Older (>=55)	410 (20.2%)	1171 (54.5%)
Young (<=28)	422 (20.8%)	195 (9.1%)
Unknown		6 (0.3%)
Ethnicity:		
African American	182 (9.0%)	
Asian	50 (2.5%)	
Other	41 (2.0%)	
White	1758 (86.6%)	2036 (94.8%)
Non-white		111 (5.2%)
Income	47,577 USD (26,705–75,203)	35,000 GBP (15,000–62,500)
Income unknown		244 (11.4%)
Smoking status:		
Smoker	1038 (51.1%)	
Dual-use	619 (30.5%)	
E-cigarette user	148 (7.3%)	
Recent quitter	226 (11.1%)	
Multiple adults in household		1751 (81.6%)
Chronic health conditions (total)		1 (0–2)

Note: Unless otherwise specified, continuous variables presented as mean (SD) if approximately normally distributed, median (Interquartile range [IQR]) if non-normally distributed and binary or categorical variables presented as *N* (% of total sample). Chronic health conditions (total): asthma, high blood pressure, heart disease, kidney disease, and overweight.

TABLE 2 Attributes and levels used in the tobacco and vaccine discrete choice experiments (DCEs).

Attribute	Product	Levels
Panel A: Tobacco data		
Flavor	Cigarette	Plain tobacco, menthol
	E-cigarette	Plain tobacco, menthol, fruit, sweet
Life years lost by user	Cigarette	10 years
	E-cigarette	2, 5, 10 years, unknown
Nicotine level	Cigarette	Low, medium, high
	E-cigarette	None, low, medium, high
Price	Cigarette	\$4.99, \$7.99, \$10.99, \$13.99
	E-cigarette	\$4.99, \$7.99, \$10.99, \$13.99
Panel B: Vaccine data		
Risk of infection out of 100,000 people	Vaccine(s)	500 (0.5%), 1500 (1.5%), 3000 (3%), 4000 (4%), 5000 (5%)
	No vaccine	7500 (7.5%)
Risk of illness out of 100,000 people, if infected	Vaccine(s)	2000 (2%), 4000 (4%), 6000 (6%), 10,000 (10%), 15,000 (15%)
	No vaccine	20,000 (20%)
Protection duration	Vaccine(s)	5 years, 2 years, 1 year, 6 months, unknown
	No vaccine	-
Risk of mild side effects out of 100,000 people	Vaccine(s)	100 (0.1%), 500 (0.5%), 1000 (1.0%), 5000 (5%), 10,000 (10%)
	No vaccine	-
Risk of severe side effects out of 100,000 people	Vaccine(s)	1 (0.001%), 5 (0.005%), 10 (0.01%), 15 (0.015%), 20 (0.02%)
	No vaccine	-
Population coverage	Vaccine(s)	>80%, 60%, 40%, 20%, <10%
	No vaccine	>80%, 60%, 40%, 20%, <10%
International travel restrictions	Vaccine(s)	No restrictions on international travel
	No vaccine	Restrictions on international travel
Waiting time	Vaccine(s) (free)	2 weeks, 1 month, 2 months, 3 months, 6 months
	No vaccine	-
Cost	Vaccine(s) (paid)	£10, £50, £100, £200, £250, £400
	No vaccine	-

Note: several levels were not available in cigarettes to reflect real-world choices. Panel A: adapted from Buckell et al. (2019), Panel B: adapted from Hess et al. (2022).

market (Table 2A). An additional questionnaire collected sociodemographic data and smoking-related variables (described in detail in Buckell et al., 2019).

The second dataset is from a DCE of COVID-19 vaccination uptake choices in the UK conducted between July and October 2020 (Hess et al., 2022). A sample from the general public comprised 2147 individuals. Respondents were aged between 21 and 75; descriptive statistics are presented in Table 1. A D-efficient design yielded 36 rows in 6 blocks; respondents made 6 choices each. Individuals chose between paid vaccines, free vaccines, and not having a vaccine. Vaccine alternatives were described by risk of infection, risk of illness, risk of mild side effects, risk of severe side effects, duration of protection, population coverage, travel restrictions, waiting time, and cost. The experimental design is presented in Table 2B.

3.2 | Modeling approaches

Random utility maximization, RRM, and DFT modeling approaches are presented below. To account for taste heterogeneity, modeling approaches were compared between base (attribute-only) models, models with deterministic taste heterogeneity, and latent class models.

For tobacco data, models included the health and nicotine attributes (using dummy coding), the price attribute (continuous), and ASCs which were interacted with the flavor attribute to create flavored-product-specific constants (e.g., "menthol cigarettes" or "fruit e-cigarettes") as per previous research (Buckell et al., 2019).

Models with deterministic taste heterogeneity included interactions of sociodemographic covariates and attributes. Alternative-specific constants were interacted with age, sex, ethnicity, and smoking status (Czoli et al., 2016; Hoffman et al., 2016; Zare & Zheng, 2021). The health attribute was interacted with smoking status (Czoli et al., 2016; Shang et al., 2018). Nicotine was interacted with sex and smoking status (Zare et al., 2018), and price and income were interacted (Townsend et al., 1994) to represent the income elasticity of demand δ: $price_i \cdot \left(\frac{income_i}{median(income)}\right)^{\delta}$. Latent class models included two latent classes, with constant-only class allocation.

For vaccine data, all attributes were continuously coded, except for international travel restrictions, which was dummy-coded. A constant was included to account for horizontal position bias (effects-coded). Deterministic heterogeneity by age, gender, comorbidities and household size was examined with interaction terms (Hess et al., 2022). The vaccine cost was interacted with income as above. Latent class models included two latent classes, with constant-only class allocation.[5]

3.2.1 | Random utility maximization

In RUM, individuals were assumed to maximize the anticipated (latent) utility associated with each alternative. Choice probabilities were modeled as (McFadden, 1974):

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt} = \alpha_{ijt} + x'_{ijt}\beta + \varepsilon_{ijt} \tag{1}$$

$$\text{with } p_{ijt} = \frac{e^{V_{ijt}}}{\sum_m e^{V_{imt}}} \text{ assuming } \varepsilon_{ijt} \sim EV\ \ Type - I\ \ iid \tag{2}$$

Here, U_{ijt} represents the utility of decision-maker i, for alternative j, at choice scenario $t = 1, \ldots, T$. Utility comprises a deterministic component, V_{ijt}, and a random component, ε_{ijt}. α_{ijt} represents the ASC, x_{ijt} represents attribute levels and β are estimated parameters. Choice probabilities p_{ijt} were derived (Maddala, 1983), assuming that error term ε is independently and identically distributed (iid) with a Type-I Extreme Value (EV) distribution, representing the probability of alternative j being chosen by individual i in scenario t. The opt-out alternative was specified by its ASC α_j only.

3.2.2 | Random regret minimization

In the RRM model (Chorus, 2010), individuals were assumed to minimize the anticipated (latent) regret associated with each alternative.

For a given alternative, each attribute is compared to other alternatives' attributes. Sub-optimal performance in a chosen alternative/attribute results in regret, and total regret is the summation of regrets over alternatives/attributes:

$$RR_{ijt} = R_{ijt} + \varepsilon_{ijt} \tag{3}$$

$$= \sum_{m \neq j}^{M} \ln\left(1 + \exp\left(\alpha_{imt} - \alpha_{ijt}\right)\right) + \sum_{m \neq j}^{M} \sum_{k=1}^{K} \ln\left(1 + \exp\left(\beta_k\left(x_{imtk} - x_{ijtk}\right)\right)\right) + \varepsilon_{ijt} \tag{4}$$

Here, RR_{ijt} represents the total regret of alternative j, with R_{ijt} representing deterministic regret, and error term $\varepsilon_{ijt,}$ iid Type-I EV distributed, representing random regret. Regret depends on both x_{ijtk}, the value of attribute k in alternative j, and x_{imtk}, the attribute value of alternative m. The ASCs were included following the premises of regret minimization (Chorus, 2012b), because product flavors (or paid/free vaccines) may create anticipated regret, even if incorporated in the constant.[6] Categorical variables were included using dummy coding, but in line with the assumptions of regret minimization (Chorus, 2012b, p. 37).[7]

3.2.3 | Decision field theory

In DFT, each alternative develops a preference value over time, based on its attributes. At each preference-updating step, decision-makers attend to a specific attribute, evaluating each alternative's performance with respect to that attribute. Evaluated outcomes are then added to preferences in a "valence vector" (Roe et al., 2001). Further, preference updates are influenced by a feedback matrix, which controls the strength of competition between alternatives and the memory of preferences at the previous preference-updating step (Hancock et al., 2018).

