

The logo for Ziment features the word "ziment" in a lowercase, sans-serif font. The letter "z" is green, while the remaining letters "iment" are black. The text is centered within a white rectangular box that is superimposed on a larger, solid green square background.

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Getting the most out of complex marketing research models

Lessons learned from
a novel approach

There is strong pressure to develop new research techniques to provide earlier insights.

- Healthcare markets in developed countries are showing slow growth.
- Breakthrough therapies in novel therapy areas are rare.
- There is more and more competition for market share in proven areas... but truly novel treatments are rare.
- The obvious is already known... We must look for difficult to find answers.

Research must be able to provide early insights into markets and categories with many unknowns: Unknown drivers ... Unknown competitors ... Unforeseen breakthroughs

But, generating insights in complex markets puts tremendous pressure on models ...

- **Complex models must be able to:**
 - Account for many new classes launching in market over 5 years
 - Produce preference share for several products within each class
 - Each with varying attributes
 - Provide insight into source of volume
 - Provide preference share for many patient types
- **This puts tremendous pressure on traditional experimental designs.**
 - It is daunting to just find enough observations to estimate models
- **But, most importantly, it puts tremendous pressure on respondents.**
 - Can they really answer questions that are this complex?
 - Will they become exhausted before providing enough observations?

... and traditional modeling approaches are inadequate to address all the challenges

Design Option

Evaluation

Self-explicated conjoint

- Ratings of importance of attributes & desirability of levels



Too many levels to be practical

- Rating scales may fail to differentiate well, particularly re: importance

Full-profile conjoint



Too many attributes will overwhelm doctors

Hybrid conjoint



Combines above; suffers from both limitations

Paired comparison partial-profile



Works very well for understanding drivers but does not estimate preference share well

A Novel Approach

Benchmark Discrete Choice offers a novel approach

Benchmark Discrete Choice

A dynamic model that produces optimal reads of attribute importance, level sensitivity, and preference shares within a broad category landscape.



- **More attributes**
 - Limited only by n
- **More flexibility**
 - Complex availability models
- **Improved discrimination**
 - More sensitive to attribute importance

Benchmark Discrete Choice fuses two well-established research methods

The philosophy:

- Respondents are able to provide accurate preference share evaluations of even complex profiles
 - Monadic measures are believable
 - Monadic reads are accurate even with several patient types because they are not done repeatedly
- Trade-offs between attribute levels can best be made when the task is simple and direct
 - Partial-profile approaches simplify complexity
 - Paired-comparison conjoint approaches measure direct trade-offs

Data for Benchmark Discrete Choice are gathered in two steps

Step One

- Obtain preference share on benchmark scenarios
 - Measure best, base, worst case
 - Typically single scenarios– the simpler the better
- Market baskets should be realistic
 - All products in market or a subset
- Evaluations should be based upon full profiles
 - 'Product profiles,' not scenario cards

Results in most realistic 'sign-posts'

Step Two

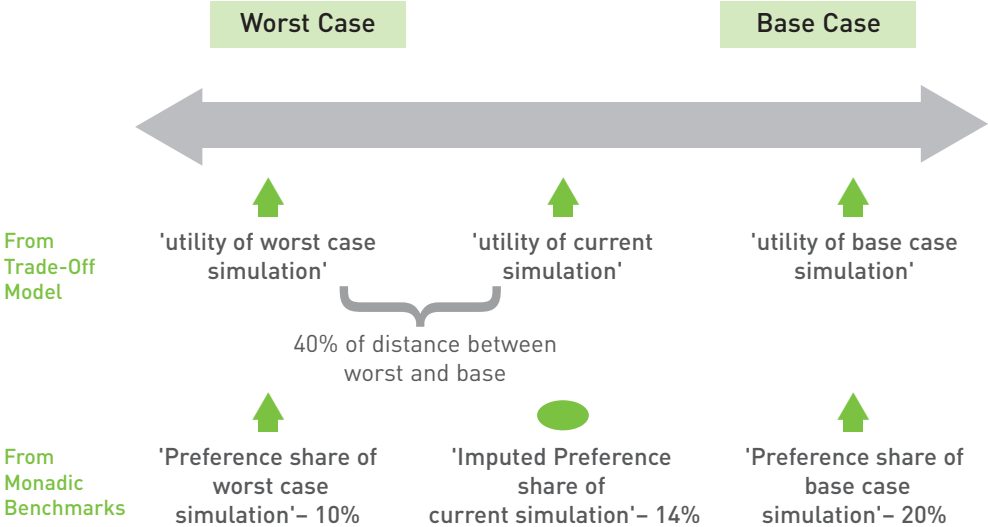
- Obtain trade-off information
 - Blocked design splits sample
 - ~ 12 – 15 scenarios evaluated
- Use partial-profile design to account for complexity
 - Each respondent evaluates scenarios trading off ~5 attributes
 - Assumes concepts are identical in all ways not contrasted in scenarios
- Measure should tap 'pure preference'
 - Strength of preference for Concept A v. Concept B

