HOLISTIC CONJOINT

MARCO VRIENS
KWANTUM
DARIN MILLS
ILLUMINAS
FELIX EGGERS
COPENHAGEN BUSINESS SCHOOL

INTRODUCTION

In today's markets, consumers are often confronted with complex choice alternatives. Alternatives are considered complex if they are defined on many features. It is easy to think of complex choices such as cars, smartwatches, hotel options, college institutions etc. However, even seemingly basic categories such as skin care, basic kitchen appliances, coffee or soap can be quite complex if one really tries to evaluate all types of features and in which combinations they come. For example, in a study on consumers' skin care perceptions, 57 brands were involved (Vriens, Chen & Vidden (2019) that differentiate on many features, e.g. type of skin (dry, sensitive, normal), for specific skin problems (Acne, redness, eczema), whether it natural or organic, if animal testing was done to develop the product, what ingredients (Aloe, retinol, cocoa butter, collagen, etc.), whether it is general moisturizer, or intended for use at night-time, for around the eyes, whether it is meant to reduce wrinkles, etc.

The dominant approach to model consumer choices is conjoint analysis (sometimes referred to as discrete choice modeling). In conjoint a product is broken down in attributes and attribute levels and respondents are shown hypothetical (but sometimes incentive-aligned) choice tasks that consist of alternatives that are variations of the attributes. In each choice task they need to select the alternative they prefer or would buy. In situations with many attributes and levels, the choice tasks respondents are being asked to evaluate become daunting. A study by Sawtooth Software found that more than 30% of their recent conjoint analysis studies involved 10 attributes or more, with 6% involving 20 attributes or more (study based on 952 projects conducted by 39 researchers, personal communication with Bryan Orme, see also Orme, 2020).

The standard conjoint model assumes that each level within an attribute has a certain utility or value for the respondent and that the overall value of an alternative is the sum of all the part utilities that comprise a choice alternative. Knowing the utilities allows understanding and predicting which products consumers choose.

With complex choice alternatives it is unlikely that consumers always fully and meticulously break down each product or service that they consider for purchase into its constituent features and review each attribute or level, and then assign values and somehow integrate these values into their mind and go for the option with the highest overall value. They may certainly initially try this, in experimental settings or in real life, but soon that task will demand too many cognitive resources (Jenke, et al., 2021). Yet, conjoint studies are still being designed and modeled with this superhuman processor in mind. In the psychology literature this paradigm has been challenged. We know consumers revert to simplification heuristics (e.g., Gigerenzer & Todd, 1999) and will likely simplify the task considerably. For example, consumers may eliminate certain alternatives because of unacceptable features (e.g., Hauser et al., 2010). This will limit the number of options but could still leave many open. Alternatively, they may quickly decide what attributes matter most and only focus on those (elimination-by-aspects, Tversky, 1972). Other decision heuristics, e.g. disjunctive or conjunctive rules, also don't seem to substantially simplify the decision difficulty at hand as we typically encounter them in conjoint studies.

As another simplification strategy, one that to our knowledge has not been fully investigated yet, consumers may look at some features very specifically while at the same time evaluating another group of attributes more holistically in terms of certain perceived benefits or goals, or even just to get a feeling for overall value-for-money. We might call this the "gestalt" heuristic.

A Holistic Approach

We assume that some sets of attributes are not, or not solely, being evaluated as separate features, but that the consumer will look at a set of features holistically and will determine whether that profile has a certain benefit they seek or whether they can achieve a certain goal. There is evidence from measuring brain activity that such mechanisms are being used by humans (e.g., Radulescu, Niv & Baillard, 2019).

Consider the example shown in Table 1:

Table 1. Illustration of the holistic dimension

Foundational attributes (features 1–4)

Holistic dimension attributes (features 5–14)

	FEATURES	ALTERNATIVE 1	ALTERNATIVE 2	ALTERNATIVE 3
1	Brand	Apple	Garmin	Fitbit
2	Price	$349	$249	$199
3	Design/form factor	Watch	Watch	Band
4	Battery life	1 day	3 days	3 days
5	GPS	Yes	Yes	No
6	Heart health	ECG	None	ECG
7	Sleep monitoring	Yes	Yes	No
8	Fitness trainer	Yes	Yes	Yes
9	Run coach	No	Yes	Yes
10	Strength training	Yes	Yes	Yes
11	Stress monitoring	Yes	No	No
12	Fall detection	Yes	No	No
13	Exercise tracking	Yes	No	No
14	Music	Yes	No	No
	HOLISTIC DIMENSION	9	5	4