We used a DFT model with an external threshold and scaling parameters, as set out by Hancock et al. (2021). In an external threshold model, the alternative with the highest preference is chosen after an estimated total number of preference-updating steps.[8] The scale-invariance of this DFT model ensures that the comparison of parameter ratios to other models is valid; ratios of the scaling parameters represent the relative importance (RI) of attributes. For individual i in choice scenario t (omitting i, t subscripts for readability), this is specified as (Hancock et al., 2021):

$$P_\tau = S \cdot P_{\tau-1} + V_\tau \tag{5}$$

$$P_0 = \left[\alpha_1, \ldots, \alpha_j, \ldots, \alpha_J\right]' \tag{6}$$

$$S = I_J - \phi_2 \cdot exp\left(-\phi_1 \cdot D^2\right) \tag{7}$$

$$D_{jm}{}^2 = \sum_{k=1}^{K} (\beta_k \cdot (x_{ijtk} - x_{imtk}))^2 \text{ : entries of } D \tag{8}$$

$$V_\tau = C \cdot M \cdot \mathrm{B} \cdot W_\tau + \varepsilon_\tau, \text{with}\, \varepsilon_{\tau,j} \sim N\left(0, \sigma^2\right) iid \tag{9}$$

Here, P_τ represents the preference vector at preference-updating step τ, of length J (number of alternatives). S represents the preference-updating matrix, defined as the identity matrix of size J (I_J), with a measure of distance D subtracted. This distance matrix is given by the Euclidean distance between alternatives' attribute values x_{ijtk}, multiplied with an attribute importance scaling coefficient β_k, for each attribute k.

At preference-updating step $\tau = 0$, P_0 represents initial preferences toward each alternative, which could include ASCs α, or may be fixed to 0. Instead, an additional attribute ($K + 1$) specifying "attendance to other attributes" may be included to incorporate ASCs (Hancock et al., 2018). In preliminary analyses, the specification of initial preferences P_0 strongly improved model fit, and was used within further models.

V_τ represents the "valence vector", denoting added preferences after deliberation at preference-updating step τ. This was defined as the product of matrix C, a matrix rescaling preferences to total zero,[9] matrix M, containing attribute values for each alternative, and vector W, containing the attention weights for each attribute. This weights vector indicates which single attribute is attended to at each preference-updating step, denoted by a vector of zeroes, with one entry of value one if this attribute is attended to at this step. The single selected attribute for deliberation follows from a uniform draw, where an attribute is selected with probability w_k (weights).

Previous applications of DFT estimated weights w_k for each attribute. Here, these are fixed to $w_k = 1/K \; \forall \, k$, which may be a reasonable assumption in experimental settings, such as DCEs (Hancock et al., 2021). Instead, each attribute value in matrix M is multiplied by scaling factors in matrix B, a diagonal matrix with scaling coefficients β on the diagonal (which results in DFT being scale-invariant, see Hancock et al. (2021)). These parameters operate as a mapping from actual (objective) attribute values to individual preferences (effectively its utility/subjective value), which will depend on the decision-maker. Coefficient β is then comparable (though not equivalent) to marginal utility coefficients in RUM. Hence, scale-invariant DFT is attractive for the comparison of preferences or RI, and allows for the interaction of preferences and sociodemographic variables (Hancock et al., 2021).

Further, ε_τ represents a normally (iid) distributed random error with variance σ^2, fixed to 1 for identification purposes. Preference-updating steps τ range from 0 to T, a finite number of total preference-updating steps, restricted to T $\geq$ 1. A larger T indicates a longer deliberation process with more attributes likely to be considered. A smaller T indicates more random deliberation and heterogeneity in attribute consideration.

Parameters ϕ_1 and ϕ_2 regulate the psychological aspects of decision-making, such as context effects. The similarity effect is controlled by ϕ_1, influencing the level of competition between similar attributes, restricted to be positive ($\phi_1 > 0$). Memory decay is influenced by ϕ_2. A larger ϕ_2 reduces the diagonal elements of S to 0, such that previous preferences are disregarded. For stability of the estimation procedure, ϕ_2 is additionally restricted between 0 and $^1/_J$. Estimated parameters are $\beta, \alpha, \phi_1, \phi_2$ and T.

It should be noted that in both datasets, some attributes were categorical, which are scarcely used in DFT models. Moreover, previous DFT models with categorical attributes (Berkowitsch et al., 2014) differed from the current scale-invariant version. The inclusion of separate DFT attributes for each dummy coded attribute level would result in a large number of additional attributes, attended to randomly following the stochastic process induced by weights vector W. Instead, current model specifications pre-multiply the scaling parameters β and dummy variables, to create a level-specific scaling value (Appendix A). The latter specification may conceptually be closer to the DFT behavioral paradigm, as decision-makers now attend to categorical attributes at each timestep, rather than dummy variables for an attribute level, and was therefore preferred.

In preliminary analyses, psychological parameters either did not have a substantial impact or were not significant, and were excluded from further analyses. Previous DFT applications indicated only a limited value of ϕ parameters in explaining DCE-based decisions, resulting in frequent restrictions of $\phi = 0$ (Hancock et al., 2018).

The estimation of choice probabilities under a DFT model does not rely on the simulation of preference updating steps nor knowledge regarding attribute attendance order. This is because choice probabilities are derived from the expectation and covariance of preference values, P_τ, after τ updating steps (Roe et al., 2001). By expanding Equation (5), Preferences P_τ are defined as:

$$P_\tau = \sum_{r=0}^{\tau-1} S^r V_{\tau-r} + S^\tau P_0 \tag{10}$$

Next, as attribute weights w_k are stationary, and ε_τ normally distributed, W_τ and V_τ are stationary stochastic processes with $E[V_\tau] = \mu = C \cdot M \cdot \mathrm{B} \cdot W$ (Roe et al., 2001), allowing the derivation of $E[P_\tau]$ and $Cov[P_\tau]$.[10] For $E[P_\tau]$, we derive (Hancock et al., 2021):

$$E[P_\tau] = \sum_{r=0}^{\tau-1} S^r \mu + S^\tau P_0 = (I_J - S)^{-1}(I_J - S^\tau)\mu + S^\tau P_0 \tag{11}$$

Further, we denote:

$$Cov[P_\tau] = \Omega_\tau = \sum_{r=0}^{\tau-1} S^r \Phi S^{r\prime} \tag{12}$$

A closed form expression for Ω_τ exists, for which we refer to the derivations in Hancock et al. (2018).

