Implementation of Conjoint Analysis at Layher Scaffolding

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Abstract

Determining a company's marketing strategy and resource allocation requires an understanding of its customers’ preferences. Conjoint analysis is a popular technique used to model customers' purchase behavior. This paper determines customer preferences based on three attributes, namely planning, product performance, and training. There are three levels of Planning (2D CAD drawing, 3D isometric drawing, Augmented Reality drawing); three levels of Product Performance (safety, reduction of shutdown time, improve equipment efficiency); and three levels of Training (online, in-house, on-site). The conjoint questionnaire consists of eight service bundles determined using an orthogonal fractional factorial design and 300 responses are simulated and analyzed using the conjoint package in R. Through the analysis, it can be concluded that customers place a higher value on training during the implementation of a project. The conjoint analysis indicates that online training is the preferred medium of training, 2D CAD drawings are favored over other options, and customers value a lower maintenance time.

1.1 Introduction

Layher Germany is a family-owned mid-size scaffolding manufacturer that also owns their direct distribution. It has 140 locations in 40 countries, over 2200 employees, and is considered a global market leader. Its North American distribution consists of six locations spread across the United States and Canada, with headquarters in Houston, TX. Layher’s customer base consists of professional scaffolding companies and large industrial and construction projects. After extensively researching methods to learn about customer preferences, the team in Houston decided upon implementing a conjoint analysis.

1.2 Background

Conjoint analysis is an extremely popular tool for marketing research and is used to determine what customers value and how they make decisions. The name is derived from the fact that attributes can be better measured jointly than in isolation. It has been a widely employed technique since the 1970s. Conjoint analysis has its roots in mathematical psychology and was developed by Paul Green at the University of Pennsylvania in 1971. Green was inspired by statisticians and psychologists Luce and Tukey's article on conjoint measurement titled "Simultaneous conjoint measurement: A new type of fundamental measurement" (1). He addressed how conjoint measurement could be applied to marketing problems in his article titled "Conjoint Measurement for Quantifying Judgmental Data" in the Journal of Marketing Research (2). Other noteworthy pioneers include Seenu Srinivasan, a professor at Stanford University, who developed a linear programming procedure named LINMAP for rank-ordered data, Richard Johnson who developed the Adaptive Conjoint analysis technique, and Jourdan Louviere from the University of Iowa, who developed choice-based techniques of conjoint analysis (3).

1.3 Motivation

When directly asked about their preferences, customers often give unenlightening and trivial answers. They are unable to accurately determine the preference of individual attributes. A conjoint analysis solves this problem by asking questions that closely resemble true customer decision-making (3). A product concept is defined across several real feature levels and customers choose from a competitive grouping of products. Customers are more comfortable with evaluating products than providing a numerical rating for individual features. Through a conjoint analysis, efficient pricing strategies can be formulated by analyzing customer trade-off behavior and marketing efforts can be tailored to customer preferences. There are various types of conjoint analysis methodologies, namely choice-based conjoint analysis, full-ranking conjoint analysis, and metric-based conjoint analysis. Choice-based conjoint analysis tasks the respondents with choosing between a series of product bundles. In full-ranking conjoint analysis, customers are asked to rank several bundles from least preferred to most preferred. Metric-based, also known as rating-based conjoint analysis, asks customers to rate a series of service bundles on a scale from 1-10. A metric-based conjoint analysis is implemented by Layher and discussed in this paper. Respondents are asked to rate eight different service bundles on a scale from 1-10. Three hundred simulated customer responses are analyzed and used to determine the marketing portfolio and assist with resource management.

3. Methods

3.1 Conjoint Analysis

Conjoint analysis is a powerful statistical method used as a market research tool to determine customer preference for a given service or product based on its features. The decompositional approach of the methodology helps determine customer preference in detail. Customers are asked to provide a rating to a service bundle, which is a combination of several attributes. Attributes are defined as features that make up a product, and levels are subcategories within the attributes. Through a conjoint analysis, one can estimate the utility or value placed by the customer on each attribute level, also referred to as part-worth. Only relative differences within utility matter since it does not have a unit (4).

Ordinary least squares regression is used to calculate the utility value per level. The Method of Least Squares estimates parameters in a linear regression model by minimizing the sum of the squared differences between the dependent variable and the corresponding fitted variable and it is used to determine the line of best fit (5). The equation is as follows:

$$y = x_1\beta, + x_2\beta_2 + x_3\beta_3 + .. + \varepsilon$$

where Y is the respondent rating for each service bundle, X_n are the input features, β_n are the regression coefficients corresponding to a set of user-defined product attributes, and ε represents a random error term. A higher utility value indicates a greater preference for that attribute level.