Features 5 to 14 comprise the holistic dimension

In this example, we assume that certain attributes are evaluated attribute by attribute and that their value does not depend on the presence or absence of other attributes. In our study, we assume brand, price, design/form factor and battery life to be these "foundational" attributes (we use the terms attributes and features interchangeably). We test the assumption that consumers process the remaining features, i.e., attributes 5-14, in a holistic, gestalt way, and semi-intuitively arrive at an assessment whether a particular fitness wearable is good enough to achieve their fitness goals. This assessment will then be merged with information on brand, price, design & battery life.

STUDY DESIGN AND MODELING

We re-analyze the data from the fitness wearable study by defining such a holistic decision dimension and developing a statistical model that can represent this type of decision making. We test whether a holistic component exists and to what extent it influences decisions using a study of fitness wearables (Vriens, Mills & Elder, 2023). This study included 5 foundational attributes (brand, price, design, battery life and charging time) and 11 specific product features and had a base size of 2,000.

The foundational attributes are considered baseline product features and are thus included in all our models. The 11 product features like heart rate monitoring and strength training are used to calculate the holistic dimension that can explain (or help explain) product choice.

To define a holistic attribute, we summed the levels of any given product option. For instance, if a product was shown with 3 health features and 4 fitness features, then the holistic attribute for that product would be 7. Further, since some of the feature attributes were not binary (e.g. not included/included) but were level-coded as a low to high hierarchy, we summed the levels across the feature set. In total, this created a possible range of holistic levels from 1 to 19. We consider this holistic dimension and benchmark it to the standard conjoint model in five models:

1. A standard model with all 16 attributes
2. A standard model with all 16 attributes plus a holistic attribute as a part-worth function
3. A standard model with all 16 attributes plus a holistic attribute as a linear function
4. A reduced model with 5 foundational attributes plus a holistic attribute as a part-worth function
5. A reduced model with 5 foundational attributes plus a holistic attribute as a linear function

We further differentiate the findings for two types of segmentation approaches. In the Vriens, Mills & Elder (2023) study, respondents were allocated to either a low, mid-, or high price task. So, in our second analysis we again evaluated the five models but now by each price segment. In another set of analyses, we derived latent-class segments.

RESULTS

As a result of modeling the holistic attribute as part-worth and given our study had up to 19 possible feature levels the number of levels and the number of parameters being estimated is important to consider in the model comparison. In Table 2 below we show the performance of the five models (the top part using the part worth specification, the bottom part using the linear function specification – the standard model is identical in both specifications).

Table 2. Hold out performance of the holistic models (mean absolute error)

	1. ALL ATTRIBUTES & NO HOLISTIC DIMESION	2. ALL ATTRIBUTES PLUS 1 HOLISTIC DIMENSION	3. FOUNDATIONAL ATTRIBUTES PLUS 1 HOLISTIC DIMENSION
		Holistic modeled as part-worth function	
	Model 1	**Model 2**	**Model 4**
# OF LEVELS	69	88	57
# OF PARAMETERS	52	71	40
MEAN ABSOLUTE HOLD OUT ERROR	5.7%	5.4%	**4.5%**
		Holistic modeled as linear function	
	Model 1	**Model 3**	**Model 5**
# OF LEVELS	69	70	39
# OF PARAMETERS	52	53	22
MEAN ABSOLUTE HOLD OUT ERROR	5.7%	5.6%	**4.0%**

Including a holistic component improved the prediction accuracy in all models. Models 2 and 3 (All Attributes plus Holistic) have more levels and more parameters to be estimated than the standard model 1. We might expect lower accuracy because of that. However, the results also show that models 4 and 5 that replace the individual feature attributes with a holistic attribute perform better than the standard model, despite having fewer parameters. In our second set of analyses, we analyzed the five models by price segment. In this study, we had two conjoint tasks: a macro and a micro conjoint (see Vriens, Mills & Elder, 2023 for details). The macro conjoint was used to allocate respondents in to a low, mid or high price segment. Price can be an effective shortcut in determining respondent needs. These low-price, mid-price, and high-price buyers can be a good representation of differing choice behavior and expectations. In table 3 we show the results of the five models for the different price segments.