Subsequently, P_τ is multivariate normal distributed, and the probability of alternative j being chosen out of the choice set CS consisting of J alternatives at the final preference updating step T is given by (Hancock et al., 2021):

$$p_j^{DFT} = Prob[P_\mathrm{T}[j] = \max_{m \in CS} P_\mathrm{T}[m]] \;\; \text{(external threshold T)} \tag{13}$$

$$= \int_{\tilde{P}_\mathrm{T}>0} \exp\Big(-\big(\tilde{P}_\mathrm{T} - \Gamma_\mathrm{T}\big)' \Lambda_\mathrm{T}^{-1} \big(\tilde{P}_\mathrm{T} - \Gamma_\mathrm{T}\big)/2\Big) / \big(2\pi |\Lambda_\mathrm{T}|^{0.5}\big) \, d\tilde{P}_\mathrm{T} \tag{14}$$

where $\tilde{P}_\mathrm{T} = [P_\mathrm{T}[j] - P_\mathrm{T}[1], \ldots, P_\mathrm{T}[j] - P_\mathrm{T}[J]]$, $\Gamma_\mathrm{T} = L_j \cdot E[P_\mathrm{T}]$ and $\Lambda_\mathrm{T} = L_j \Omega_\mathrm{T} L_j{}'$, with L_j the matrix constructing differences between the preference of the alternative j and other alternatives, consisting of a column vector of ones in column j and the negative identity matrix of size $J - 1$, such that for $j = 1$:

$$L_1 = \begin{bmatrix} 1 & -1 & 0 & \ldots & 0 \\ 1 & 0 & -1 & \ddots & \vdots \\ 1 & \vdots & \ddots & \ddots & 0 \\ 1 & 0 & \ldots & 0 & -1 \end{bmatrix} \tag{15}$$

3.3 | Comparison of modeling approaches

Modeling approaches were compared in base (attribute-only) models and taste heterogeneous models using log-likelihood, Akaike information criterion (AIC), Bayesian information criterion (BIC) and Vuong non-nested likelihood ratio tests (Hensher et al., 2015; Vuong, 1989). As models were non-nested, the Vuong test indicated the statistical significance of difference in model fit between decision rules (Hensher et al., 2015), with test statistic V defined as (Vuong, 1989):

$$V = \frac{\overline{v}}{\frac{1}{n-1}\left(\sum_i v_i - \overline{v}\right)^2 / \sqrt{n}} \tag{16}$$

$$v_i = log(L)_{i,dr_1} - log(L)_{i,dr_2} \tag{17}$$

where $log(L)_{i,dr_1}$, $log(L)_{i,dr_2}$ are the contributions of individual $i = 1, ..., n$ to the overall log-likelihood of models with decision rule dr. Under the null hypothesis that models are equally close to the "true" model, V has a standard normal distribution. A test statistic of $V \in (-1.96, 1.96)$ does not reject the null, while $V < -1.96 \ (dr_2)$ and $V > 1.96 \ (dr_1)$ provided statistical evidence in favor of either model (Hensher et al., 2015).

A sensitivity analysis investigated the impact of linearity assumptions on covariates. Decision field theory may incorporate non-linear effects in continuous variables to some extent, even if attributes are included continuously, because of its dynamic nature. In contrast, the RUM models applied do not allow for non-linearities in continuous variables. A difference in model fit between DFT and RUM may therefore arise due to non-linear attribute effects, rather than behavioral assumptions. Models were estimated with all covariates categorically coded, or all variables continuously coded where possible. This allowed the investigation of robustness to alternative linearity assumptions. If the difference in model fit between decision rules remained unchanged, behavioral assumptions were more likely to have driven differences. If models performed similarly, non-linearities may have driven initial differences.

3.3.1 | Choice model outputs: Relative importance

We use parameter ratios as a measure of "relative importance", but not as an MRS. Estimates of the MRS cannot be obtained from DFT models. One reason for this is that the trade-offs between attribute values are dependent on the choice task at hand. Preference values for alternative j depend not only on attributes x_{ij}, but also on the other attribute values x_{im} of unchosen alternatives (as is the case for RRM models). The probabilities for a chosen alternative in a DFT model therefore depend on the values of other alternatives' attributes, introducing a choice-set dependency. Parameter ratios must be interpreted conditional on the choices made by the consumer at the individual level. This context dependency prevents the derivation of an MRS that holds for all changes in attribute values. Hence, welfare measures and economic model outputs such as WTP cannot be derived for consumers.

In addition, the random and sequential attribute attendance in DFT models adds a covariance between preference values of different alternatives. A change in one attribute could offset a change of another attribute within an average choice task (trial), but the total preference at the end of deliberation is not always the same. A trade-off occurs in expected valence levels (Equation 9), but cannot be interpreted as an MRS in the overall probability. Instead, we note that the RI estimates must be interpreted as a trade-off over expected valence, and thus also over average attribute attendance. Further detail is provided in Appendix D.

However, as parameter ratios are scale-free and represent inferred RI of attributes across all models (de Bekker-Grob & Chorus, 2013; Hancock et al., 2018), they can be compared. Appendix D sets this out in detail, also giving examples of indifference curves under DFT, RRM and RUM.

Relative importance between price, a direct policy-making instrument, and other attributes were computed. For tobacco, a change in levels was used for categorical attributes. Hence, the RI of life years lost (10 to 2 years) to price, and nicotine (medium to none) to price, respectively, was compared between decision rules, with RI defined as:

$$RI_{dr,i} = \frac{\beta_{dr,i,k}}{\beta_{dr,i,l}} \tag{18}$$

where β represents the parameters of attributes k and l for decision rule dr.

Relative importance was estimated in base models, with standard errors (SEs) and significance tests for RI differences between decision rules presented. Standard errors were derived using bootstrap methods (Efron, 1982). Note that traditional hypothesis tests for equality of parameters (ratios) between non-nested models are non-trivial, as $cov(\beta_{RUM,k}, \beta_{DFT,l})\,\forall\, k, l$ is unknown after estimation. Given the data, model outputs made separately from both decision-making models were likely positively correlated. Bootstrap methods readily account for this correlation structure of RI and were therefore preferred over the more frequently used delta method in this setting. Standard errors were derived using 200 paired bootstrap draws without asymptotic refinement. A block bootstrap at individual level was performed to account for the panel structure of the data. Bootstrapped SEs were presented. Next, two-sided asymptotic hypothesis tests were conducted for the difference in RI between decision rules using bootstrapped SEs. The bootstrap was potentially limited by the low number of draws, but further bootstraps were prevented by the computational intensity of DFT models. This may cause a loss of power (Davidson & MacKinnon, 2000), or non-normality.[11] Tibshirani and Efron (1993) argue that 200 bootstraps are sufficient, while others argue for 348 bootstraps in hypothesis tests at 5%-level to maintain sufficient power (Andrews & Buchinsky, 2000; Cameron & Trivedi, 2005). The distribution of bootstrapped estimates was inspected for stability/normality after 200 draws.

In models with deterministic heterogeneity, bootstrapping could not be performed due to computational complexity. This prevented the derivation of subsequent hypothesis tests. In a sensitivity analysis, RI was derived, but with delta-method SEs (Daly, Hess, & de Jong, 2012). Mean RI $\left(\overline{RI_{dr}} = \frac{1}{n}\sum_{i} RI_{dr,i}\right)$ was compared, as estimates differed over individual decision-makers due to sociodemographic interactions. Estimates were compared to base models to test the robustness of results.

3.3.2 | Choice model outputs: Predicted choice shares

Predicted choice shares were derived in policy scenarios, alongside choice shares at baseline. Predicted choice shares were computed as the sample average of each alternative's probability (e.g., for tobacco data: cigarette, e-cigarette, and opt-out) (Hensher et al., 2015).

In base models, bootstrapped SEs, and subsequent p-values of hypothesis tests for difference between estimates were presented for DFT and RRM, compared to RUM. In a sensitivity analysis, estimates were presented in models with deterministic heterogeneity without hypothesis tests, as before, and compared to base models to assess robustness. Here, SEs were obtained from 200 parameter draws of the estimated multivariate normal distribution (Krinsky & Robb, 1986).

3.3.3 | Choice model outputs: Elasticities

Elasticities were averaged over all scenarios and decision-makers (i.e., sample enumeration). As earlier, elasticities were derived in base models with bootstrapped SEs and hypothesis tests for elasticity difference between decision rules presented, comparing DFT/RRM to RUM. In a sensitivity analysis, elasticities were derived in models with deterministic heterogeneity with simulated SEs (200 Krinsky-Robb draws) and no significance tests.

