Make conjoint analyses your standard approach to understand how patient preferences vary across different subgroups

Daniel Saure\textsuperscript{1}, Marco Boeri\textsuperscript{2}, Katharine Thorn\textsuperscript{1}, Alexander Schacht\textsuperscript{1}

\textsuperscript{1}Eli Lilly and Company
\textsuperscript{2}RTI Health Solutions, Belfast (UK)
INTRODUCTION
Introduction

• When developing a product, it is crucial to understand the preferences of the customer with respect to different features (referred to as attributes) of the product

• In medical research, treatments should incorporate patients’ preferences and their willingness to trade off among treatment attributes
  – e.g., efficacy vs. safety or efficacy vs. route of application
Introduction

- This study employed a discrete-choice experiment (DCE)
  - DCE is a well-known survey method for investigating how consumers choose between competing products or services and what tradeoffs they are willing to accept between risks or costs and benefits
- DCE can also be used to predict (simulate) consumer choices for alternative products or services in development
Introduction

• Patients have different preferences, and not everyone prefers the same outcome
  – Preference heterogeneity is unavoidable

• Ideally, the analysis should account for preference heterogeneity in the overall sample

• It can also be important to understand whether
  – Subgroups with specific preferences exist
  – Specific patient characteristics are associated with different preferences within the sample
DCE: STATISTICAL ANALYSIS
In DCE, we assume respondents make choices maximizing the following utility function, where $V$ is the deterministic portion, $X$ is a vector of attribute levels (all effects coded in this analysis), $\beta$ is a vector of parameters (preference weights), and $\varepsilon$ is an unobserved error term; thus, we have the following:

$$U_i = V(\beta, X_i) + \varepsilon_i$$

If the error term ($\varepsilon_i$) is assumed to follow an independently and identically distributed type-1 extreme value distribution, then we can derive the conditional multinomial logit (MNL) model:

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Note: The original work by McFadden (1974) refers to the conditional logit in which choices are regressed on the treatment attributes. In the MNL, choices are also regressed on the characteristics of the respondent making the choice.
DCE: Statistical Analysis

- MNL relates choices to the attributes of the alternatives available to decision makers and is consistent with the random utility theory.
- McFadden (1974) originally applied this framework to observed transportation choices. His work laid the foundation for what is now known as conjoint analysis involving hypothetical or stated choices.
- Note: the MNL model is based on very strong assumptions:
  - All respondents have the same preferences (homogenous preferences).
  - Each observation is independent of the other observations from the same respondent.

DCE: Statistical Analysis

We can use different types of models (known as mixed logit models) to account for preference heterogeneity.

The 2 main mixed logit models used to analyze DCEs are as follows:

1. Random parameters logit (RPL)
   - Which assumes a continuous “mixing” distribution to account for preference heterogeneity
   - To test for differences in preferences between subgroups, we can interact respondent characteristics with the explanatory variables in the utility function (treatment attributes)

2. Latent class (LC)
   - Which assumes a discrete “mixing” distribution to account for preference heterogeneity
   - The class membership probability can be expressed as a function of respondent characteristics
CASE STUDY
Case Study

• Elicited patient preferences for psoriasis treatments
Case Study: Descriptive Statistics

<table>
<thead>
<tr>
<th>Age (years)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>1,123*</td>
</tr>
<tr>
<td>Mean (SD)</td>
<td>40.6 (12.76)</td>
</tr>
<tr>
<td>Median</td>
<td>39.0</td>
</tr>
<tr>
<td>Min, max</td>
<td>18, 74</td>
</tr>
</tbody>
</table>

*Note: 1,155 respondents completed the DCE, but 15 were excluded as they always selected the same alternative (either Treatment A or Treatment B) to the DCE questions or did not answer any DCE questions. 17 respondents did not answer any other questions in the survey; therefore, the DCE sample size is 1,140. The descriptive statistics are presented for 1,123 respondents.
RESULTS

Lilly
Preference Analysis: RPL Full Sample (N = 1,140)

Note: The vertical bars surrounding each mean preference weight denote the 95% confidence interval about the point estimate.
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Preference Analysis: RPL Full Sample (N = 1,140)

Vertical distance between preference weights indicates strength of preference for changes within an attribute.