Results in most sensitive trade-offs

Data from monadic evaluations and trade-offs are combined in the final model and market simulator

- **Benchmarks provide preference share 'sign-posts'**
- **Partial-profile evaluations provide attribute-level sensitivities**
 - The strength of each driver
 - The 'shape' of the effect– relative impact of each level
- **In the simulator, preference share is imputed from the benchmarks**

To impute preference share, Benchmark Discrete Choice measures the distance between benchmarks using the trade-off data



A Sampling of Our experience

We've now used Benchmark Discrete Choice in enough real research settings to begin to look back upon what we've seen

- **Ziment has applied Benchmark Discrete Choice methods to dozens of studies in several therapeutic areas, including:**
 - Diabetes
 - RA and OA
 - Auto-immune diseases
 - Obesity
- **Benchmark Discrete Choice was implemented where the study parameters specifically called for it:**
 - High number of attributes and levels
 - Numerous products to be evaluated
 - Main desired output was 'landscape,' not 'narrow'

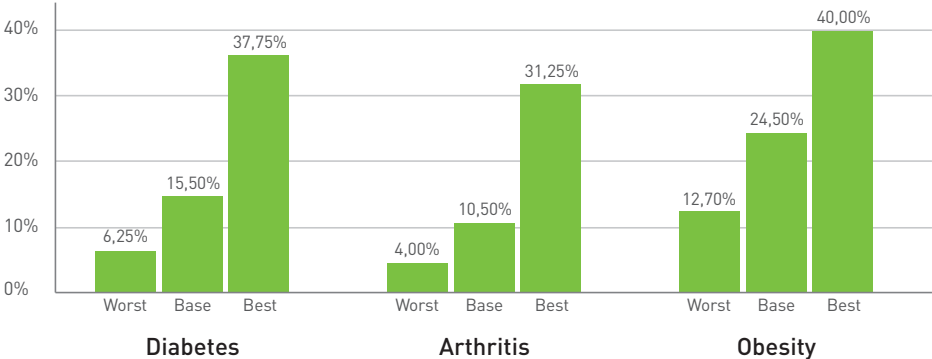
Benchmark Discrete Choice is flexible enough to allow a broad range of design possibilities

Some selected BDC studies

	Diabetes	Arthritis	Obesity
Number of Attributes	57	18	30
Number of Levels	194	46	94
Number of new products	4	1-4	2
Availability Model?	--	Yes	--
Number of Patient Types	7	4	6
Benchmarks collected per respondent	1	4	1
Partial profile tasks per respondent	15	10	12

In each study, we observed an impressive spread in preference shares

Obtained preference share ranges – worst, base, best product profiles



Because of the added flexibility, BDC is able to test a wider range of attributes that matter than we could have tested before

Instead of ...

Efficacy

... BDC can test

- Impact on HbA1c
- Impact on long-term disease progression
- Effect on bio-markers of CHF
- Effect on insulin sensitivity
- Impact on beta cell function
- Effect on post-prandial glucose
- Effect on fasting glucose
- Effect on TGL
- Impact on waist circumference

Side Effects

- Neuropsychiatric side effects
- Impact on sleep apnea
- Impact on CV side effects
- Incidence of nausea
- Injection site effects
- Impact on cognition

But, because we are sensitive to changes in so many things that matter, average changes in preference share per attribute will be smaller than in traditional conjoint studies.

In a BDC study with 25 attributes ...



... The average impact of each attribute will be 1.2% (30/25)
... Assuming all the attributes we test impact Rx-ing

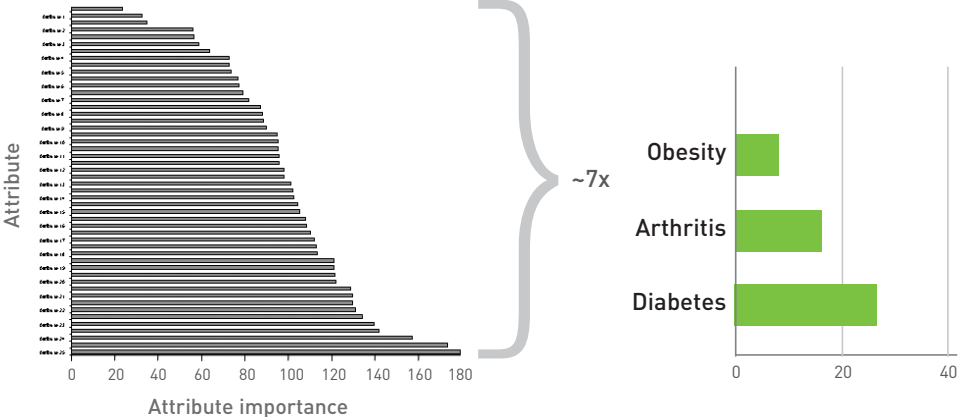
And, in all studies, all of the attributes mattered -they all significantly impacted choice