For the vaccine choice data, elasticities were derived for continuous attributes. As choices were unlabeled, mean direct elasticities were calculated over vaccines A and B (Thiene et al., 2012), as elasticities could not be interpreted separately.

Elasticities could not be derived for categorical attributes in the tobacco choice experiment, as they only hold for small changes. Pseudo-elasticities, defined as the change in probability of an alternative being chosen (under any of the models) following a change in (dummy) attribute levels, were therefore derived for tobacco attributes (Washington et al., 2003):

$$E_{ijt} = \frac{Prob\left[y_{ijt} = 1 | x_{ijkt} = 1\right] - Prob\left[y_{ijt} = 1 | x_{ijkt} = 0\right]}{Prob\left[y_{ijt} = 1 | x_{ijkt} = 0\right]} \tag{19}$$

Hence, $E_{ijt} \cdot 100$ is interpreted as the percentage change in the probability of choosing alternative j, by individual i, when attribute k changes from 0 to 1 in alternative j (direct elasticity). Cross elasticities were similarly derived, but reflect the responsiveness of choice for one alternative, after attribute change in another alternative.

3.4 | Latent class decision field theory: Taste and decision rule heterogeneity

Decision field theory models do not frequently incorporate taste heterogeneity. Previous specifications incorporated deterministic interactions or mixing distributions (Hancock et al., 2018). Here, we extend DFT to a latent class model, which has not previously been applied. The latent class log-likelihood was given by (Greene & Hensher, 2003):

$$LL = \sum_{i=1}^{N} log\left(\sum_{c} \pi_c \cdot LC_i(\Omega_c)\right) \tag{20}$$

$$LC_i(\Omega_c) = \prod_t \prod_j \left(p_{ijt}(\Omega_c)\right)^{y_{ijt}} \tag{21}$$

With $LC_i(\Omega_c)$ representing the likelihood of class c at class-specific parameters Ω_c, where individuals belong to one of C latent classes with probability π_c. y_{ijt} takes the value of one if the alternative was chosen; 0 otherwise. Here, choice probabilities $p_{ijt}(\Omega_c)$ are now constructed using DFT models in each class, with Ω_c representing DFT parameters $\beta_{DFT}, \alpha, \phi_1, \phi_2$ and T as presented above, while further specifications of the log-likelihood remain similar to base DFT models.

Single-decision-rule models imply a "one-size-fits-all" approach: all individuals followed either DFT, RUM or RRM to make decisions. Latent class, decision rule heterogeneous models were applied to allow multiple decision rules simultaneously (Buckell et al., 2021; Hess et al., 2012). In these models, latent classes allow for both taste and decision rule heterogeneity, where decision rule heterogeneity can be established by comparison to a single-rule counterpart (Hancock & Hess, 2021).

Latent class models were presented with multiple and single decision rules, for RUM-RRM, RUM-DFT and DFT-RRM combinations. The log-likelihood was presented, given by (Hancock & Hess, 2021; Hess & Stathopoulos, 2013):

$$LL = \sum_{i=1}^{N} log\left(\sum_{c} \pi_c \cdot LC_{i,dr_c}\left(\Omega_{dr_c}\right)\right) \tag{22}$$

$$LC_{i,dr_c}\left(\Omega_{dr_c}\right) = \prod_t \prod_j \left(p_{ijt,dr_c}\left(\Omega_{dr_c}\right)\right)^{y_{ijt}} \tag{23}$$

where π_c denotes the probability of being in class c, $LC_{i,dr_c}\left(\Omega_{dr_c}\right)$ represents the likelihood within class c with class-specific decision rule dr and class/decision-rule-specific parameters Ω_{dr_c}, and $p_{ijt,dr_c}\left(\Omega_{dr_c}\right)$ the decision-rule-specific probabilities. Decision rule heterogeneous models were compared to the best-performing single-rule counterparts (out of two rules used) to assess the presence of decision rule heterogeneity. Absolute log-likelihood improvement and Vuong tests were presented. To investigate the implications of this model, RI was presented, but derived from latent class models (Appendix B). Estimates of the decision rule heterogeneous model were compared to single-rule models for RUM and DFT.

4 | RESULTS

4.1 | Model fit

Model fits for RUM, RRM and DFT modeling approaches are presented in Table 3. The optimal DFT specification excluded psychological parameters, which were insignificant in initial models (tobacco likelihood-ratio test: $\chi^2(2) = 0.56$, $p = 0.7558$). For brevity, focus is given to parameter estimate comparisons rather than the parameters themselves, but patterns of estimates in all models (detailed in Appendix C) were similar to those in previous research (Buckell et al., 2019; Hess et al., 2022).

Turning to model fit, RUM and RRM performed similarly. For both datasets, RUM was slightly preferred over RRM in base models and models with deterministic heterogeneity. For tobacco, RRM was preferred in latent class models. For vaccines, RUM was preferred. For both datasets, DFT was preferred over other decision rules in all models. In base models, DFT had the best model fit, and with one additional parameter (the preference-updating steps), DFT also achieved the lowest AIC and BIC. In models with preference heterogeneity, the difference in model fit was reduced in both datasets, but DFT was still preferred by AIC and BIC.

Vuong tests indicated DFT improved fit compared to RUM and RRM in base models (additionally, there was evidence to suggest RUM improved model fit compared to RRM). On tobacco data, Vuong tests were inconclusive for comparisons (Table 4A) with deterministic heterogeneity included, suggesting DFT did not improve performance compared to other decision

TABLE 3 Model fit across decision rules: base models, models with preference heterogeneity and latent class models.

Decision rule	Tobacco data RUM	Tobacco data RRM	Tobacco data DFT	Vaccine data RUM	Vaccine data RRM	Vaccine data DFT
Base						
Log-likelihood	−37,198.58	−37,202.78	−37,165.81	−16,782.28	−16,817.19	−16,588.08
AIC	74,423.16	74,431.57	74,359.63	33,598.55	33,660.39	33,204.17
BIC	74,528.47	74,536.88	74,473.04	33,695.58	33,757.42	33,308.66
Free parameters	13	13	14	13	13	14
Deterministic heterogeneity						
Log-likelihood	−35,568.19	−35,574.51	−35,555.41	−16,509.22	−16,543.27	−16,322.68
AIC	71,314.38	71,327.02	71,290.82	33,076.45	33,144.54	32,705.36
BIC	72,035.38	72,048.03	72,019.92	33,292.68	33,360.77	32,929.04
Free parameters	89	89	90	29	29	30
Latent class						
Log-likelihood	−33,240.89	−33,234.17	−33,210.55	−15,308.41	−15,344.00	−15,186.44
AIC	66,535.78	66,522.33	66,479.09	30,670.81	30,742.00	30,430.88
BIC	66,754.51	66,741.07	66,714.03	30,872.33	30,943.52	30,647.32
Free parameters	27	27	29	27	27	29
Individuals	2031			2147		
Observations	24,372			12,882		

Note: deterministic heterogeneity includes a priori selected interactions of attributes and socioeconomic characteristics. Tobacco data: age, sex, ethnicity, smoking status, and income. Vaccine data: age, age^2, sex, income, number of adults in household, and number of chronic illnesses. Latent class models consist of two classes of preference heterogeneity.

Abbreviations: AIC, Akaike information criterion; BIC, Bayesian information criterion.

rules with the inclusion of interactions. In contrast, latent class models did indicate significant differences. Here, there was evidence in favor of DFT compared to RUM ($p = 0.0143$), but not for DFT compared to RRM ($p = 0.1270$). Vuong tests favored DFT over RUM and RRM in all cases for vaccine data ($p < 0.001$) (Table 4B).