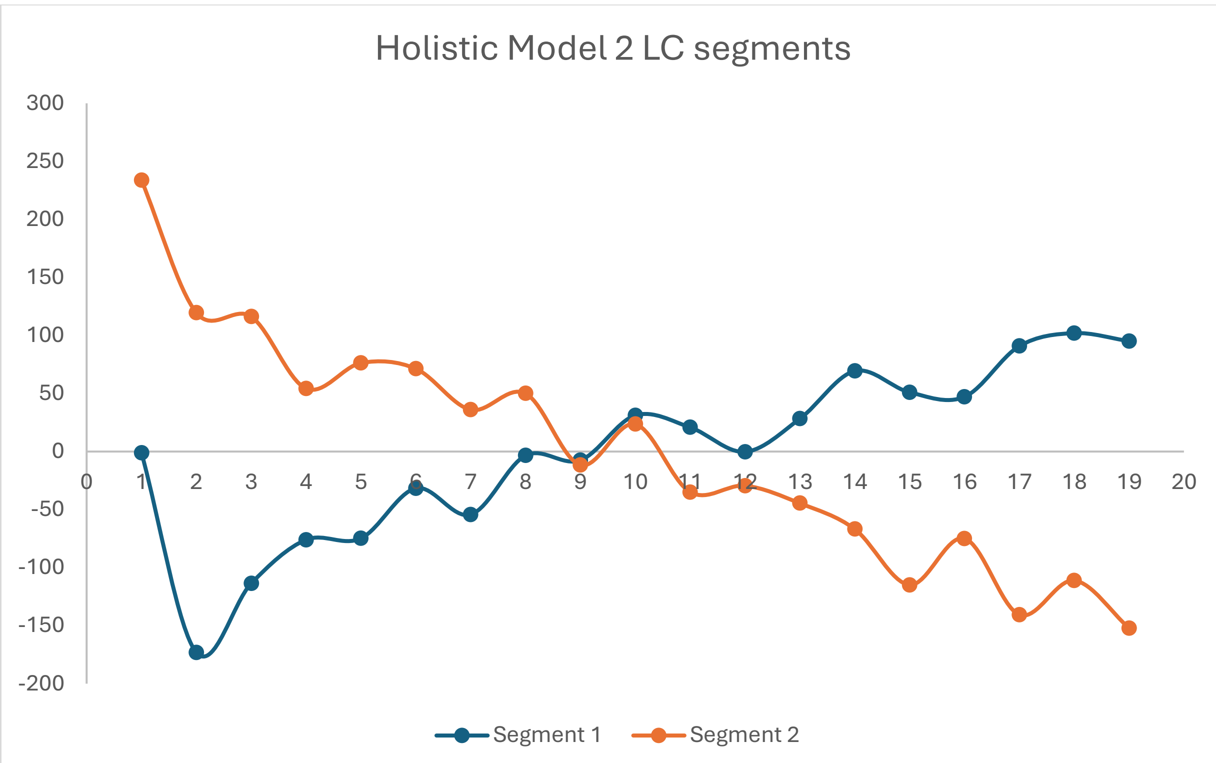
Table 3. Hold out performance models for different price segments (mean absolute error)

	1. ALL ATTRIBUTES & NO HOLISTIC DIMESION	2. ALL ATTRIBUTES PLUS 1 HOLISTIC DIMENSION	3. FOUNDATIONAL ATTRIBUTES PLUS 1 HOLISTIC DIMENSION
		Holistic modeled as part-worth function	
	Model 1	**Model 2**	**Model 4**
Low price band(n=175)	14.9%	13.9%	4.6%
Mid price band (n=943)	6.0%	6.4%	6.5%
High price band (n=882)	6.3%	5.7%	**2.5%**
		Holistic modeled as linear function	
	Model 1	**Model 3**	**Model 5**
Low price band(n=175)	14.9%	13.3%	7.3%
Mid price band (n=943)	6.0%	6.1%	7.0%
High price band (n=882)	6.3%	5.0%	**3.0%**

As shown, the low-price band and high-price band MAE is significantly improved when substituting individual features with the holistic attribute. But when including the holistic dimension for the mid-price band segment, the model performance does not improve. Thus, the inference that respondents can have different heuristics when answering complex conjoint tasks holds true.

