Case Studies on Designing and Analysing Discrete Choice Experiments using JMP®

Dr. Roselinde Kessels
University of Antwerp

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Universiteit Antwerpen

Outline

- Packaging choice study
- Choice study on healthcare systems
- Aggregate multinomial logit model
- Individual-level multinomial logit model

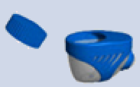
Packaging study

- To help define the brand packaging strategy for P&G laundry liquids in Latin America
  - By identifying the key liquid packaging attributes that drive trial
- The experiment was virtual and executed in Mexico

Respondent selection

- Two respondent groups:
  - Leg 1: Women Seeking Perfection (WSP)
  - Leg 2: Practical & Experiential (P&E)
- We designed for 150 respondents per leg, but eventually we had 160 respondents per leg
  - We assigned one of the generated surveys to the 10 additional respondents
- We used the same design for WSP and P&E, but different brands were shown to them (cfr. next slide)

Attributes and attribute levels

Attributes	Levels					
Material	Transparent	Semi transparent	Opaque			
Shape	Mas color 	Pure 	Isis 	Goldie 	Pure shrink 	Cooper 
Cap functionality	Roller ball 	Dosing ball 	Double wall cap 	Spout + cap 		
Brand	Mas Color	**Ariel – Leg 1**	**Ace – Leg 2**			

There are 3 x 6 x 4 x 2 = 144 different bottles

Design setup

- Design set up for 150 respondents in leg 1 and replicated for another 150 respondents in leg 2
- The design consists of 5 different surveys randomly assigned to 5 groups of 30 respondents each
- Each survey consists of 12 choice sets of 3 profiles

Sample choice set

A1-1

Todos estos detergentes líquidos están disponibles a 29 pesos, ¿Cuál de ellos estaría más interesada en comprar?

1	2	3
		

Design problem

- In total, there are 144 different bottles
- The number of possible choice sets of size 3 is

$$\binom{144}{3} = \frac{144!}{3!141!} = 487{,}344$$

- JMP will select the choice sets that provide most information, i.e. result in estimates that are precise

Bayesian approach: prior mean

"Opaque Cooper bottle with Spout+Cap could be the winner…"

Conversion into prior mean parameter or part-worth values:

Attribute	Level	Prior mean
Material	FullTrans	–0.5
	SemiTrans	–0.5
Shape	MasColor	–0.2
	Pure	–0.2
	ISIS	–0.2
	Goldie	–0.2
	PureShrink	–0.2
CapFunct	RollerBall	–0.34
	CurrentDosing	–0.33
	DoubleCap	–0.33
Brand	MasColor	0

$\sum = -1$

$\sum = -1$

$\sum = -1$

No guess

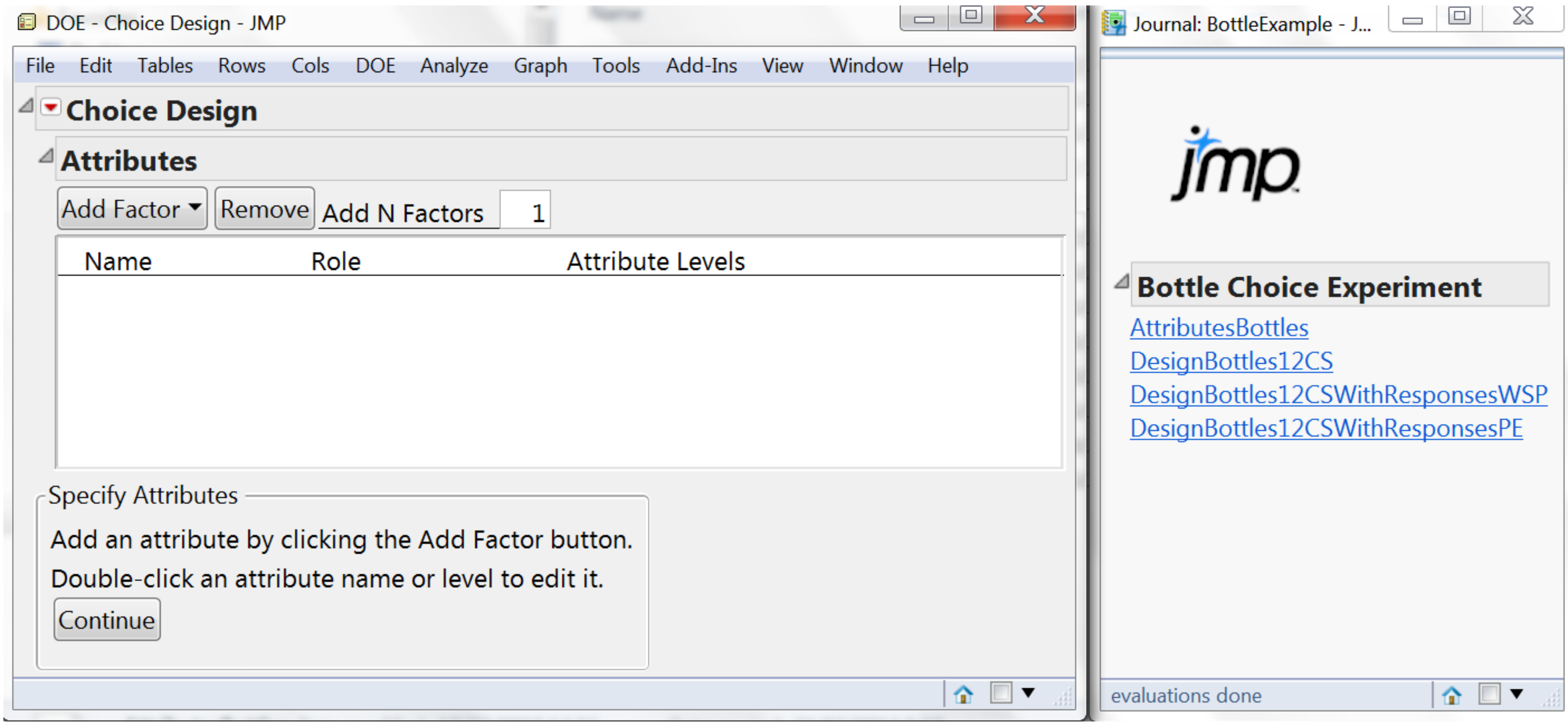
Bayesian approach: prior variance

- We allow for a great deal of *uncertainty* around the prior mean part-worths by specifying prior variances of 1
- For an attribute with more than 2 levels, say L levels, we also specify negative covariances between the (first L – 1) part-worths of that attribute using a correlation coefficient of -1/(L – 1)
- This ensures equal prior variances for all (L) part-worths of the attribute