In a sensitivity analysis, the impact of alternative linearity assumptions on covariates was investigated (Table 5). A specification with all variables included categorically allowed for non-linearities in all decision-making models (for methodology, see Appendix A). The difference in model fit between DFT and RUM decreased in this specification compared to the main findings. This suggested that non-linear effects, which were better picked up by DFT, may have partly driven the main findings. However, linearity assumptions did not change the direction of results, as DFT was still the preferred decision rule in all specifications.

4.2 | Comparison of model outputs

Beyond model fit, RI was considered (see Appendix D for a discussion of RI measures across decision rules).

For tobacco, the RI of nicotine and life years lost, compared to price, was presented in Table 6 for base models. Behavioral interpretations differed. In RUM models, for life years lost, the ratio implied that a change from 2 to 10 years of life lost may be offset by a 6.701 USD decrease in price to keep utility (and hence choices) constant. In RRM models, this change may create as much potential regret as a 7.064 USD price increase. Finally, in DFT models, the potential preference decrease from a change of 2–10 years of life lost, when considering this attribute, is similar to the potential preference decrease caused by a 5.024 USD price increase when considering price. Although these interpretations differed, comparisons could be made across models. Following the above, compared to RUM, decision-makers appeared to place less importance on life years lost compared to price when using DFT. For nicotine, estimates were more similar, especially between RRM and RUM (0.641 and 0.653, respectively), but were still lower using DFT (0.463). Comparing DFT to RUM, there was strong evidence against equal RI for both life years lost and nicotine ($p < 0.001$ and $p = 0.0447$, respectively).

Relative importance also differed significantly between decision rules in the vaccine choice experiment. In these models, the same reductions in the risk of serious illness were valued equivalently in price by £27.40 for RUM, £27.86 for RRM, and

TABLE 4 Non-nested likelihood-ratio tests for comparison of model fit between decision rules, in base models and models with preference heterogeneity.

	RUM versus RRM	RUM versus DFT	RRM versus DFT
Panel A: Tobacco data			
Base models			
Vuong test statistic	2.226	−3.329	−3.302
p-value	0.0260	<0.001	<0.001
Deterministic heterogeneity			
Vuong test statistic	1.498	−1.076	−1.4677
p-value	0.1341	0.2819	0.1422
Latent class (2-class)			
Vuong test statistic	−0.990	−2.450	−1.525
p-value	0.3224	0.0143	0.1270
Panel B: Vaccine data			
Base models			
Vuong test statistic	9.265	−7.899	−8.650
p-value	<0.001	<0.001	<0.001
Deterministic heterogeneity			
Vuong test statistic	9.057	−6.880	−7.709
p-value	<0.001	<0.001	<0.001
Latent class (2-class)			
Vuong test statistic	9.473	−5.362	−6.513
p-value	<0.001	<0.001	<0.001

Note: for Vuong tests, the first model listed is the reference model. Size of the log-likelihood-difference and Vuong test statistic may not correspond directly, due to scaling with standard deviation. A value $V < -1.96$ represents statistical evidence in favor of the alternative model, while a value of $V > 1.96$ represents evidence in favor of the reference model.

TABLE 5 Model fit (log-likelihood) for alternative treatment of attribute levels, by decision rule.

	Tobacco data			Vaccine data		
	RUM	RRM	DFT	RUM	RRM	DFT
Base models	−37,198.57	−37,202.78	−37,165.81	−16,782.28	−16,817.89	−16,588.08
Categorical coding	−37,167.24	−37,258.89	−37,154.64	−16,485.48	−16,510.91	−16,421.47
Continuous coding	−37,233.43	−37,242.83	−37,187.40	-	-	-

Note: tobacco data: continuous coding applies to nicotine, price and life-years lost attribute. Flavor remains categorical. Continuous nicotine attribute: none = 0 mg/cigarette, low = 0.1 mg/cigarette, medium = 0.3 mg/cigarette, high = 0.6 mg/cigarette, from primary DCE. Vaccine data: categorical coding applied to mild side effects, severe side effects, protection duration, waiting time, fee and population coverage. Risk of infection and illness remain continuous for identification of opt-outs.

TABLE 6 Relative importance (RI) in base models, with bootstrapped standard errors (SEs) and *p*-values for comparison between frameworks.

	RUM		RRM		DFT	
	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value
Panel A: Tobacco data						
Nicotine to price	0.641 (0.360)	-	0.653 (0.370)	0.3620	0.463 (0.295)	0.0447
Life years lost to price	−6.701 (0.573)	-	−7.064 (0.614)	<0.001	−5.024 (0.391)	<0.001
Panel B: Vaccine data						
Risk of serious illness to price	27.401 (1.644)	-	27.864 (1.611)	0.0464	41.707 (3.354)	<0.001
Protection duration to price	−4.624 (0.252)	-	−5.005 (0.270)	<0.001	−6.674 (0.754)	0.0015

Note: Bootstrapped standard errors in parentheses. *p*-values presented under null hypothesis of similar relative importance, compared to RUM. For categorical attributes (tobacco data) ratios are computed using coefficients for medium to no nicotine and 2 to 10 life-years lost.

TABLE 7 Predicted choice shares under policy scenarios in base models, by decision rule, with p-values for comparison between decision rules.

	RUM			RRM			DFT		
Panel A: Tobacco data	**Cigarette**	**E-cigarette**	**Opt-out**	**Cigarette**	**E-cigarette**	**Opt-out**	**Cigarette**	**E-cigarette**	**Opt-out**
Base model	51.1% (0.7751)	35.9% (0.7476)	13.0% (0.4869)	51.1% (0.7759)	35.9% (0.7479)	13.0% (0.4867)	50.9% (0.7722)	36.0% (0.7463)	13.1% (0.4845)
50% price increase, all products	46.6% (0.7845)	35.4% (0.7315)	18.0% (0.6793)	47.1% (0.7764)	35.8% (0.7322)	17.2% (0.6356)	45.2% (0.7776)	34.1% (0.7123)	20.7% (0.7226)
p-values (vs. RUM)	-	-	-	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
50% price increase, cigarettes	41.0% (0.8084)	43.2% (0.8041)	15.8% (0.5892)	41.1% (0.8041)	43.5% (0.8074)	15.4% (0.5745)	41.7% (0.7472)	41.5% (0.7714)	16.9% (0.5831)
p-values (vs. RUM)	-	-	-	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Panel B: Vaccine data	**Vaccine (free)**	**Vaccine (paid)**	**Opt-out**	**Vaccine (free)**	**Vaccine (paid)**	**Opt-out**	**Vaccine (free)**	**Vaccine (paid)**	**Opt-out**
Base model	63.4% (0.6967)	29.8% (0.7267)	6.8% (0.3497)	63.4% (0.6962)	29.8% (0.7265)	6.8% (0.3497)	63.3% (0.7014)	29.8% (0.7193)	6.9% (0.3457)
50% price increase	68.1% (0.6364)	24.6% (0.6264)	7.3% (0.3662)	68.1% (0.6342)	24.6% (0.6249)	7.3% (0.3663)	66.7% (0.6326)	26.2% (0.6315)	7.1% (0.3500)
p-values (vs. RUM)	-	-	-	0.5262	0.4814	<0.001	<0.001	<0.001	<0.001
50% increase in protection duration	64.3% (0.6956)	29.8% (0.7236)	6.0% (0.3015)	64.3% (0.6950)	29.8% (0.7235)	5.9% (0.3004)	63.7% (0.7029)	30.1% (0.7190)	6.3% (0.3172)
p-values (vs. RUM)	-	-	-	0.0022	0.9553	<0.001	<0.001	<0.001	<0.001

Note: Bootstrapped SEs in parentheses (200 draws), bootstrapped p-values presented for comparison (test for mean difference) between RRM/DFT and RUM predicted choice shares.

