

Drivers of Liking® with Incomplete Block Designs

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Background: Incomplete block (IB) designs¹ were originally constructed to improve precision in agricultural experiments by limiting exposure to variability within blocks and thus improve the reliability of treatment comparisons. Their use in product testing arises from the practical fact that respondents (blocks) sometimes cannot (or should not) be exposed to the full set of products to be tested. IB designs provide a convenient approach to setting up incomplete sets of products to be tested by individuals and analyzed using Landscape Segmentation Analysis® (LSA). LSA² assumes that a liking response depends on a combination of past and present experience. The method, called unfolding, provides the basis for identifying individual ideal and item points in a low-dimensional space of hedonic drivers. Typically, in consumer product categories, the drivers of liking space is two- or three-dimensional. Figure 1 displays the concept of unfolding through the action of unfolding a fan. In the folded, or barely unfolded, state a fan displays images that later may appear in different parts of the space. Inspecting the fan in the folded state provides very little information about the complex images that unfolding will generate. Images of the same color seen on the folded fan may appear surprisingly different and in different locations when the fan is unfolded.



Figure 1. Unfolding a fan.

Scenario: You work as a data science manager for a market research supplier and provide design and analysis services for large consumer product clients. Your clients conduct sequential monadic product tests through your company on a regular basis. LSA is one of the tools you use to study comparative performance of your clients' and their competitors' products. Typically, these studies involve complete tests where every participant evaluates every product, but periodically there is a need for incomplete block designs. These designs arise because sometimes it is impractical to require every respondent to evaluate every product. Although you have used complete datasets when using LSA in the past, and you know that incomplete data can be analyzed using LSA, you have questions about its use with incomplete block experiments.

These questions are: At what level of incompleteness does LSA become unreliable regarding product placements when products have

1. Similar liking means,
2. Dissimilar liking means.

These are important questions because product placements determine the identification of liking drivers, and the comparative liking performance of the products depends on their relative locations. In addition, the location of individual ideal points may also influence both outcomes.

Theoretical Expectations: If the liking means for a set of products are identical, and if the ideal points are uniformly distributed in the space, then the theory and the process underlying LSA makes certain predictions. One of these predictions is that the products tested will be expected to be located on a circle in two dimensions or on the surface of a sphere in three dimensions. This is the configuration that will explain the identical product means best. This was demonstrated in the images displayed in the fan in Figure 1 and in a previous technical report². If product means are different, the location of product and ideal points will appear in the drivers of liking space in a pattern and locations that optimally accounts for individual ratings. An incomplete block design may not contain enough information to properly locate the product points, and this could affect the identification of the liking drivers. It is useful to know the degree of incompleteness that is acceptable so that the best incomplete block design can be chosen for an application.

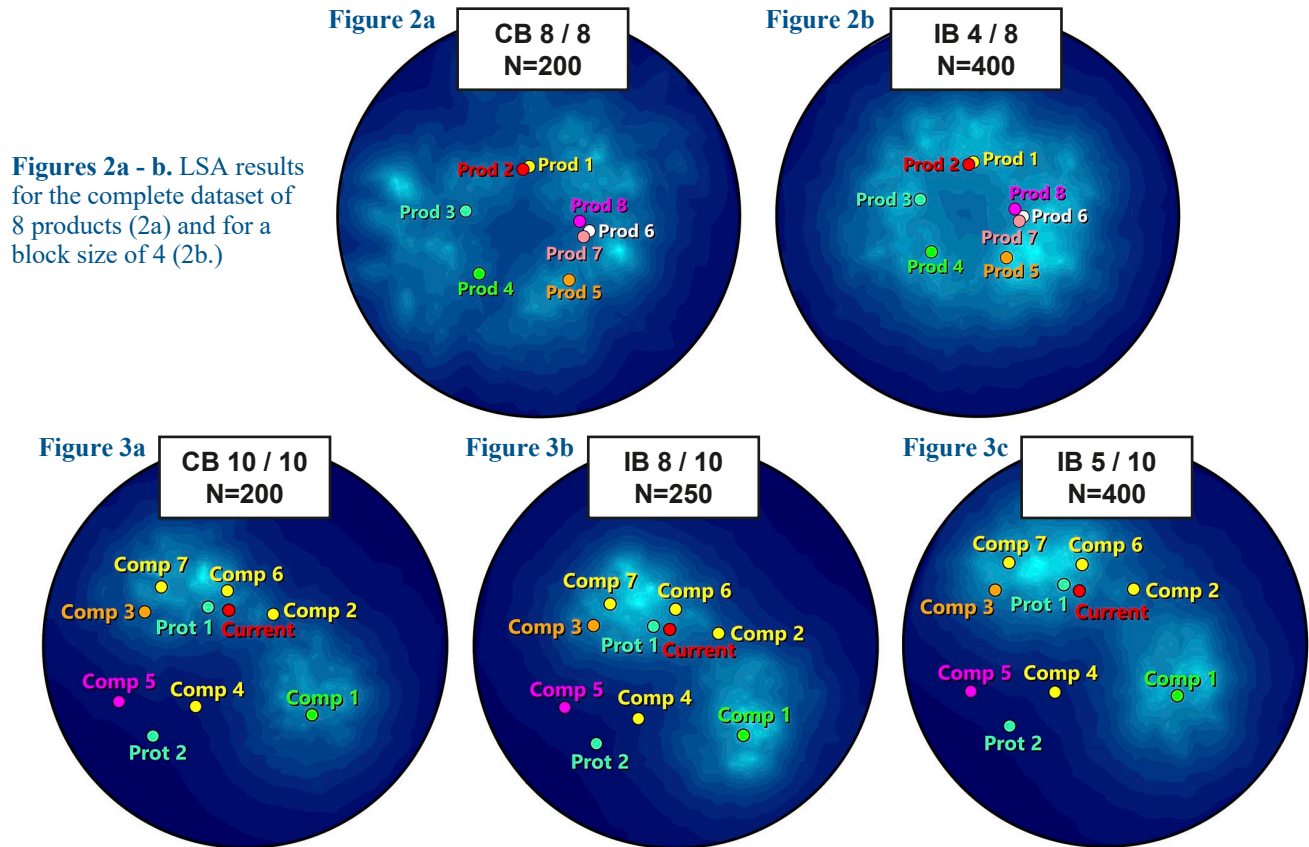
Generation of the Incomplete Block Designs: In order to evaluate the level of incompleteness that you can accept, you design simulated tests based on previous actual product tests. Using the **CR&S method**³ (Column Randomization and Search) for generating complete and incomplete block designs in IFPrograms^{®4} you create datasets for two levels of incompleteness. The CR&S method uses a computer-intensive search method to find designs that meet position, sequence and spread equality criteria across the design. Using this method reduces the likelihood of bias due to product positions and sequences in the design. You construct a set with 8 products per block (complete) and an incomplete case with 4 products per block. In this case, respondents are distributed randomly in the drivers of liking space and the product means are almost identical as shown