To further dive into the differences, we found Latent-Class segments using model 2 choice data (all attributes + holistic) to see if the resulting segment utilities produced differentiated results. Below, Figure 1 shows the rescaled holistic part-worth attribute utilities (Y axis) against the value of the holistic variable (X axis).

Figure 1. The part-worth utilities of the holistic dimension by latent class segment



These two segments show dramatically different behaviors. While segment 1 has increasing utility with more features, segment 2 shows a diminishing utility. Thus, two differentiating segments can help with understanding choice behavior. For segment 1, the brand should really consider marketing its products holistically, i.e. emphasizing the many features, value for money or fitness/health goals that can be achieved. For segment 2 that is much less the case and too many features may start to distract.

DESIGN ISSUES

The conjoint study used in this paper was not optimized to enable estimating the holistic dimension. There are two design issues that need to be recognized. First, the number of profiles at the lower end and upper end of the holistic dimension will be substantially smaller than profiles that fall in the middle of the holistic dimension. This will result in less reliable estimates for the utilities in the lower and upper range of the holistic dimension. Of course, this is mainly a concern if we use the part-worth specification for the holistic dimension. A second design issue is that our experimental design was not created with the holistic dimension in mind. Hence, there is multi-collinearity between the holistic dimension and the other attributes. This means we must be cautious interpreting the specific utility values for the holistic dimension. However, the predictions of the model are not affected by the multi-collinearity, so we can still be confident that holistic decision-making is very likely.

DISCUSSION

In this paper, we challenged the foundational assumption that consumers evaluate complex alternatives in the market or in a conjoint study by breaking down an alternative into attributes and levels, then assign values to these attribute levels and somehow integrate this into an overall value. Once having done that for all alternatives they select the alternative with the highest value. Once can easily see if we describe the choice process like this, that it seems unlikely consumers really do this.

We propose an alternative conjoint model, holistic conjoint, that allows for more holistic choice processes. We show that both models with the holistic component outperform the standard conjoint model, and the model that only has the holistic component fared best overall, i.e., a standard conjoint model may be subject to overfitting and attributing value to features that are not evaluated separately. Apart from the statistical estimation model, we also propose experimental conjoint designs that account for a holistic dimension and therefore allow better identification of the impact and, for example, whether a certain threshold needs to be reached before the holistic dimension starts generating value.

These findings have substantial marketing implications. It means that firms cannot just market by talking about features, or commission research only from a "should we add this feature" point of view. If consumers process information holistically, a feature may be valuable to add even though it has little importance as a single feature.

REFERENCES

Gigerenzer, G. & Todd, P. M. (1999). Simple heuristics that make us smart. Oxford University Press.

Hauser, J. R., Toubia, O., Evgeniou, T., Befurt, R., & Dzyabura, D. (2010). Disjunctions of Conjunctions, Cognitive Simplicity, and Consideration Sets. Journal of Marketing Research, 47(3), 485–496.

Jenke, L., Bansak, K., Hainmueller, J. & Hangartner, D. (2021). Using eye-tracking to understand decision-making in conjoint experiments. Political Analysis, 29, 75-101.

Orme, B. (2020). One-third of conjoint analysis projects use 10+ attributes. LinkedIn: https://www.linkedin.com/pulse/one-third-conjoint -analysis-projects-use-10-attributes-bryan-orme.

Radulescu, A., Niv, Y., & Ballard, I. (2019). Holistic reinforcement learning: the role of structure and attention. *Trends in cognitive sciences*, *23*(4), 278-292.

Tversky, A. (1972). Elimination by Aspects. Psychological Review, 79, 4, 281-299.

Vriens, M., Chen, S. & Vidden, C. (2019). Mapping brand similarities: Comparing consumer online comments versus survey data. International Journal of Market Research, 61, 2, 130-139.

Vriens, M., Mills, D. & Elder, A. (2023). Integrating consumer goals in conjoint using Archetypes. Proceedings of the 2023 Analytics and Insights Summit (Sawtooth).