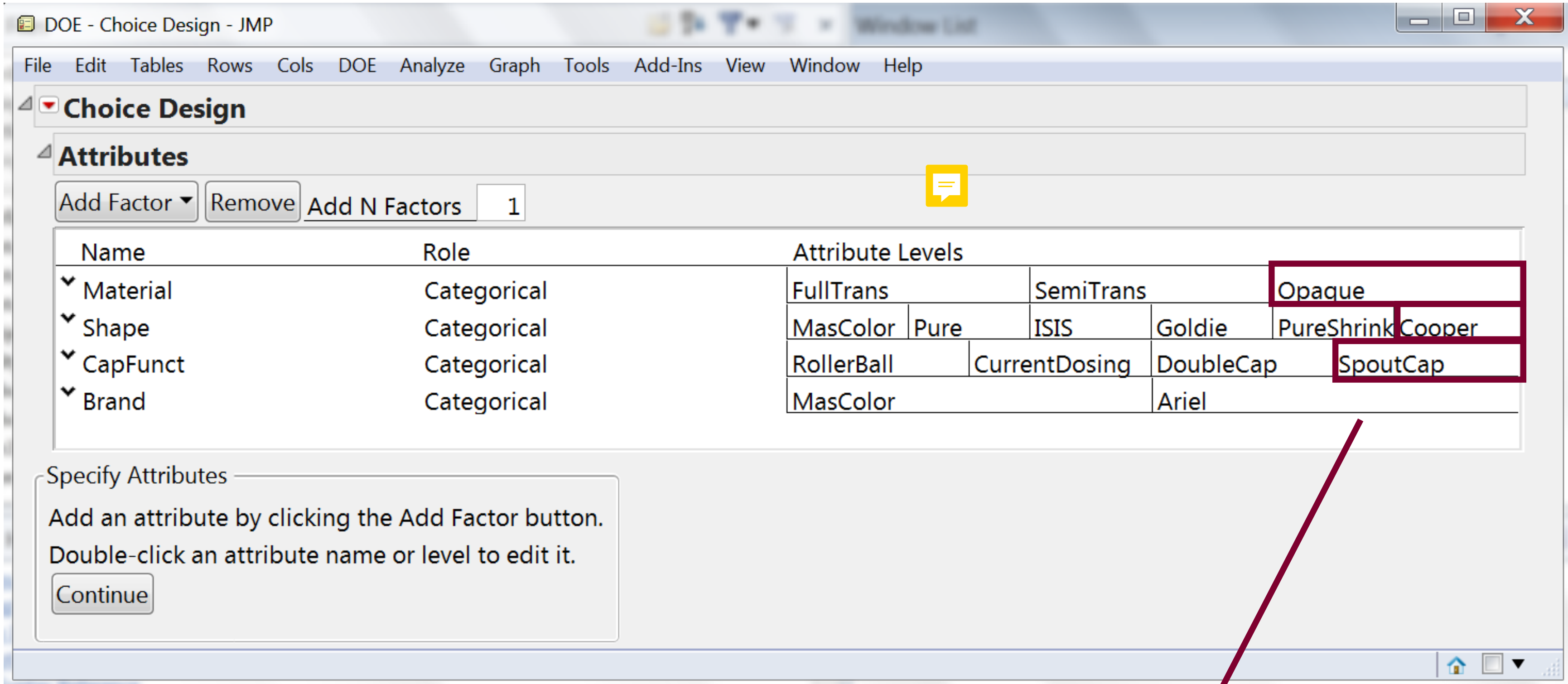
Statistical remarks

- We start from the estimation of the 11 part-worths
  → Then we need 11 df
- 1 choice set of 3 profiles accounts for 3 – 1 = 2 df
- 1 survey of 12 choice sets accounts for 12 x 2 = 24 df
- 24 df > 11 df so that it is possible to estimate part-worths for each individual

JMP Choice Design Platform

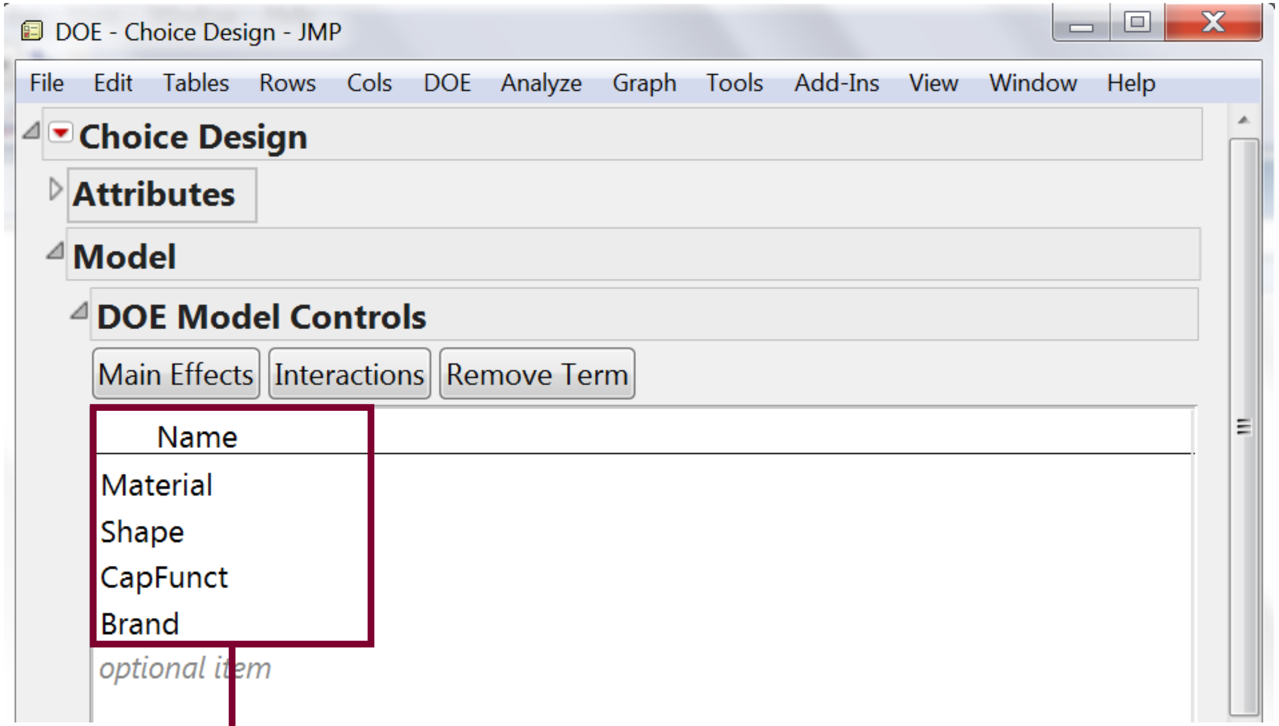


Attributes



The most likely preferred attribute levels appear last

Main-effects model



Main-effects model of (3-1)+(6-1)+(4-1)+(2-1)
= 11 part-worths

Prior mean

DOE - Choice Design - JMP

File Edit Tables Rows Cols DOE Analyze Graph Tools Add-Ins View Window Help

Choice Design

Model

Prior Specification

☐ Ignore prior specifications. Generate the Utility Neutral design.

Prior Mean

Effect	Prior Mean
Material 1	-0.50
Material 2	-0.50
Shape 1	-0.20
Shape 2	-0.20
Shape 3	-0.20
Shape 4	-0.20
Shape 5	-0.20
CapFunct 1	-0.34
CapFunct 2	-0.33
CapFunct 3	-0.33
Brand	0.000

Prior variance matrix

DOE - Choice Design - JMP

File Edit Tables Rows Cols DOE Analyze Graph Tools Add-Ins View Window Help

Choice Design

Model

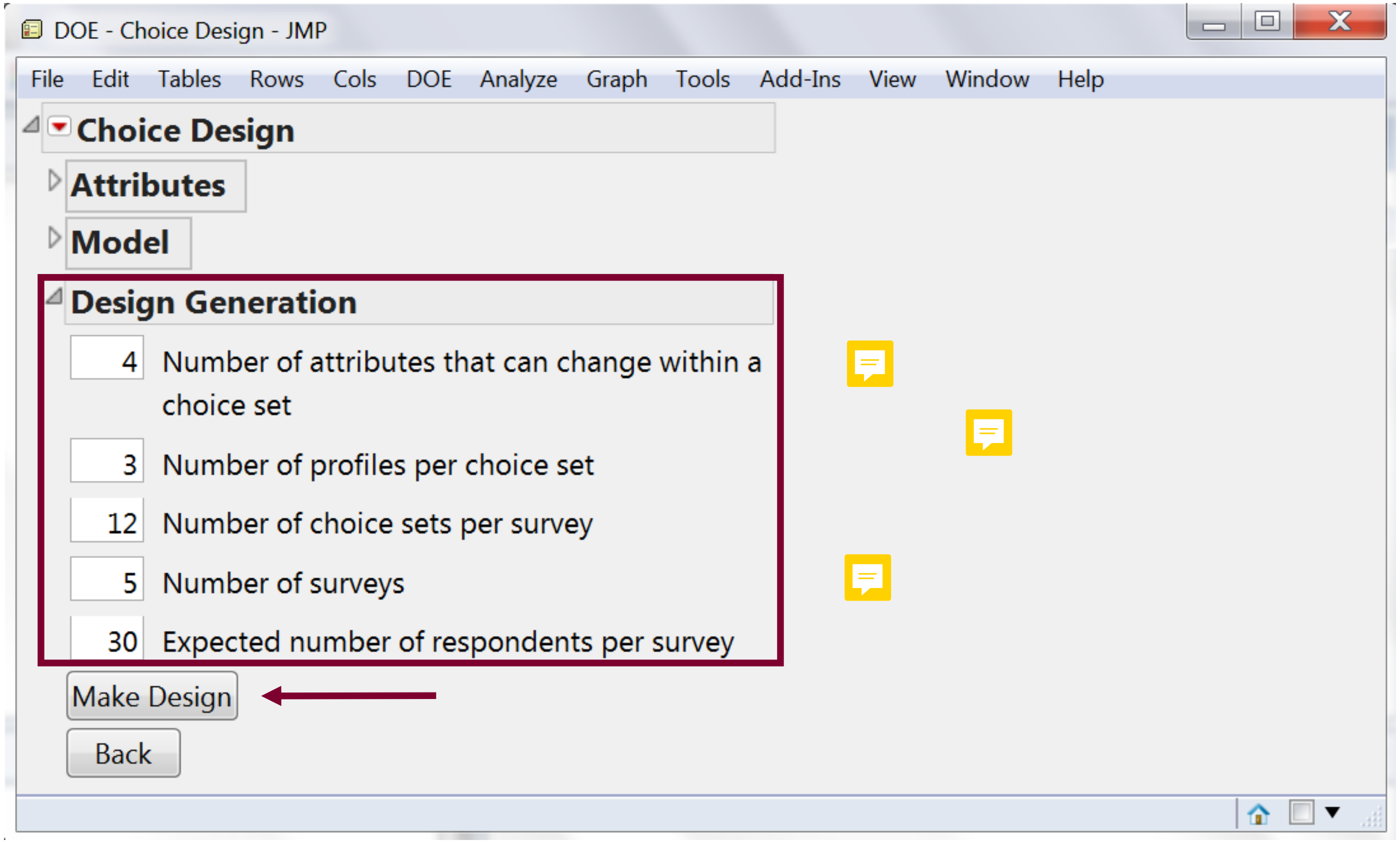
Prior Specification

☐ Ignore prior variance. Generate the local design for the prior mean.

