Supplemental Materials

Ranges of the Estimated Parameters

In the following Tables S1 to S7 we provide the ranges of the estimated parameters for all models in Studies 1 and 2. For the logit model we estimated the n weights w_i for each attribute i, allowed to vary between 0 and ∞. The parameters used to estimate the probit model were the $n - 1$ weights w_i for $n - 1$ attributes, which were restricted to sum to 1, and the variance v of the normal distributed error component **ε** in the diagonal of the variance–covariance matrix, allowed to vary between 0 and 1,000. Finally, for the MDFT we estimated the $n - 1$ weights w_i allocated to the $n - 1$ attributes, restricted to sum to 1, the variance v of the normal distributed error component **ε**, restricted to values between 0 and 1,000, the sensitivity parameter φ_1, restricted to vary between 0.01 and 1,000, and the decay parameter φ_2, restricted to values between 0 and 1. In Study 1, we fixed the weight parameter ***wd***, which weights distances in the dominance direction relative to distances in the indifference direction, to a value of 12, following Hotaling et al. (2010) and we estimated its value in Study 2, restricting values to between 1 and 50.

Table S1

Study 1—Logit Model: Estimated Parameter Ranges of the Attribute Weights (w_1-w_5)

Quantile	w_1	w_2	w_3	w_4	w_5
$Q_{0.25}$	1.31	0.55	1.46	0.24	0.59
$Q_{0.50}$	2.14	1.09	2.86	1.01	0.92
$Q_{0.75}$	3.61	1.70	4.84	3.01	1.64

Table S2

Study 1—Probit Model: Estimated Parameter Ranges of the Attribute Weights (w_1-w_5) and Variance (v)

Quantile	w_1	w_2	w_3	w_4	w_5	v
$Q_{0.25}$	0.15	0.05	0.20	0.01	0.06	0.02
$Q_{0.50}$	0.24	0.13	0.30	0.10	0.09	0.02
$Q_{0.75}$	0.41	0.19	0.45	0.29	0.14	0.03

Table S3

Study 1—MDFT: Estimated Parameter Ranges of the Attribute Weights (w_1-w_5), Variance (v), Decay Parameter (φ_2), and Sensitivity Parameter (φ_1)

Quantile	w_1	w_2	w_3	w_4	w_5	v	φ_2	φ_1
$Q_{0.25}$	0.10	0.03	0.19	0.05	0.07	0.27	0.02	0.14
$Q_{0.50}$	0.19	0.10	0.33	0.09	0.10	0.88	0.09	0.42
$Q_{0.75}$	0.40	0.21	0.50	0.23	0.18	1.64	0.22	1.68

Table S4

Study 2—Logit Model: Estimated Parameter Ranges of the Attribute Weights (w_1-w_2)

Quantile	Digital camera		Color printer		Notebook computer		Racing bike		Vacuum cleaner		Washing machine	
	w_1	w_2	w_1	w_2	w_1	w_2	w_1	w_2	w_1	w_2	w_1	w_2
$Q_{0.25}$	5.67	2.90	7.52	4.98	3.46	8.78	7.35	7.59	8.14	4.35	9.37	0.20
$Q_{0.50}$	10.80	17.52	12.49	11.15	8.41	15.31	14.12	14.48	19.59	13.52	24.00	8.46
$Q_{0.75}$	25.23	30.62	34.57	18.60	18.83	30.81	28.30	34.01	38.67	24.14	62.52	23.53

Table S5

Study 2—Probit Model: Estimated Parameter Ranges of the Attribute Weights (w_1-w_2) and Variance (v)

Quantile	Digital camera			Color printer			Notebook computer			Racing bike			Vacuum cleaner			Washing machine		
	w_1	w_2	v	w_1	w_2	v	w_1	w_2	v	w_1	w_2	v	w_1	w_2	v	w_1	w_2	v
$Q_{0.25}$	0.33	0.04	0.00	0.37	0.20	0.00	0.00	0.58	0.00	0.27	0.24	0.00	0.19	0.11	0.00	0.41	0.05	0.00
$Q_{0.50}$	0.59	0.41	0.01	0.59	0.41	0.01	0.24	0.76	0.02	0.49	0.51	0.00	0.58	0.42	0.01	0.62	0.38	0.01
$Q_{0.75}$	0.96	0.67	0.08	0.80	0.63	0.21	0.42	1.00	0.40	0.76	0.73	0.04	0.89	0.81	0.19	0.95	0.59	0.69

Table S6

Study 2—MDFT: Estimated Parameter Ranges of the Attribute Weights (w_1-w_2), Variance (v), Decay Parameter (φ_2), Sensitivity Parameter (φ_1), and Dominance Parameter wd

Quantile	Digital camera			Color printer			Notebook computer			Racing bike			Vacuum cleaner			Washing machine			φ_2	φ_1	*wd*
	w_1	w_2	v	w_1	w_2	v	w_1	w_2	v	w_1	w_2	v	w_1	w_2	v	w_1	w_2	v			
$Q_{0.25}$	0.30	0.05	0.01	0.46	0.26	0.01	0.12	0.48	0.02	0.33	0.36	0.03	0.39	0.27	0.03	0.53	0.06	0.01	0.05	28.68	1.09
$Q_{0.50}$	0.67	0.33	0.09	0.57	0.43	0.11	0.36	0.64	0.11	0.45	0.55	0.10	0.58	0.42	0.18	0.67	0.33	0.11	0.05	58.68	3.47
$Q_{0.75}$	0.95	0.70	1.16	0.74	0.54	0.47	0.52	0.88	3.30	0.64	0.67	1.84	0.73	0.61	0.51	0.94	0.47	0.56	0.06	93.20	11.85