£41.71 in DFT. Decision field theory differed statistically significantly from RUM; RRM showed weak evidence for a difference from RUM. Reductions in duration of protection may be offset by decreases in price of £4.62 for RUM, £5.00 for RRM, and £6.67 for DFT. Here, both DFT and RRM RI differed significantly from RUM.

In a sensitivity analysis, mean RI was estimated for models with deterministic heterogeneity (not shown). Similar patterns were observed (but without hypothesis tests) suggesting results were robust to the model specification.

4.2.1 | Predicted choice shares

Predicted choice shares in policy scenarios were presented alongside choice shares at baseline in Table 7.

For tobacco, compared to RUM, results significantly differed for DFT and RRM. When increasing all prices by 50%, DFT predicted a decrease in e-cigarette choice share to 34.1%, a decrease of 1.9% points compared to the baseline. In RUM models, this was only 35.4%, a 0.5% point decrease. Opt-out choice shares also differed, with DFT predicting a 20.7% share of opt-outs, representing a 7.6% points increase compared to the baseline. This was 18% in RUM, an increase of 5% points. When only increasing cigarette prices by 50%, a similar pattern was observed. Again, DFT predicted a lower share of e-cigarettes than RUM, and a larger share of opt-outs. Comparing RRM to RUM, predictions were more similar, but still significantly differed.

In the vaccine choice dataset, predicted choice shares were again significantly different between DFT and RUM, but not between RRM and RUM. For example, increasing vaccine prices by 50% resulted in a 3.6% point decrease in paid vaccine choices for DFT and a 5.2% point decrease in paid vaccine choices for RRM and RUM. The DFT-RUM difference was statistically significant; the RRM-RUM difference was not. Overall, the results showed that predicted DFT policy responses significantly differed from RUM.

In a sensitivity analysis, choice shares were predicted using models with deterministic preference heterogeneity. Choice shares were similar to models with homogeneous preferences, likely because predicted shares were aggregated. Hence, differences between decision rules appeared robust to other model specifications.

4.2.2 | Elasticities

A presentation of elasticities is provided in Table 8. In absolute value, elasticities were highest for the life years lost attribute. In RUM models, the direct life-years lost elasticity of e-cigarette choice equaled 0.5239. This is interpreted as a reduction of life years lost from 10 to 2 years leading to, on average, a 52.39% increase in the probability of e-cigarettes being chosen. The cross life years lost elasticity of cigarette choice was 0.2011. That is, the probability of cigarette choice decreases by 20.11% if the life-years lost from e-cigarettes decreases from 10 to 2 years. Tests of equal elasticities were performed for DFT and RRM, compared to RUM. Elasticities were similar for nicotine between decision rules. For other attributes, significant differences were found. Between RUM and DFT, elasticity differences were of a larger magnitude than between RRM and RUM. The strongest (significant) differences were obtained for price. Decision field theory appeared significantly more price elastic (cigarettes: −0.1414 vs. −0.1158, and e-cigarettes: −0.1914 vs. −0.1634), and cross-price elasticities varied strongly for the opt-out choice (cigarettes: 0.4498 vs. 0.1843). For the vaccine data, direct elasticities significantly differed between RRM and RUM; for example, the direct price elasticities (RUM: −0.0888; RRM: −0.0950). For DFT, only the direct price elasticity was significantly different from RUM (RUM: −0.0888; DFT: −0.0604). Contrary to tobacco results, DFT appeared less price elastic. Overall, the results showed elasticities significantly differed between decision rules, even if model fit was similar, such as between RUM and RRM. In a sensitivity analysis, similar variations were observed in models with deterministic heterogeneity (results not shown).

4.3 | Decision rule heterogeneity

Finally, decision rule heterogeneous model fits are presented in Table 9. Multi-rule models significantly increased model fit compared to homogeneous counterparts for the tobacco choice experiment, showing evidence for decision rule heterogeneity. Model fit improved in RUM-DFT models, compared to DFT-only, but this was not significant for tobacco ($p = 0.1081$, Table 9A). For tobacco, the strongest, significant gain in model fit was observed when combining DFT and RRM decision rules, compared to a 2-class DFT model. The RRM decision rule therefore contributed to the explanation of choice behavior, despite its weaker performance in single-rule models.

For vaccines, the 2-class DFT model remained preferred over all decision rule heterogeneous specifications.

Decision rule heterogeneous models impacted model outputs. Relative importance was compared to single-rule models in Table 10. For tobacco, the composite estimate of RUM-DFT RI of life years lost (−5.330) now appeared to lie in between single-rule RUM (−6.110) and DFT models (−4.521). This reflected both RUM-behavior (higher RI) and DFT-behavior (lower RI). This was not observed in the vaccine data, where the RI of the RUM-DFT model was outside the range of its single-class counterparts, for example, for risk of serious illness, the RUM-DFT estimate of £18.08 was outside of the range of 2-class RUM (£11.81) and 2-class DFT (£16.09) models. Finally, note that SEs increased for multi-rule estimates, likely because outputs represented pooled overall RI from multiple decision rules.

5 | DISCUSSION

This study introduced DFT to health economics, in the context of risky health behaviors, and developed novel DFT models. Comparisons between DFT and other decision rules were made, introducing bootstrapped SEs and hypothesis tests for comparison. Model fit significantly improved using DFT compared to RUM. Model outputs differed significantly between decision rules, but were at times of small magnitude. The presence of decision rule heterogeneity was shown, and subsequent model outputs differed. The improved fit of these models is interpreted as better reflecting decision-making.

Evidence was divided on whether DFT models with deterministic preference heterogeneity improved fit compared to RUM. In both datasets, model fit improved, but this was not significant for tobacco data. Previous results also showed reduced

TABLE 8 Elasticities in base models, by decision rule, with *p*-values for comparison between decision rules.

Panel A: Tobacco data		RUM Cigarette	RUM E-cigarette	RUM Opt-out	RRM Cigarette	RRM E-cigarette	RRM Opt-out	DFT Cigarette	DFT E-cigarette	DFT Opt-out
Nicotine: High to low	Cigarette	−0.0072 (0.0061)	0.0076 (0.0065)	0.0077 (0.0066)	−0.0168 (0.0122)	0.0176 (0.0131)	0.0180 (0.0134)	−0.0044 (0.0119)	0.0049 (0.0133)	0.0038 (0.0104)
		-	-	-	$p = 0.1203$	$p = 0.1310$	$p = 0.1315$	$p = 0.6456$	$p = 0.6990$	$p = 0.3527$
	E-cigarette	0.0055 (0.0047)	−0.0098 (0.0082)	0.0058 (0.0049)	0.0125 (0.0083)	−0.0219 (0.0144)	0.0129 (0.0086)	0.0068 (0.0086)	−0.0110 (0.0139)	0.0040 (0.0054)
		-	-	-	$p = 0.111$	$p = 0.1145$	$p = 0.1142$	$p = 0.7846$	$p = 0.0046$	$p = 0.4527$
Life years lost: 10 to 2 years	E-cigarette	−0.2011 (0.0138)	0.5239 (0.0507)	−0.2064 (0.1040)	−0.1932 (0.0142)	0.5497 (0.0511)	−0.1957 (0.0144)	−0.2092 (0.0129)	0.5514 (0.0440)	−0.1322 (0.0102)
		-	-	-	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p = 0.0278$	$p = 0.1064$	$p < 0.001$
Flavor: Tobacco to menthol	Cigarette	−0.1751 (0.0156)	0.2232 (0.0242)	0.2298 (0.0249)	−0.1828 (0.0160)	0.2295 (0.0250)	0.2613 (0.0288)	−0.1768 (0.0153)	0.2298 (0.0244)	0.2162 (0.0237)
		-	-	-	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p = 0.1025$	$p = 0.0038$	$p = 0.0090$
	E-cigarette	0.0646 (0.0192)	−0.1056 (0.0297)	0.0668 (0.0199)	0.0576 (0.0171)	−0.1014 (0.0287)	0.0814 (0.0247)	0.0596 (0.0185)	−0.0958 (0.0283)	0.0607 (0.0190)
		-	-	-	$p = 0.0023$	$p = 0.0172$	$p = 0.0026$	$p < 0.001$	$p < 0.001$	$p = 0.0048$
Price: 5 to 8 USD	Cigarette	−0.1158 (0.0038)	0.1739 (0.0073)	0.1843 (0.0075)	−0.1124 (0.0036)	0.1781 (0.0071)	0.1644 (0.0062)	−0.1413 (0.0065)	0.1646 (0.0079)	0.4498 (0.0382)
		-	-	-	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$
	E-cigarette	0.1167 (0.0047)	−0.1634 (0.0052)	0.1204 (0.0050)	0.1177 (0.0048)	−0.1588 (0.0049)	0.1002 (0.0039)	0.1069 (0.0047)	−0.1914 (0.0077)	0.2610 (0.0190)
		-	-	-	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$	$p < 0.001$