Prior Variance Matrix

Effect	Material 1	Material 2	Shape 1	Shape 2	Shape 3	Shape 4	Shape 5	CapFunct 1	CapFunct 2	CapFunct 3	Brand
Material 1	1.000	-0.50	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Material 2		1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Shape 1			1.000	-0.20	-0.20	-0.20	-0.20	0.000	0.000	0.000	0.000
Shape 2				1.000	-0.20	-0.20	-0.20	0.000	0.000	0.000	0.000
Shape 3					1.000	-0.20	-0.20	0.000	0.000	0.000	0.000
Shape 4						1.000	-0.20	0.000	0.000	0.000	0.000
Shape 5							1.000	0.000	0.000	0.000	0.000
CapFunct 1								1.000	-0.33	-0.33	0.000
CapFunct 2									1.000	-0.33	0.000
CapFunct 3										1.000	0.000
Brand											1.000

Design generation



Also, don’t forget to increase the number of random starts!

Design

DesignBottles12CS - JMP

File Edit Tables Rows Cols DOE Analyze Graph Tools Add-Ins View Window Help

DesignBottles12CS
Design Discrete Choice
Choice

Columns (8/0)
Respondent
Survey
Choice Set
Response Indicator
Material
Shape
CapFunct
Brand

150 x 36

Rows
All rows 5,400
Selected 0

	Respondent	Survey	Choice Set	Response Indicator	Material	Shape	CapFunct	Brand
1	1	1	1	•	FullTrans	Pure	SpoutCap	Ariel
2	1	1	1	•	FullTrans	Goldie	RollerBall	MasColor
3	1	1	1	•	SemiTrans	ISIS	CurrentDosing	Ariel
4	1	1	2	•	SemiTrans	MasColor	DoubleCap	MasColor
5	1	1	2	•	FullTrans	ISIS	RollerBall	Ariel
6	1	1	2	•	FullTrans	Pure	CurrentDosing	Ariel
7	1	1	3	•	FullTrans	Pure	SpoutCap	Ariel
8	1	1	3	•	SemiTrans	ISIS	CurrentDosing	MasColor
9	1	1	3	•	Opaque	PureShrink	DoubleCap	Ariel
10	1	1	4	•	SemiTrans	ISIS	SpoutCap	Ariel
11	1	1	4	•	FullTrans	MasColor	CurrentDosing	Ariel
12	1	1	4	•	Opaque	Pure	DoubleCap	Ariel
13	1	1	5	•	Opaque	Pure	DoubleCap	MasColor
14	1	1	5	•	SemiTrans	MasColor	RollerBall	MasColor
15	1	1	5	•	FullTrans	Goldie	SpoutCap	MasColor
16	1	1	6	•	Opaque	Goldie	DoubleCap	Ariel

Analysis

- Based on the random utility model

$$U_{js} = \boxed{\mathbf{x}'_{js}\boldsymbol{\beta}} + \varepsilon_{js}$$

  - □ U_{js} is the utility that a respondent attaches to alternative j in choice set s
  - □ $\mathbf{x}_{js}$ is a k x 1 vector containing the attribute levels of alternative j in choice set s
  - □ $\boldsymbol{\beta}$ is a k x 1 vector of parameter values (or *part-worths* in case of main effects only)
  - □ ε_{js} is the IID Gumbel error term

Multinomial logit model

- Multinomial / conditional logit probability that a respondent chooses alternative *j* in choice set *s*:

$$p_{js}\begin{pmatrix}\text{option } j \text{ chosen} \\ \text{in choice set } s\end{pmatrix} = \frac{e^{\mathbf{x}'_{js}\boldsymbol{\beta}}}{\sum_{t=1}^{J} e^{\mathbf{x}'_{ts}\boldsymbol{\beta}}}$$

Analysis of the **WSP data**

- Only "Shape Design" has a significant impact on bottle choice

DesignBottles12CSWithResponsesWSP - Choice - JMP

Choice Model

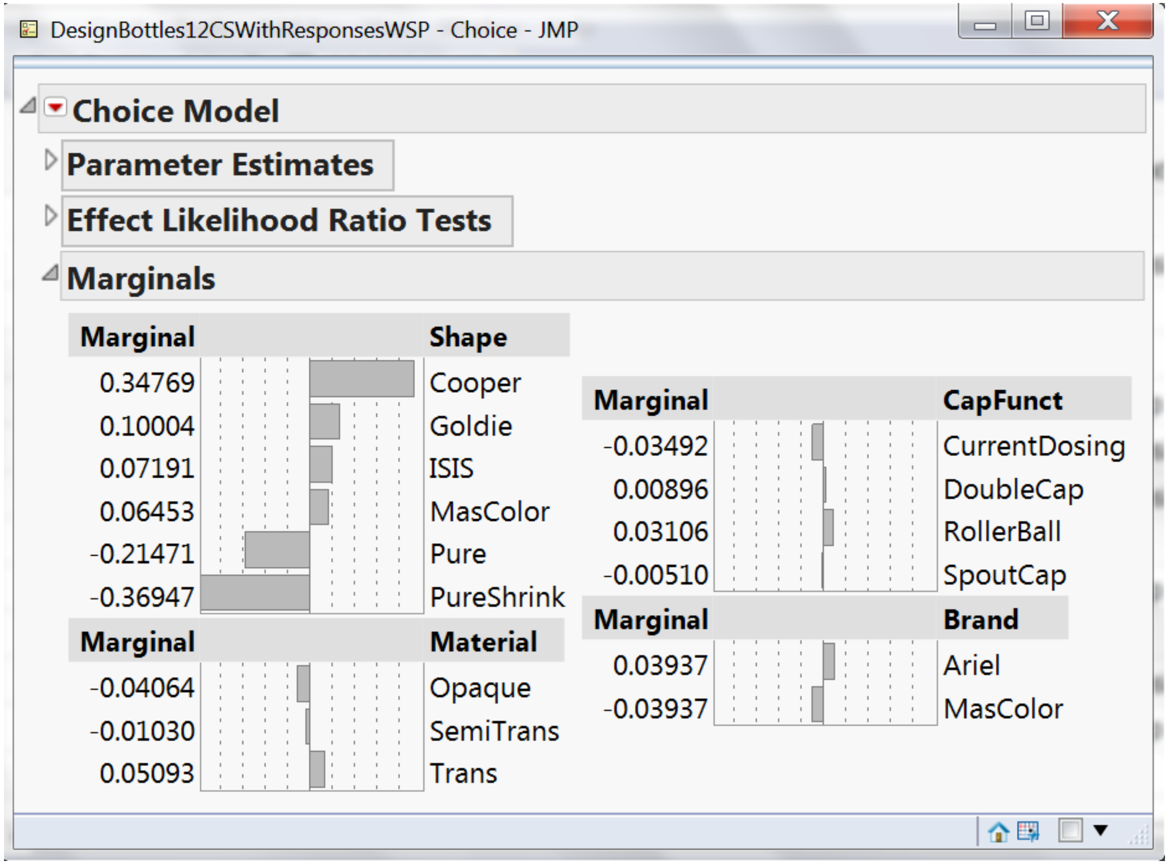
Parameter Estimates

Effect Likelihood Ratio Tests

Source	L-R ChiSquare	DF	Prob>ChiSq
Shape	70.357	5	<.0001*
Material	2.010	2	0.3660
CapFunct	1.096	3	0.7782
Brand	2.108	1	0.1465