Note: The vertical bars surrounding each mean preference weight denote the 95% confidence interval about the point estimate.
The relative importance of a change from 50% spot reduction to 100% spot reduction is 1.6 (1.6 = 0.74 − [-0.86]).
The relative importance of change from reaching results after 6 months to reaching results after 2 weeks is 0.45 (0.45 = 0.22 − [−0.23]).
The relative importance of a change from 50% spot reduction to 100% spot reduction is 3.6 \((1.6 / 0.45)\) times the relative importance of a change from reaching results after 6 months to reaching results after 2 weeks.

Note: The vertical bars surrounding each mean preference weight denote the 95% confidence interval about the point estimate.
SUBGROUP ANALYSIS BASED ON PATIENT CHARACTERISTICS (AGE AND GENDER)
Preference Analysis: RPL by Age (N = 1,123)

Note: The vertical bars surrounding each mean preference weight denote the 95% confidence interval about the point estimate.
Preference Analysis: RPL by Gender (N = 1,123)

Note: The vertical bars surrounding each mean preference weight denote the 95% confidence interval about the point estimate.
LATENT CLASS ANALYSIS
Preference Analysis: Latent Class (N = 1,140)

Note: The vertical bars surrounding each mean preference weight denote the 95% confidence interval about the point estimate.
The LC analysis indicated 4 as the optimal number of classes (using BIC) with the following preferences:

BIC = Bayesian information criterion.

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The LC analysis indicated 4 as the optimal number of classes (using BIC) with the following preferences:
- Class 1 (blue, 34.5%) strongly preferred lower risk of impairing side effects.
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- Class 2 (black, 14.3%) strongly against injections

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- Class 2 (black, 14.3%) strongly against injections
- Class 3 (green, 32.1%) rather indifferent (all attributes with similar relative importance)

BIC = Bayesian information criterion.

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The LC analysis indicated 4 as the optimal number of classes (using BIC) with the following preferences:

- Class 1 (blue, 34.5%) strongly preferred lower risk of impairing side effects
- Class 2 (black, 14.3%) strongly against injections
- Class 3 (green, 32.1%) rather indifferent (all attributes with similar relative importance)
- Class 4 (orange, 19.1%) strongly preferred higher efficacy

BIC = Bayesian information criterion.

Note: The vertical bars surrounding each mean preference weight denote the 95% confidence interval about the point estimate.
DISCUSSION AND CONCLUSIONS
Discussion

• The preliminary results presented show heterogeneity across respondents in the sample

• Subgroup analysis based on patient characteristics (e.g., age and gender) did not explain much preference heterogeneity
  – These are biological characteristics; it is plausible that preferences are determined by other (latent) characteristics (e.g., fear of injections)

• LC analysis allows us to explore preferences independently from these characteristics by accommodating latent preference heterogeneity
  • Then, with additional analysis, class membership probability can be linked to the respondents’ characteristics to explore how their characteristics affect their preferences
Conclusions

• DCE is a type of conjoint analysis widely used to explore patient preferences and the tradeoffs they are willing to accept between risks and benefits

• It is important to remember that not everybody has the same preferences and analysis should explore preference heterogeneity

• We used 2 methods to explore preference heterogeneity
  – An RPL model with interaction terms for subgroups that provides information on whether and how preferences vary based on specific patient characteristics
  – An LC model that identifies patterns of preferences that are latent in the sample

• The RPL subgroup analysis did not reveal large differences in preferences based on age and gender, but the LC analysis indicated that there are patients with distinct preferences in the sample

• Information on heterogeneity in patient preferences can be important in the development of new treatments and for doctors trying to find the right treatment for a patient
QUESTIONS?