Panel B: Vaccine data	RUM Vaccine (average A & B)	RRM Vaccine (average A & B)	DFT Vaccine (average A & B)
Risk of severe side effects	−0.1066 (0.0092)	−0.1153 (0.0095)	−0.1081 (0.0079)
	-	$p < 0.001$	$p = 0.7364$
Risk of serious illness	−0.2099 (0.0081)	−0.2015 (0.0077)	−0.2176 (0.0085)
	-	$p < 0.001$	$p = 0.2354$
Price	−0.0888 (0.0033)	−0.0950 (0.0036)	−0.0604 (0.0093)
	-	$p < 0.001$	$p = 0.0012$

Note: Bootstrapped SEs in parentheses (200 draws), bootstrapped *p*-values presented for comparison (test for mean difference) of elasticities between RRM/DFT and RUM. Panel A: Pseudo-elasticities for increase in categorical attributes. Panel B: Direct elasticities, averaged over vaccines A and B (multiplied by 100 to represent percentage increase).

TABLE 9 Model fit of single-rule latent class models and decision rule heterogeneous models, with non-nested likelihood ratio tests for presence of decision rule heterogeneity.

	Log-likelihood	Log-likelihood difference	Vuong (*p*-value)
Panel A: Tobacco data			
2-class RUM	−33,240.89	-	-
2-class RRM	−33,234.17	-	-
2-class DFT	−33,210.55	-	-
RUM-RRM	−33,229.10	+5.06 (vs. 2-class RRM)	−3.641 (<0.001)
RUM-DFT	−33,199.36	+11.19 (vs. 2-class DFT)	−1.607 (0.1081)
RRM-DFT	−33,188.02	+22.53 (vs. 2-class DFT)	−2.497 (0.0125)
Panel B: Vaccine data			
2-class RUM	−15,308.41	-	-
2-class RRM	−15,344.00	-	-
2-class DFT	−15,186.44	-	-
RUM-RRM	−15,329.50	−21.09 (vs. 2-class RUM)	−6.469 (<0.001)
RUM-DFT	−15,226.90	−40.46 (vs. 2-class DFT)	−2.486 (0.0129)
RRM-DFT	−15,245.92	−59.48 (vs. 2-class DFT)	−3.409 (<0.001)

Note: decision rule heterogeneous models are compared to the best-performing latent-class counterpart with a single decision rule. Size of the log-likelihood difference and Vuong test statistic may not correspond directly, due to scaling with standard deviation.

TABLE 10 Relative importance (RI) in latent class, decision-rule heterogeneous models.

	2-class RUM	2-class DFT	2-class RUM-DFT
Panel A: Tobacco data			
Nicotine to price	0.871 (0.470)	0.715 (0.371)	0.946 (0.934)
Life years lost to price	−6.110 (0.682)	−4.521 (0.429)	−5.330 (1.162)
Panel B: Vaccine data			
Risk of serious illness to price	11.806 (0.922)	16.090 (1.296)	18.081 (1.342)
Protection duration to price	−2.101 (0.139)	−2.510 (0.279)	−2.862 (0.263)

Note: Standard errors (delta-method) in parentheses. In tobacco data, for categorical attributes, relative importance of a change in categorical attribute levels is used. Nicotine attribute: medium to no nicotine, health attribute: 2 to 10 life-years lost, flavor: sweet versus tobacco.

improvement when including interaction terms (Hancock et al., 2018). However, it should be noted that DFT is designed to resemble the psychological decision-making process. The incorporation of interactions on scaling parameters in a DFT model may impose considerable complexity on the decision-making process at each preference-updating step, lowering psychological advantages, and reducing performance compared to other decision rules. In contrast, latent class DFT models maintain their simplicity within classes, while still allowing for preference heterogeneity. These models continued to outperform other decision rules. Therefore, the advantage of DFT may diminish when deterministic heterogeneity is present, but preference heterogeneity can still be incorporated through latent classes.

Unlike psychological applications, deterministic interactions are often required to capture the tastes of individual decision-makers (Soekhai et al., 2019). This was the first application of DFT with many interactions between scaling parameters and sociodemographic characteristics. Previous applications introduced this, but had fewer interactions in different specifications or settings (Hancock et al., 2018, 2021).[12] Moreover, the large number of parameters used here could be an extreme case. Most health-based DCEs may find fewer interactions sufficient, in which DFT performs well.

5.1 | Choice model outputs

Relative importance differed between decision rules. Results were more significant than previous work in RRM models, which found no significant results (de Bekker-Grob & Chorus, 2013). There may be several reasons for this. First, few studies present test statistics for the comparison of estimates between decision rules. In health, de Bekker-Grob & Chorus (2013) derive test statistics for the comparison of parameter ratios, while most studies present point estimates only. When presented, SEs and hypothesis tests were derived using the delta method, while bootstrap methods were used in this application. These hypothesis tests fully incorporate the covariance structure of parameters between decision rules, while delta method-based tests may represent only a lower bound of significance. Second, de Bekker-Grob & Chorus (2013) indicate their small sample sizes (1872 and 2808 observations) may have influenced the significance of results, and highlight that larger studies may find significant differences. Both datasets here are much larger (24,372 and 12,882 observations). Third, this study provided estimates of RI for only two attributes. Using RRM, ratios appeared higher than when using RUM, but only repeated studies with more attributes can show whether a consistent pattern exists.

Evidence was mixed on the directions of RI between decision rules. Previous applications found a lower importance of non-price attributes to price when assuming a DFT decision rule, compared to RUM and RRM (Hancock et al., 2021). This was true in the case of tobacco, but not in the case of vaccines. In line with this, decision-makers appeared more price elastic when following a DFT decision rule for tobacco data, but less price elastic for the vaccine choice data.

Turning to predicted choice shares, a 50% price increase, analogous to a tax levy, resulted in a significantly lower prediction of e-cigarette shares in DFT models than in RUM models. An earlier study with this dataset already indicated that RUM models overpredicted e-cigarette choice compared to observed choice shares (Buckell & Hess, 2019). Although this study did not assess external validity, DFT predicted a lower e-cigarette choice share than RUM in two policy scenarios. When assuming DFT behavior, model outputs seemed to mirror real-world behavior more closely. Significance between decision rules was previously not assessed, but the magnitudes of differences (1%–2%) were similar (de Bekker-Grob & Chorus, 2013). Significant differences were observed between RUM and DFT for vaccine data, but whether that corrected a bias is unknown.

Whilst it is not possible to derive WTP measures from DFT models, the above findings demonstrate two key points. Firstly, that DFT offers insights into the individuals' deliberative decision-making processes which may give additional policy information that is not available under RUM (nor RRM). Secondly, that for a given dataset, there is nothing to prevent an analyst from using DFT alongside RUM if measures such as WTP are required, as long as the results do not differ substantially across models.