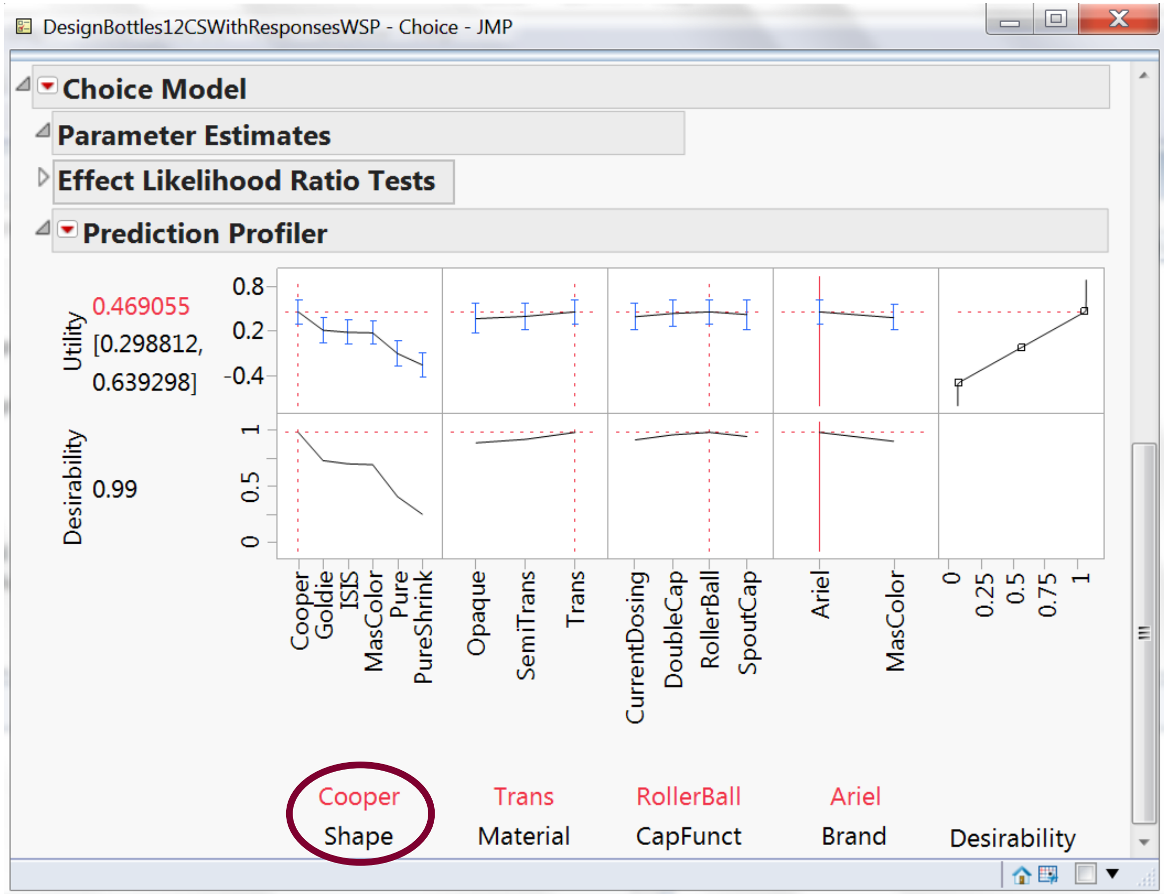
Part-worth estimates

Cooper design is the key driver of bottle choice



Prediction profiler

Optimal settings for Ariel bottle: **Cooper**



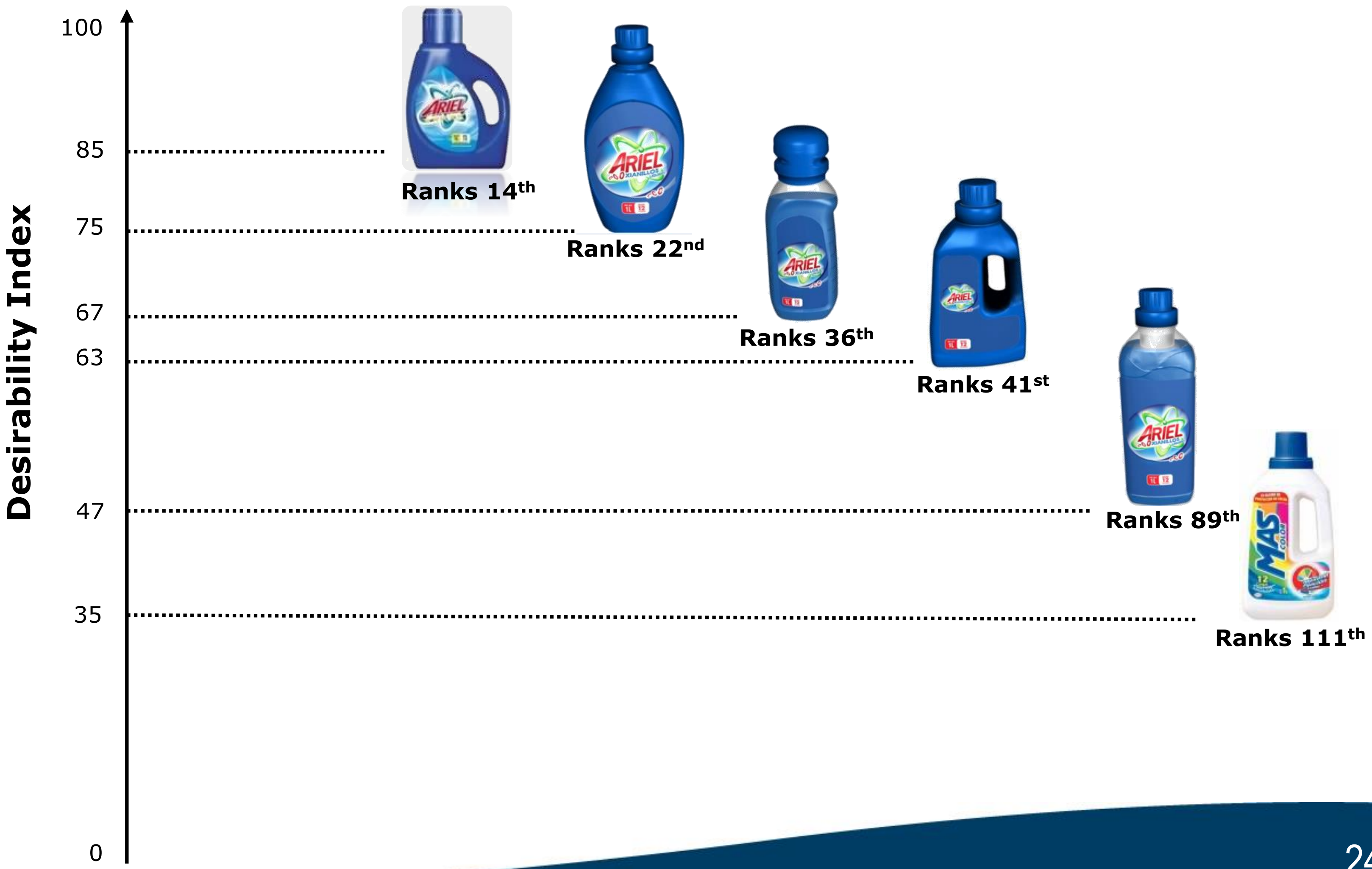
Bottle rankings

- Preference ranking of the 144 bottle profiles

	Shape	Material	CapFunct	Brand	Utility	Desirability
1	Cooper	Trans	RollerBall	Ariel	0.4690546367	0.9899996266
2	Cooper	Trans	DoubleCap	Ariel	0.4469530659	0.9672826048
3	Cooper	Trans	SpoutCap	Ariel	0.432889118	0.9528270204
4	Cooper	SemiTrans	RollerBall	Ariel	0.4078261102	0.9270660787
5	Cooper	Trans	CurrentDosing	Ariel	0.4030671924	0.9221746375
6	Cooper	Trans	RollerBall	MasColor	0.3903162183	0.9090685806
7	Cooper	SemiTrans	DoubleCap	Ariel	0.3857245393	0.9043490343
8	Cooper	Opaque	RollerBall	Ariel	0.377483784	0.8958787931
9	Cooper	SemiTrans	SpoutCap	Ariel	0.3716605915	0.8898934378
10	Cooper	Trans	DoubleCap	MasColor	0.3682146475	0.8863515319
11	Cooper	Opaque	DoubleCap	Ariel	0.3553822131	0.8731617419
12	Cooper	Trans	SpoutCap	MasColor	0.3541506996	0.8718959333
13	Cooper	SemiTrans	CurrentDosing	Ariel	0.3418386659	0.8592410348
14	Cooper	Opaque	SpoutCap	Ariel	0.3413182653	0.8587061421
15	Cooper	SemiTrans	RollerBall	MasColor	0.3290876918	0.8461349717