Lilly
Daniel Saure
Email: saure_daniel:@lilly.com
ADDITIONAL SLIDES
CONDITIONAL RELATIVE ATTRIBUTE IMPORTANCE
Conditional Relative Attribute Importance

- Maximum change in utility achievable with any attribute given the attributes and levels included in the study
- Calculated for each attribute as the difference between the level with the highest preference weight and the level with the lowest preference weight
Attribute Relative Importance:
Full Sample (N = 1,140)

Note: The vertical bars surrounding each mean preference weight denote the 95% confidence interval about the point estimate.
Attribute Relative Importance, by Age (N = 1,123)

Note: The vertical bars surrounding each mean preference weight denote the 95% confidence interval about the point estimate.
Attribute Relative Importance, by Gender (N = 1,123)

Note: The vertical bars surrounding each mean preference weight denote the 95% confidence interval about the point estimate.
Attribute Relative Importance: Latent Class (N = 1,140)

Note: The vertical bars surrounding each mean preference weight denote the 95% confidence interval about the point estimate.
RESULTS BY COUNTRY
Preference Analysis: RPL by Country (N = 1,140)

Note: The vertical bars surrounding each mean preference weight denote the 95% confidence interval about the point estimate.
Attribute Relative Importance, by Country (N = 1,140)

Note: The vertical bars surrounding each mean preference weight denote the 95% confidence interval about the point estimate.
DCE: STATISTICAL MODELS
In DCE, we assume respondents maximize the following utility function when making choices:

\[ U_i = V(\beta, X_i) + \varepsilon_i, \]

Where:

- \( V \) is the deterministic portion of the utility function
  - \( X \) is a vector of attribute levels (all effects-coded in this analysis)
  - \( \beta \) is a vector of parameters (preference weights)
- \( \varepsilon \) is an unobserved error term (random walk)
DCE: Statistical Models

- If the error term ($\varepsilon_i$) is assumed to follow an independently and identically distributed type-1 extreme value distribution, then

$$\Pr(\text{choice} = i) = \frac{e^{V(\beta, x_i)}}{\sum_j e^{V(\beta, x_j)}}$$

- The probability of choosing alternative $i$ is a function of both the attribute levels of alternative $i$ and the attribute levels of all other profiles presented in a choice task

- Note the MNL model is based on very strong assumptions
  - All respondents have the same preferences (homogenous preferences)
  - Each observation is independent of the other observations from the same respondent
DCE: Statistical Models

• RPL model accounts for preference heterogeneity:

\[ \Pr(y_n | \Omega, x_n) = \int \prod_{t=1}^{T_n} \frac{\exp(\beta' x_{nt})}{\sum_{j=1}^{J} \exp(\beta' x_{njt})} f(\beta | \Omega) d\beta. \]

• To test for differences in preferences between subgroups, we can interact respondent characteristics with the explanatory variables in the utility function (treatment attributes)
LC models can account for preference variation across latent (unobserved) groups of respondents:

\[
\Pr (y_n | x_n) = \sum_{c=1}^{C} \pi_c \prod_{i=1}^{T_n} \frac{\exp (\beta_c' x_{ni})}{\sum_{j=1}^{C} \exp (\beta_c' x_{nj})}.
\]

Where the membership probability can be expressed as a function of respondent characteristics:

\[
\pi_c = \frac{\exp (\alpha_c + \gamma_c' z_n)}{\sum_{c=1}^{C} \exp (\alpha_c + \gamma_c' z_n)}
\]

Note: 1 of the classes is normalized to zero for estimation purposes
Preference Analysis: Latent Class (N = 1,140); Optimal Number of Classes

- When using an LC approach, the analyst has to determine the optimal number of classes to be used.
- We employed the BIC index to establish that 4 was the optimal number of classes in our data set.

BIC = Bayesian information criterion.
LIMITATIONS
Limitations

• Data from multiple countries have been aggregated assuming the same data-generating process without testing for scale heterogeneity
• Not all possible sources of heterogeneity have been explored in the subgroup analysis
• The class membership probability in the LC model was not regressed against the respondent characteristics used for the subgroup models (age and gender), so we cannot compare the results from the RPL subgroup models and the results from the LC models