5.2 | Decision rule heterogeneity

Mixed results were found on the presence of decision rule heterogeneity. For tobacco, the RRM model improved model fit when combined with DFT models, while it performed worse within single-rule analyses. A small, but substantial share of individuals may have followed regret-like behavior. Accounting for multiple decision rules within the data may also substantially influence measures of RI. For vaccines, the 2-class DFT model performed strictly better than any model with multiple decision rules. In this setting, it may be that the DFT model dominated other decision rules (as also evidenced by the strong increase in model performance), yielding no evidence for decision rule heterogeneity.

Recent empirical findings in health (Buckell et al., 2021; Dennis et al., 2020) indicated that decision rule heterogeneous models could improve understanding of decision-making within the sample, as also previously argued (Boeri et al., 2013; Chorus, 2010; de Bekker-Grob & Chorus, 2013; Smith, 1996). Part of the results found here corroborate this conclusion. Of course, some settings may show a wider variety of decision rules than others. The potential insights derived from a model with multiple decision rules could still warrant its application.

5.3 | Implications

Predictions and the implied policy recommendations were found to differ based on the decision rule used. This raises the discussion of which decision rule is best. Several issues are to be considered.

First, predicted choice shares were relatively robust. Significant differences were found, but were at times only 0.5% points. This is unlikely to change policy recommendations. Therefore, it is important to distinguish public health significance from the statistical significance of differences (see e.g., Hess et al., 2020). These results suggest that the choice of decision rule has little bearing on predicted choice shares, which accords with empirical evidence elsewhere (Buckell et al., 2021).

Some outputs, however, differed markedly between decision rules, similar to previous studies (de Bekker-Grob & Chorus, 2013; Dennis et al., 2020). Then, the use of DFT outputs may be preferred, as it appeared to better depict behavior in this dataset. Moreover, using multiple decision rules is frequently recommended (Boeri et al., 2013; Buckell et al., 2021; de Bekker-Grob & Chorus, 2013). Model outputs differed from single-rule models when multiple decision rules were simultaneously used. There is potential for these models to achieve a better model fit by incorporating behavior from a large share of decision-makers, better depict behavior, and subsequently enhance overall estimates. Hence decision rule heterogeneous models may then be considered.

Whilst the datasets explored in this work are from SP settings, it is possible that DFT may also be a valuable tool for RP data analysis. This requires DFT to handle real-world substitution patterns and unbalanced choice data, while the DFT model applied in this work lends itself best to SP or experimental settings. Hancock, Hess, Choudhury and Tsoleridis (2022) demonstrate that a simple extension to DFT models to account for heteroskedasticity allows for better predictions of RP travel mode choice behavior than standard models. Additionally, Hancock et al. (2022) demonstrate that DFT models can be extended to account for longer-term decisions where the attributes of alternatives change over time, particularly for choice contexts where the choice deliberation process is over a relatively short period of time. These extensions result in DFT models that are not just for laboratory settings, and are not dataset-specific, thus may also transfer effectively to RP health settings. This may allow for the application of DFT models to RP data collected over a long time period, for example, the choice of a smoker to use cigarettes or e-cigarettes over several years.

Finally, the setting also has a strong influence (Boeri et al., 2013). To some policy questions, RUM's economic welfare framework may be more relevant, which allows for the straightforward derivation of WTP and other policy-relevant measures. Alternative frameworks may be more relevant for emotional decisions (Araña et al., 2008). Random regret minimization may be more suitable under disincentives, which generate anticipated regret (Boeri et al., 2013), or when decisions are of high significance (Zeelenberg & Pieters, 2007). Decision field theory may be advisable in situations where there are concerns of potential context effects (similarity, attraction, and compromise), since DFT can ably handle these (e.g., Roe et al., 2001). We note that it is possible to run all three approaches on any dataset. This enables the researcher's economic interpretation as well as any further behavioral insights that alternative paradigms are permissive of.

5.4 | Limitations

The study had several limitations. First, DFT performance was assessed in only two datasets and risky health choices. The importance to risky health behaviors was shown, but the generalizability of this result to wider health settings is not known. Second, our decision rule heterogeneous models only included classes of constant-only class allocation. These models can be extended to let sociodemographic variables explain the decision rules used (Hess et al., 2012). This would allow researchers to uncover the characteristics of utility maximisers, regret minimisers, or DFT-like behavior. Third, the methods were limited by the high computational requirements of DFT models. Bootstrapped test statistics could not be derived in complex models due to high DFT run-times, hence hypothesis tests were not always performed. The computational complexity of DFT presents a boundary for wider application. Fortunately, efficient estimation techniques are a topic of continuing interest (Bunch, 2014) and the application of DFT models is easier as a result of its introduction to the Apollo choice modeling package in *R* (Hess & Palma, 2019).

6 | CONCLUSIONS

This study compared the performance of DFT, RUM and RRM for explaining choice behavior in risky health settings. Overall, the results showed improved performance when using DFT. Novel latent class DFT models and bootstrapped comparisons of model outputs strengthened the conclusions. Model outputs differed significantly between RUM, RRM, and DFT, emphasizing the importance of the decision rule used for the analysis of choice behavior. We find mixed results for the presence of decision rule heterogeneity. For both datasets, the best-fitting model included a DFT component, demonstrating that it provides avenues toward improved explanations of choice behavior for public health research.

AUTHOR CONTRIBUTIONS

David A. J. Meester: Conceptualization; methodology; software; formal analysis; data curation, writing - original drafting. **Stephane Hess**: Methodology; software; writing - review & editing; resources; supervision. **John Buckell**: Conceptualization; methodology; data curation; writing - review & editing; resources; supervision. **Thomas O. Hancock**: Conceptualization; methodology; software; writing - review & editing; resources; supervision.

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CONFLICT OF INTEREST STATEMENT

The authors have nothing to declare.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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ENDNOTES

[1] Recent reviews indicate around 600 choice modeling studies in health economics, of which fewer than 10 use RRM.

[2] DFT models almost exclusively study choices between two to three alternatives. More recently, Hancock et al. (2023) implement DFT with four alternatives.

[3] Advanced RUM models (e.g., probit, mixed multinomial logit) do relax this assumption.

[4] Berkowtitsch et al. (2014) use two to five attributes, Hancock et al. (2018) use two to six attributes.

[5] Hess et al. (2022) used a latent class model with three nested logits, which achieved a better model fit than the two class models used here. However, two class models were used in this work to allow for a direct comparison with the results for the smoking dataset. Furthermore, equivalent "nested" DFT models allowing for correlation across alternatives do not currently exist, thus a fair comparison against nested logit counterparts is not possible. A study of the results of decision rule heterogeneous models with three classes is beyond the scope of this work.

[6] Under this specification, when the operator $\ln(1 + \exp(\ldots))$ is replaced by $\ln(0 + \exp(\ldots))$, the RRM model reduces to the RUM model (Hess & Chorus, 2015), ensuring comparability.

[7] In further analyses, we explored the use of the μ-RRM model (Van Cranenburgh et al., 2015), but this model collapsed to a RUM model for both datasets (high estimates of μ, low profundity of regret). This follows from the RUM being preferred to RRM base models in both datasets (Table 4); that is, when RUM fits the data better than RRM, a model that generalizes both will tend to the preferred decision rule.

[8] As the number of preference-updating steps is estimated, the choice response times are not required to estimate the choice probabilities, unlike alternative DFT specifications that require such information for estimation.

[9] With elements $c_{jj} = 1$ and $c_{jm} = \frac{1}{J-1} \forall\, m \neq j$, of size $\boldsymbol{J}$ x $\boldsymbol{J}$

[10] It should be noted that the expectation and covariances here incorporate the expectation and covariance of W_τ, which account for the impact of attribute attendance order.

[11] This remains relevant, as asymptotic tests were performed (MacKinnon, 2006).

[12] Hancock et al. (2018) did not use the scale-invariant DFT model (one interaction). Hancock et al. (2021) used revealed preference data (two interactions).

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