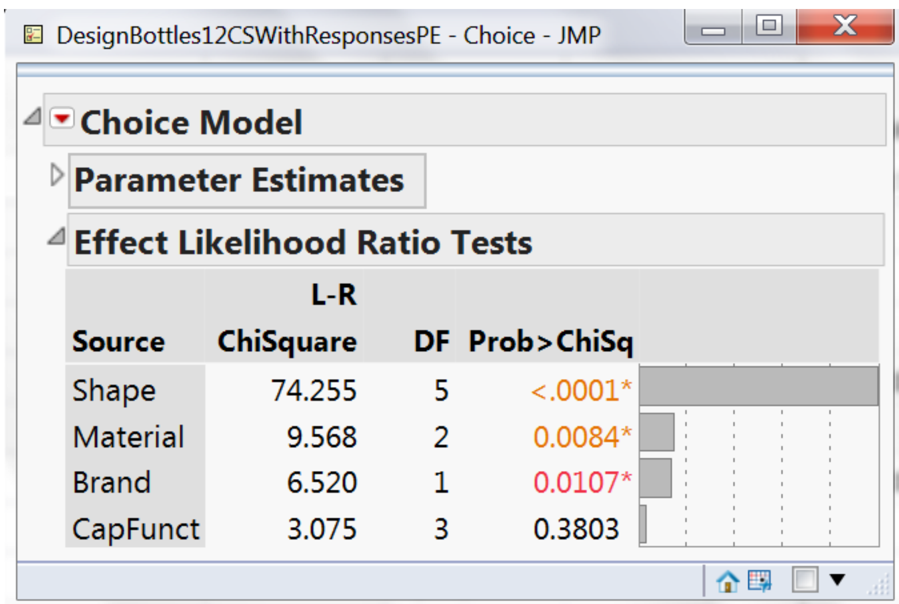
Ariel's current execution

Bottle rankings



Analysis of the P&E data

- "Shape Design", "Material" and "Brand" have a significant impact on bottle choice
- "Shape Design" is about 7 times more important than "Material" and "Brand"

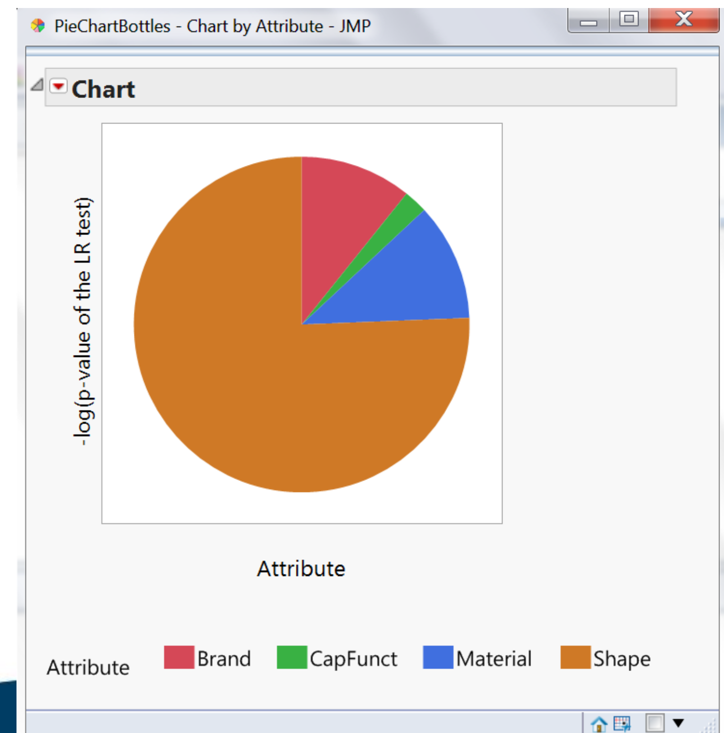

DesignBottles12CSWithResponsesPE - Choice - JMP

Choice Model

Parameter Estimates

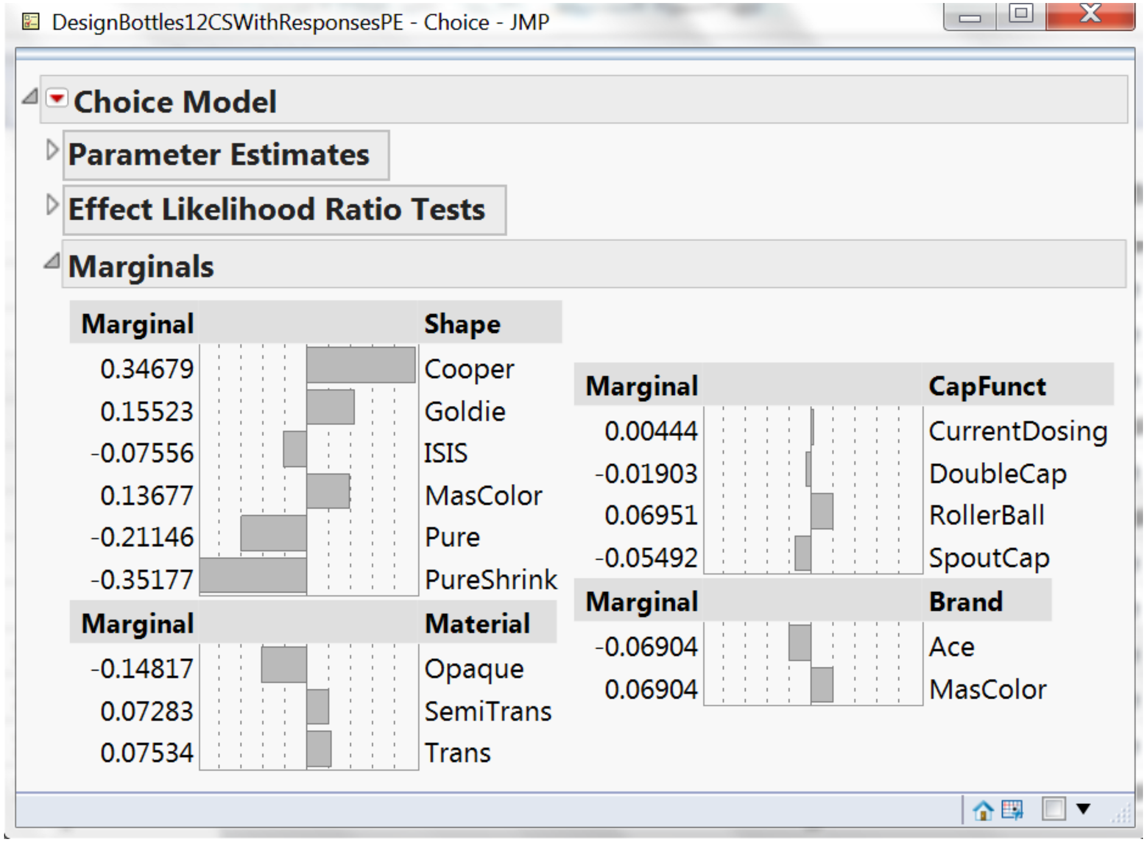
Effect Likelihood Ratio Tests

Source	L-R ChiSquare	DF	Prob>ChiSq
Shape	74.255	5	<.0001*
Material	9.568	2	0.0084*
Brand	6.520	1	0.0107*
CapFunct	3.075	3	0.3803



Part-worth estimates

Cooper design, transparency and MAS Color brand are the key bottle drivers



Marginal	Shape
0.34679	Cooper
0.15523	Goldie
-0.07556	ISIS
0.13677	MasColor
-0.21146	Pure
-0.35177	PureShrink