- **Multivariate statistical tests show that each attribute contributed significantly to the model**
 - The test determines whether each attribute adds explanatory power in the presence of all the other attributes
- **Therefore, additional precision was obtained by incorporating and examining each attribute in the model**

Up-front qualitative research was instrumental in guiding which attributes to include. The densely constructed PPCE model then confirmed the significance of each attribute.

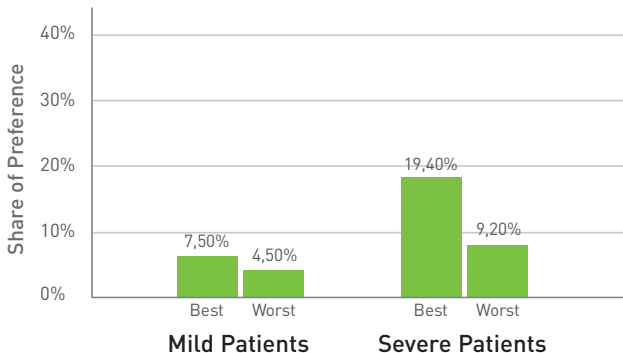
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Example of attribute importances



To get a better sense of attribute importance, we report preference shares in “buckets” of attributes.

Sample Preference Shares with four efficacy attributes at best/worst levels



By collapsing efficacy attributes together, their combined impacts can be seen, while still retaining the impact of each individual attribute.

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Four efficacy-related attributes all set to their “best” levels, then “worst” levels, to obtain preference shares at each point, holding all other attributes at base case.

**When to use BDC, when not to,
and what to do to get the most value**

BDC is ideal when breadth of knowledge is the primary research objective

BDC is best to use when:

- **The goal is to obtain a broad view of a treatment category:**
 - Which attributes drive the category;
 - Which new products will achieve the highest preference shares;
 - How the category will be impacted by a wide range of attributes and levels.
- **The focal product is in very early development or even pre-development:**
 - BDC provides excellent 'landscape' analysis

Sometimes, traditional conjoint is a better choice than Benchmark Discrete Choice for your project

BDC may not be necessary if:

- **The focal product is in late-stage development:**
 - By this point, usually only a handful of attributes are still 'in play'; traditional conjoint methods are sufficient to explore these attributes
- **Much is already known about the relevant product(s) and attributes in a category:**
 - In these cases, there is the risk of only using the BDC output to explore a small subset of the full space. This can lead to a sense of small effects, because the full breadth of the model is ignored.

In these situations, traditional conjoint methods can achieve project objectives with a smaller sample size.

As with any research technique, Benchmark Discrete Choice brings potential pitfalls that should be avoided

Potential Pitfall

High number of attributes requires more observations to obtain precision

Availability models make benchmarks complicated

Including extraneous attributes

Small absolute changes in preference share

How to Avoid

Use adequate sample size: BDC may require higher samples than traditional conjoint techniques

Use a benchmark model, but keep number of cards/scenarios low

Although BDC is more flexible and can incorporate more attributes and levels, up-front qualitative research and attribute generation is still essential

Use the appropriate design space – explore the full range of all the attributes, not just a select subset

To get the most out of BDC, make full use of all parts of the research process and outcomes

- **Use up-front qualitative research:**

- to determine which attributes are relevant to the broad category space;
- to capture the appropriate levels, making sure that the full breadth is covered without 'over-stepping' reasonable ranges; and
- to ascertain the proper language for the attributes and levels – this is particularly important with such a potentially large attribute set.

- **Make full use of the findings:**

- 'Stretch the rubber band' – Explore the full preference shares of all the products, from worst to best possible profiles;
- Don't restrict analysis to a small handful of attributes and levels.

Benchmark Discrete Choice is a flexible and expansive new tool in conjoint methodology

BDC can deliver:

- Category knowledge in expanding, developing, and existing markets
- Finer detail of market drivers
- Precise preference shares for a wide range of new products
 - to feed forecasts
 - to help guide licensing and development decisions