Product	Mean
Product 8	8.11
Product 7	8.08
Product 2	8.06
Product 1	8.04
Product 6	8.03
Product 3	8.01
Product 4	7.99
Product 5	7.98

Table 1. Liking means for 8 very similarly liked products on a 9-point scale.

Product	Mean
Current Product	7.14
Prototype 1	7.03
Competitor 2	6.94
Competitor 6	6.89
Competitor 4	6.38
Competitor 7	6.21
Competitor 3	6.11
Competitor 1	6.09
Prototype 2	5.06
Competitor 5	4.91

Table 2. Liking means for 10 products on a 9-point scale.



Figures 2a - b. LSA results for the complete dataset of 8 products (2a) and for a block size of 4 (2b.)

Figures 3a - c. LSA results for the complete dataset with blocks of size 10 (3a) and for the blocks of size 8 (3b) and 5 (3c).

in Table 1. You ensure that each product is evaluated by the same number of respondents irrespective of the degree of incompleteness. This means that the total number of participants for an incomplete block design will be greater than a corresponding complete block design. For example, a complete block design of 200 participants evaluating 8 products corresponds to 400 participants evaluating only 4 products each.

For a more extensive set of products, you use blocks of 10 (complete), 8, and 5 products per block. In this case you also simulate two large segments to evaluate the effect of respondent locations on the product locations as the degree of incompleteness increases. The product means are quite different as shown in Table 2.

The Effect of Incompleteness on Product Locations:

Figures 2a-b show the LSA results for the complete dataset (2a) of 8 products and for a block size of 4 (2b.) The location of the 8 products in a circle is due to their almost identical means and occurs as expected and the products are clustered on the circle similarly for the 8 and 4 block cases. Figures 3a-c show the LSA results for the complete dataset (3a) with blocks of size 10 and for the blocks of size 8 and 5. It can be seen from these figures that in the presence of strong segmentation the product locations are maintained as the degree of incompleteness increases, at least to the level of blocks sizes of 5 out of 10. Increasing the degree of incompleteness further may cause an unacceptable level of product shift in the drivers of liking space which would have consequences for the reliability of the liking drivers.

These results are similar to those obtained by Cleaver when he compared methods using incomplete block designs⁵. You conclude that, as a rule, you will require that incomplete block designs should not have blocks with a block size of less than 50% of the complete design block size to maintain the integrity of the product locations, whether there is strong segmentation or not and whether the product means differ or not. In two-dimensions the lower limit for block size per individual to properly locate an individual’s ideal point is 3. In three-dimensions it is 4. Choosing a minimum of 50% of the total product set size and meeting the analytic minimum of 3 and 4, depending on dimensionality, appears to be an appropriate choice.

Conclusion: Incomplete block designs can be fit to the LSA unfolding model and will provide reliable results provided that the level of incompleteness is not extreme. The general recommendation is that the block sizes should not be less than 50% of the complete block size and there should be a minimum of 4 products per block.

References

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