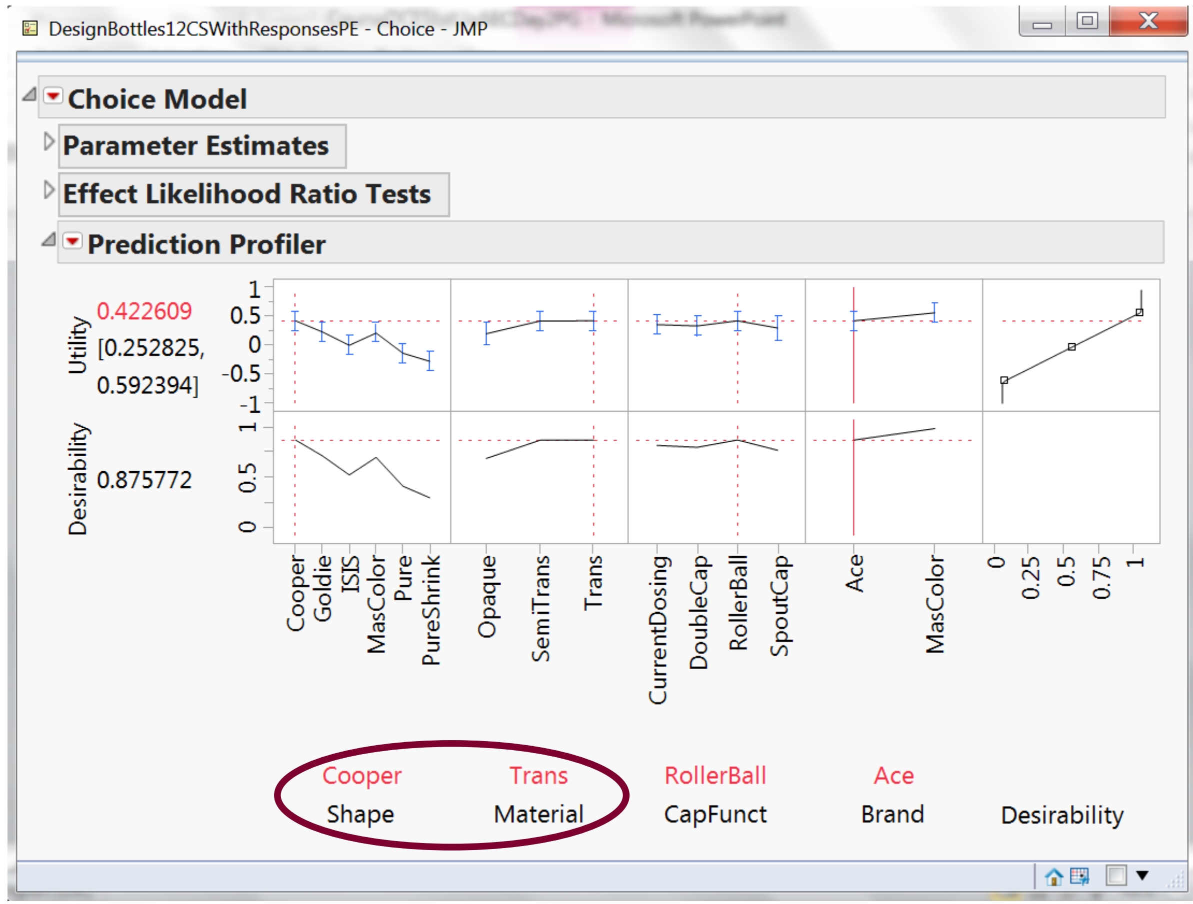
Marginal	Material
-0.14817	Opaque
0.07283	SemiTrans
0.07534	Trans

Marginal	CapFunct
0.00444	CurrentDosing
-0.01903	DoubleCap
0.06951	RollerBall
-0.05492	SpoutCap

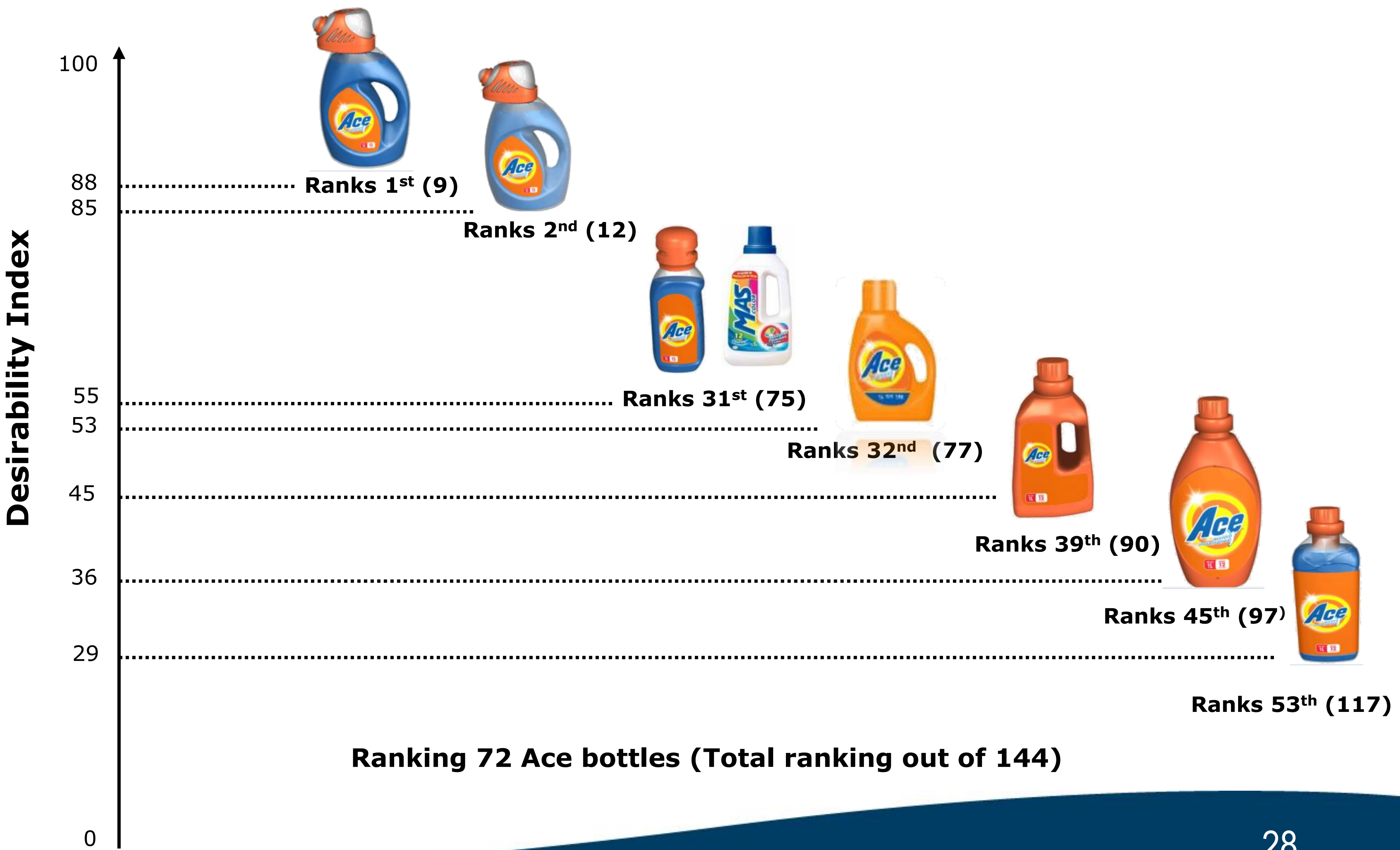
Marginal	Brand
-0.06904	Ace
0.06904	MasColor

Prediction profiler

Optimal settings for Ace bottle:
Cooper – Transparent



Bottle rankings



Individual-level preference estimates

- Make sure the option “Firth Bias-adjusted Estimates” is checked
- Use a JSL script to speed up the individual-level analysis
- Look at the distributions of the individual-level estimates in the Distribution Platform
- Firth individual-level estimates prove useful for market segmentation in the Clustering Platform

Healthcare system preference study

- To measure people's preferences for changes in the healthcare system due to care payment system effects
- Four types of respondents:
  1. Individual care providers
  2. Provider organizations' executives
  3. Policy makers
  4. Healthcare experts
- In Europe, US, Canada, Australia and New Zealand
- Led by the Center for Health Services and Nursing Research of the Catholic University of Leuven

11 healthcare system performance domains

1. Clinical effectiveness and patient safety
2. Best practice of service use
3. Care equity
4. Care coordination, teamwork and continuity
5. Patient centeredness
6. Timeliness
7. ST cost containment and budget safety
8. LT cost containment and budget safety
9. Provider wellness
10. Innovation
11. Gaming the system