Table S7

Study 2—MDFT: Estimated Parameters of Selected Participants with RST > .50 and PRST > .50 Simultaneously for Attraction, Compromise, and Similarity Choice Triplets

Participant	Digital camera			Color printer			Notebook computer			Racing bike			Vacuum cleaner			Washing machine			φ_2	φ_1	*wd*
	w_1	w_2	v	w_1	w_2	v	w_1	w_2	v	w_1	w_2	v	w_1	w_2	v	w_1	w_2	v			
3	0.40	0.60	0.01	0.52	0.48	0.11	0.45	0.55	0.28	0.34	0.66	0.00	0.40	0.60	0.08	0.55	0.45	0.10	0.05	120.58	9.19
10	0.00	1.00	0.00	0.94	0.06	0.48	0.44	0.56	0.13	0.11	0.89	0.16	0.52	0.48	0.07	1.00	0.00	0.00	0.05	105.94	1.04
38	1.00	0.00	0.00	1.00	0.00	0.00	0.36	0.64	0.02	0.62	0.38	0.20	0.73	0.27	0.10	0.40	0.60	0.14	0.05	71.01	1.43

Reducing the MDFT to a Probit Model

This section shows how MDFT can be transformed into a probit model. Technically, this can be achieved by setting the feedback matrix and by omitting the variance–covariance matrix of the product-relevant attention weights.

One of the main differences between MDFT and a probit model is the dynamic aspect of MDFT. To reduce MDFT to a static model, such that the preference state **P** remains constant over time, we set the feedback matrix **S** to a zero matrix. A zero feedback matrix indicates no previous memory of previous preference states and no competition between the options (IIA property). Technically, a zero matrix for **S** can be achieved by setting φ_2 to 1 (no memory of the previous preference state) and $\varphi_1 \rightarrow \infty$.

In a next step, we set the variance–covariance matrix of the product-relevant attributes **Ψ** to zero, such that only the variance–covariance matrix of the product-irrelevant attributes remains. **Ψ** is calculated within the variance–covariance matrix of the valence vector **V**. As described in Roe and colleagues (2001), the valence vector **V** consists of the valence produced by product-relevant attributes [$\mathbf{CM_1W_1}(t)$] and the valence of the product-irrelevant attributes ([$\mathbf{CM_2W_2}(t) = \boldsymbol{\varepsilon}(t)$] where **C** is a contrast matrix to compute the momentary advantage or disadvantage of each option relative to the average of the other options. $\mathbf{M_1}$ represents a $J \times n$ subjective evaluation matrix, where J are the number of options and n are the number of attributes describing option j. $\mathbf{W_1}(t)$ is an $n \times 1$ vector containing the attention weights of each attribute i at time point t. The variance–covariance matrix of **V** can be expressed as (Roe et al., 2001)

$$Cov[\mathbf{V}(t)] = Cov[\mathbf{CM}_1\mathbf{W}_1(t) + \boldsymbol{\varepsilon}(t)] = \mathbf{CM}_1 Cov[\mathbf{W}_1(t)]\mathbf{M}_1'\mathbf{C}' + Cov[\boldsymbol{\varepsilon}(t)]$$

$$= \mathbf{CM}_1\boldsymbol{\Psi}\mathbf{M}_1'\mathbf{C}' + \varsigma = \Phi \qquad \text{(S1)}$$

where

$$\boldsymbol{\Psi} = Cov[\mathbf{W}_1(t)] = E[(\mathbf{W}_1(t) - \mathbf{w}_1)(\mathbf{W}_1(t) - \mathbf{w}_1)'] \qquad \text{(S2)}$$

is the variance–covariance matrix for the product-relevant weights and

$$\varsigma = Cov[\boldsymbol{\varepsilon}(t)] = E[\boldsymbol{\varepsilon}(t)\boldsymbol{\varepsilon}(t)'] = \text{diag}(\boldsymbol{\varepsilon}(t)) \quad \text{(S3)}$$

is the variance–covariance matrix of the product-irrelevant weights. If we assume that the attention shifts according to a Bernoulli process in an all-or-none manner from one attribute to another (see Appendix B of Roe et al., 2001), the probability of focusing on the product-relevant attributes can be written as

$$\mathbf{w}_1 = E[\mathbf{W}_1(t)]. \quad \text{(S4)}$$

Accordingly, $\mathbf{\Psi}$ reduces to

$$\mathbf{\Psi} = \text{diag}(\mathbf{w}_1) - \mathbf{w}_1\mathbf{w}_1'. \quad \text{(S5)}$$

By setting $\mathbf{\Psi}$ to a zero matrix, we reduce the variance–covariance matrix of $\mathbf{V}$ to ς. To achieve this, we multiply $\mathbf{\Psi}$ by the scalar 0, which otherwise is set to 1. This turns $\mathbf{CM}_1 Cov[\mathbf{W}_1(t)]\mathbf{M}_1'\mathbf{C}'$ into a zero matrix. Thus, only the covariance of the product-irrelevant attributes ς remains. The assumption that the product-irrelevant attributes are uncorrelated with the product-relevant attributes and uncorrelated with each other implies that $Cov[\boldsymbol{\varepsilon}]$ is a diagonal matrix. Thus the variance–covariance matrix of the valence vector ($\mathbf{V}$) can be rewritten as

$$Cov[\mathbf{V}(t)] = Cov[\mathbf{V}] = Cov[\mathbf{CM}_1\mathbf{W}_1 + \boldsymbol{\varepsilon}] = 0 + Cov[\boldsymbol{\varepsilon}] = \text{diag}(\boldsymbol{\varepsilon}), \quad \text{(S6)}$$

which is the same as the variance–covariance matrix of the (independent) probit model.