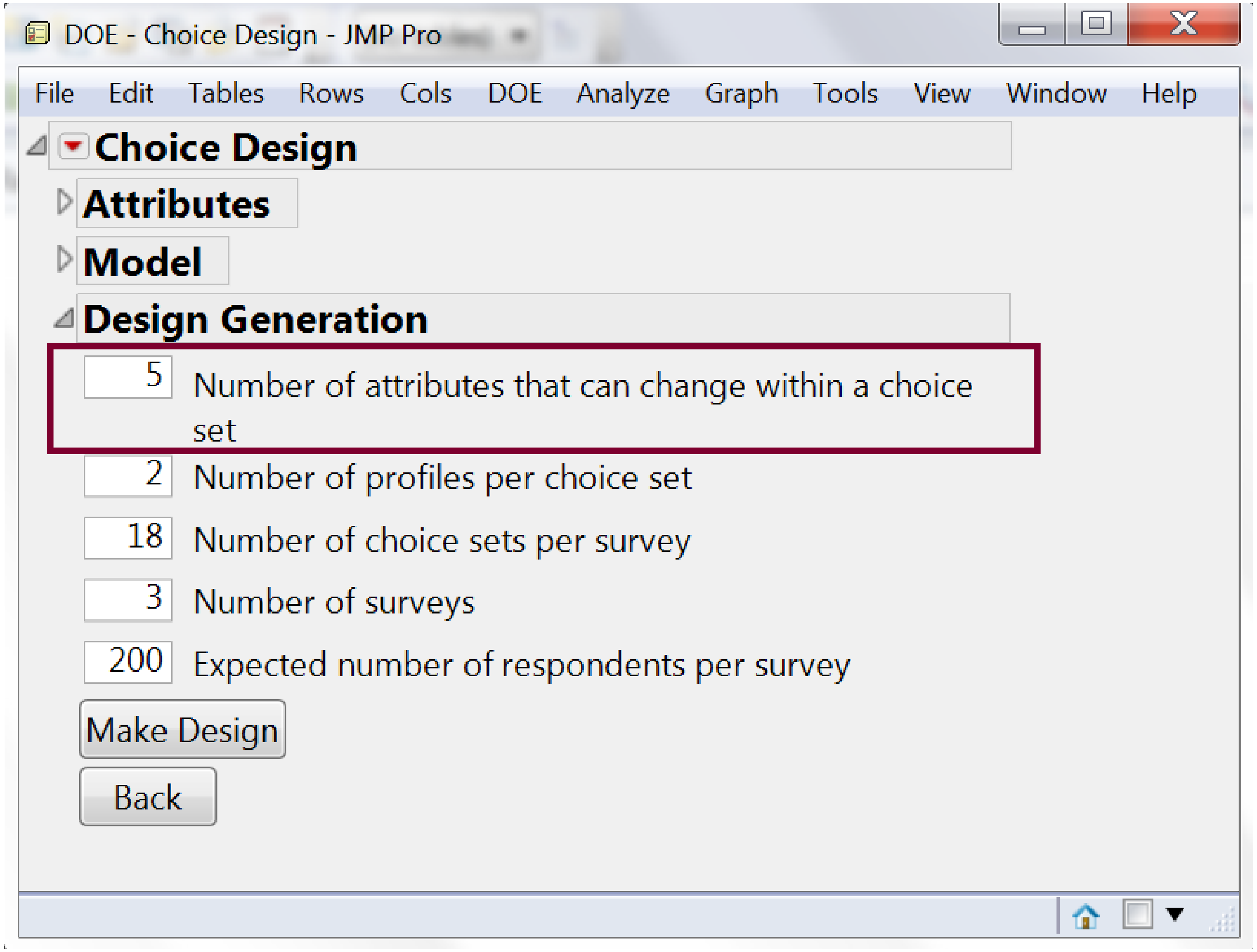
Choice set with partial profiles

Change to your current healthcare system performance due to payment system effects	
Situation A	Situation B
Improved level of care equity (avoiding care variation between patients with equal needs)	Current level of care equity (avoiding care variation between patients with equal needs)
Current level of care coordination, teamwork and continuity	Deteriorated level of care coordination, teamwork and continuity
Improved level of timeliness (avoiding waiting and delays)	Deteriorated level of timeliness (avoiding waiting and delays)
Deteriorated level of patient centeredness (respecting preferences and values)	Improved level of patient centeredness (respecting preferences and values)
Deteriorated level of short term cost containment and budget safety	Current level of short term cost containment and budget safety

Partial profiles

- The levels of some attributes remain constant in every choice set
- This reduces the cognitive burden on the respondents when “many” attributes are used
- It may also avoid the use of lexicographic choice behavior, i.e., when respondents make choices based on only one attribute or a small subset of the attributes, which violates the assumption of non-compensatory decision-making

Partial profiles in JMP



Prior beliefs about attributes

RANK	PERFORMANCE DOMAIN
1	Clinical effectiveness and patient safety
2	Best practice of service use
	LT cost containment and budget safety
3	Gaming the system
	Care equity
	Care coordination, teamwork and continuity
4	Timeliness
	Patient centeredness
	Innovation
	Provider wellness
	ST cost containment and budget safety

Prior beliefs about attribute levels

RANK	OUTCOME IN A PERFORMANCE DOMAIN
1	Positive
	V
2	No change or neutral
	V
	V
3	Negative

People are loss averse!

Reflection on the prior mean

RANK	PERFORMANCE DOMAIN	-
1	Clinical effectiveness and patient safety	-0.6
2	Best practice of service use	-0.4
	LT cost containment and budget safety	-0.4
3	Gaming the system	-0.35
	Care equity	-0.35
	Care coordination, teamwork and continuity	-0.35
4	Timeliness	-0.3
	Patient centeredness	-0.3
	Innovation	-0.3
	Provider wellness	-0.3
	ST cost containment and budget safety	-0.3

Reflection on the prior mean

RANK	PERFORMANCE DOMAIN	-	N	+
1	Clinical effectiveness and patient safety	-0.6	0.1	0.5
2	Best practice of service use	-0.4	0.05	0.35
	LT cost containment and budget safety	-0.4	0.05	0.35
3	Gaming the system	-0.35	0.05	0.3
	Care equity	-0.35	0.05	0.3
	Care coordination, teamwork and continuity	-0.35	0.05	0.3
4	Timeliness	-0.3	0.05	0.25
	Patient centeredness	-0.3	0.05	0.25
	Innovation	-0.3	0.05	0.25
	Provider wellness	-0.3	0.05	0.25
	ST cost containment and budget safety	-0.3	0.05	0.25

Prior mean

$$\boldsymbol{\beta}_0 = [-0.6, 0.1 \ , -0.4, 0.05, -0.4, 0.05, -0.35, 0.05, -0.35, 0.05, -0.35, 0.05,$$

$$-\ 0.3, 0.05, -0.3, 0.05, -0.3, 0.05, -0.3 \ \ , 0.05, -0.3 \ \ , 0.05]'$$

Reflection on the prior variance

RANK	PERFORMANCE DOMAIN	N	+
1	Clinical effectiveness and patient safety	0.1	0.5
2	Best practice of service use	0.05	0.35
	LT cost containment and budget safety	0.05	0.35
3	Gaming the system	0.05	0.3
	Care equity	0.05	0.3
	Care coordination, teamwork and continuity	0.05	0.3
4	Timeliness	0.05	0.25
	Patient centeredness	0.05	0.25
	Innovation	0.05	0.25
	Provider wellness	0.05	0.25
	ST cost containment and budget safety	0.05	0.25

Reflection on the prior variance

RANK	PERFORMANCE DOMAIN	N	+	Std.
1	Clinical effectiveness and patient safety	0.1	0.5	0.3
2	Best practice of service use	0.05	0.35	0.25
	LT cost containment and budget safety	0.05	0.35	0.25
3	Gaming the system	0.05	0.3	0.2
	Care equity	0.05	0.3	0.2
	Care coordination, teamwork and continuity	0.05	0.3	0.2
4	Timeliness	0.05	0.25	0.15
	Patient centeredness	0.05	0.25	0.15
	Innovation	0.05	0.25	0.15
	Provider wellness	0.05	0.25	0.15
	ST cost containment and budget safety	0.05	0.25	0.15

Prior variance

$$
\Sigma_0 = \begin{bmatrix}
0.09 & -0.05 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
 & 0.09 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
 & & 0.06 & -0.03 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
 & & & 0.06 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
 & & & & 0.06 & -0.03 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
 & & & & & 0.06 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
 & & & & & & 0.04 & -0.02 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
 & & & & & & & 0.04 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
 & & & & & & & & 0.04 & -0.02 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
 & & & & & & & & & 0.04 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
 & & & & & & & & & & 0.04 & -0.02 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
 & & & & & & & & & & & 0.04 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
 & & & & & & & & & & & & 0.02 & -0.01 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
 & & & & & & & & & & & & & 0.02 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
 & & & & & & & & & & & & & & 0.02 & -0.01 & 0 & 0 & 0 & 0 & 0 & 0 \\
 & & & & & & & & & & & & & & & 0.02 & 0 & 0 & 0 & 0 & 0 & 0 \\
 & & & & & & & & & & & & & & & & 0.02 & -0.01 & 0 & 0 & 0 & 0 \\
 & & & & & & & & & & & & & & & & & 0.02 & 0 & 0 & 0 & 0 \\
 & & & & & & & & & & & & & & & & & & 0.02 & -0.01 & 0 & 0 \\
 & & & & & & & & & & & & & & & & & & & 0.02 & 0 & 0 \\
 & & & & & & & & & & & & & & & & & & & & 0.02 & -0.01 \\
 & & & & & & & & & & & & & & & & & & & & & 0.02
\end{bmatrix}
$$

Table 4 Survey 1 of the Bayesian D-optimal partial profile design

Choice	Attributes										
set	1	2	3	4	5	6	7	8	9	10	11
1	*	*	*	*	+	N	+	–	*	*	–
1	*	*	*	*	N	–	–	+	*	*	N
2	*	*	–	*	*	–	*	+	–	N	*
2	*	*	+	*	*	N	*	N	N	–	*
3	*	*	–	*	*	+	N	+	N	*	*
3	*	*	+	*	*	N	+	–	–	*	*
4	*	*	N	+	*	–	*	–	*	+	*
4	*	*	–	N	*	+	*	N	*	–	*
5	*	–	*	*	§	§	*	*	*	N	+
5	*	N	*	*	§	§	*	*	*	+	–
6	*	N	*	§	–	*	N	+	*	*	*
6	*	–	*	§	N	*	–	–	*	*	*
7	*	–	*	*	N	+	*	*	*	–	–
7	*	N	*	*	–	N	*	*	*	N	+
8	*	N	§	–	–	*	*	*	N	*	*
8	*	–	§	N	N	*	*	*	–	*	*
9	*	+	N	*	+	*	N	*	*	+	*
9	*	N	+	*	N	*	–	*	*	–	*
10	N	*	*	§	*	*	+	+	§	*	*
10	–	*	*	§	*	*	–	N	§	*	*
11	N	*	*	*	*	+	–	–	–	*	*
11	+	*	*	*	*	–	+	N	+	*	*
12	+	*	*	*	N	*	*	N	N	*	–
12	–	*	*	*	+	*	*	–	+	*	N
13	N	*	*	*	+	–	*	*	*	N	–
13	+	*	*	*	N	N	*	*	*	+	N
14	+	*	*	N	*	+	*	*	–	*	N
14	–	*	*	–	*	N	*	*	+	*	+
15	+	*	*	–	*	*	N	–	*	+	*
15	–	*	*	+	*	*	–	+	*	–	*
16	–	*	–	*	N	*	+	*	*	*	N
16	+	*	+	*	–	*	–	*	*	*	+
17	–	+	–	*	*	*	–	*	*	*	+
17	+	N	+	*	*	*	N	*	*	*	N
18	N	–	+	N	*	*	N	*	*	*	*
18	–	N	N	–	*	*	+	*	*	*	*

Table 5 Survey 2 of the Bayesian D-optimal partial profile design

Choice	Attributes										
set	1	2	3	4	5	6	7	8	9	10	11
19	*	*	*	*	+	§	–	*	–	*	N
19	*	*	*	*	N	§	N	*	N	*	–
20	*	*	*	*	–	N	§	N	§	*	*
20	*	*	*	*	N	–	§	+	§	*	*
21	*	*	*	+	–	§	*	*	+	*	–
21	*	*	*	–	N	§	*	*	N	*	+
22	*	*	*	N	N	*	*	N	*	N	N
22	*	*	*	+	+	*	*	+	*	–	–
23	*	*	–	N	*	*	*	*	N	+	–
23	*	*	+	–	*	*	*	*	+	–	N
24	*	*	+	+	*	*	N	*	*	–	N
24	*	*	N	N	*	*	–	*	*	+	–
25	*	N	*	*	+	*	*	N	+	–	*
25	*	–	*	*	–	*	*	+	–	N	*
26	*	–	*	*	–	+	+	*	*	*	N
26	*	+	*	*	N	–	N	*	*	*	–
27	*	–	*	+	*	*	*	–	N	*	+
27	*	+	*	–	*	*	*	+	+	*	–
28	*	N	§	+	§	*	–	*	*	*	*
28	*	–	§	–	§	*	+	*	*	*	*
29	*	N	N	*	*	+	*	*	*	–	+
29	*	–	–	*	*	N	*	*	*	+	–
30	*	–	N	*	*	N	*	+	*	*	+
30	*	+	–	*	*	–	*	–	*	*	N
31	+	*	§	§	*	*	–	*	*	N	*
31	N	*	§	§	*	*	+	*	*	+	*
32	N	*	*	*	N	N	–	N	*	*	*
32	+	*	*	*	–	+	+	–	*	*	*
33	N	N	*	*	*	*	N	*	–	+	*
33	+	–	*	*	*	*	+	*	+	N	*
34	–	+	*	N	*	*	*	*	–	–	*
34	N	N	*	–	*	*	*	*	+	N	*
35	N	+	–	§	*	N	*	*	*	*	*
35	+	N	N	§	*	+	*	*	*	*	*
36	+	–	–	*	–	*	*	*	*	+	*
36	–	+	+	*	N	*	*	*	*	–	*

Table 6 Survey 3 of the Bayesian D-optimal partial profile design

Choice	Attributes										
set	1	2	3	4	5	6	7	8	9	10	11
37	*	*	+	*	*	§	+	§	*	§	*
37	*	*	N	*	*	§	–	§	*	§	*
38	*	*	+	*	*	*	–	N	–	+	*
38	*	*	N	*	*	*	+	–	N	–	*
39	*	*	+	§	*	+	*	*	§	+	*
39	*	*	–	§	*	–	*	*	§	N	*
40	*	*	–	*	N	*	+	*	N	*	+
40	*	*	+	*	+	*	N	*	–	*	–
41	*	–	*	*	*	N	+	*	N	–	*
41	*	N	*	*	*	+	N	*	–	+	*
42	*	+	*	+	*	+	*	N	*	*	–
42	*	–	*	N	*	–	*	+	*	*	N
43	*	N	*	–	–	*	+	N	*	*	*
43	*	–	*	+	N	*	N	+	*	*	*
44	*	N	N	*	N	*	*	+	–	*	*
44	*	+	+	*	+	*	*	N	N	*	*
45	–	*	*	*	*	*	*	+	N	N	N
45	+	*	*	*	*	*	*	N	+	–	–
46	–	*	*	§	*	–	+	*	*	*	+
46	+	*	*	§	*	+	–	*	*	*	N
47	–	*	§	N	N	*	*	*	N	*	*
47	+	*	§	+	+	*	*	*	+	*	*
48	–	*	*	N	+	*	*	N	*	N	*
48	+	*	*	–	N	*	*	+	*	+	*
49	+	*	*	+	–	N	*	*	*	–	*
49	N	*	*	N	N	–	*	*	*	+	*
50	–	*	+	–	*	+	*	*	*	*	+
50	+	*	N	+	*	–	*	*	*	*	N
51	+	–	*	*	*	*	*	N	*	–	+
51	N	+	*	*	*	*	*	–	*	+	N
52	N	–	*	+	*	+	*	*	N	*	*
52	–	N	*	N	*	N	*	*	+	*	*
53	–	+	+	*	*	*	*	N	*	*	–
53	N	–	N	*	*	*	*	–	*	*	+
54	–	–	N	*	+	*	*	*	N	*	*
54	N	+	+	*	N	*	*	*	–	*	*

Experiment Yourself!

Experiment!
Make it your motto day and night.
Experiment!
And it will lead you to the light.

The apple on top of the tree
Is never too high to achieve,
So take an example from Eve ...
Experiment!

Be curious,
Though interfering friends may frown.
Get furious
At each attempt to hold you down.

If this advice you only employ,
The future can offer you infinite joy
And merriment ...
Experiment!
And you'll see!

-- Cole Porter, in "Nymph Errant" (1933)

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Contact: roselinde.kessels@uantwerpen.be