3.2 Conjoint package in R

The R package "conjoint" is used to implement a traditional conjoint analysis for this project. The GNU R basic version and additional packages are required to use the conjoint package. The package can be installed from the CRAN R repository. The package offers 16 functions allowing for estimation of model parameters and customer segmentation, calculation of part-worth and total utilities, attribute importance, and aggregated results of the selected simulations. The package also offers tools to support the design of the survey questionnaire. The functions that will be used in this project are as follows. *caFactorialDesign* will be used to determine the factorial design, followed by *caEncodedDesign*, which proceeds to encode the previously determined factorial design. The *conjoint* function is used to calculate the basic results of the conjoint analysis at an aggregated level. *caImportance* is then used to generate the average relative importance of the different attributes on an aggregated level (6).

3.3 Defining the attributes and levels

The first step of conducting a conjoint analysis is defining the attributes and levels of the product. The attributes and levels in a conjoint analysis are required to behave in a certain manner to be considered valid and useful. Each attribute must be independent, with no overlap with the other attributes. Additionally, each level and attribute should be easily understandable on its own. Certain attributes might have a halo-effect, where customers might infer that a product is of high quality based on just one level (3). The attributes and levels in our survey are defined by taking these behaviors into account. The attributes are Planning, Product Performance, and Training. Under Planning, the levels are 3D isometric drawings, augmented reality drawings, and 2D CAD drawings. 2D CAD is a computer-aided two-dimensional design. 3D isometric drawings are made with two-dimensional geometry but appear 3D and are created using 30-degree angles. Augmented reality drawings involve placing a three-dimensional model of the proposed design over a real-world view. Under Product Performance, the levels are safety, reduction of shutdown time, and improve overall equipment efficiency. Shutdown time refers to a temporary closure of a plant for maintenance purposes. The addition of this attribute provides a customer perspective on what is considered most important in our service, i.e., safety, the maintenance time, or efficiency of the equipment which in turn can be used to figure out how to market Layher. Under Training, the levels are online, in-house, and on-site training. Training involves the correct assembly and disassembly of scaffolding products and addresses the safety and benefits of using authentic Layher equipment. Online training consists of pre-recorded videos delivered online that are accessible at any time. On-site training involves sending professionals to the customer’s site to provide scaffold training. In-house training involves flying the customers out to Layher’s warehouses to provide training.

3.4 Survey Design

A full-factorial design measures the responses at every possible combination of the different attribute levels. Given that there are N attributes and k levels within each attribute, the number of bundles to be evaluated is $k \cdot\ k \cdots k\ (N\ times) = k^N$. In our case, that translates to 3 (Planning) x 3 (Product Performance) x 3 (Training) $= 3^3$ = 27 different combinations that must be rated by each respondent. However, asking a customer to rate 27 different combinations is not reasonable and it may lead to survey fatigue. Survey fatigue is known as the phenomenon in which respondents lose attention and get tired of answering the survey, which affects the quality of their responses. The respondents might begin choosing answers in the same column of the page, known as “straight-line” responding, which would especially be harmful to the conjoint analysis which relies on ratings (7). Thus, a way to remedy that is by using an orthogonal design that allows a selection of a fraction of the different combinations without losing information. An orthogonal design is used to determine the survey questions to guarantee that each service bundle can be evaluated independently of one another (8). The *expand.grid()* function in R is used to create a data frame consisting of all possible combinations of the different attribute levels. Next, the function *caFactorialDesign()* from the conjoint package takes the data frame as input and is used to specify the design type, which in our case is orthogonal. Finally, the function *caEncodedDesign()* is used to convert the design to a matrix of profiles. In addition to implementing an orthogonal design, an incentive of a $15 gift card is offered to encourage the customers to complete the survey. Figure 1 below shows the survey link sent out to the customers.

***Figure 1**: Layout of the Survey link*

Figure 2 below shows the different service bundles decided upon after implementing an orthogonal design, where each row is one service bundle. The design serves as input for the survey questionnaire in the format "How would you rate the combination of" followed by a service bundle. For example, the first question is "How would you rate the combination of 3D isometric drawings, safety, and online class training?". The survey is set up in google forms and is sent out to the customers three times in the span of two months.

Planning	ProductPerformance	Training
3D Isometric Drawings	Safety	Online Class Training
Augmented Reality Drawings	Reduction of shutdown time	Online Class Training
2D CAD Drawings	Improve Overall equipment efficiency	Online Class Training
Augmented Reality Drawings	Safety	In-House Training
2D CAD Drawings	Reduction of shutdown time	In-House Training
3D Isometric Drawings	Improve Overall equipment efficiency	In-House Training
2D CAD Drawings	Safety	On-Site Training and Field Support
Augmented Reality Drawings	Improve Overall equipment efficiency	On-Site Training and Field Support

***Figure 2**: Service bundles*

Planning	ProductPerformance	Training
2	1	1
3	2	1
1	3	1
3	1	2
1	2	2
2	3	2
1	1	3
3	3	3

***Figure 3**: Encoded service bundles*

The levels are then encoded using the function caEncodedDesign, as seen in figure 3. Within the Planning attribute, "2D CAD drawings" is assigned to 1, "3D isometric drawings" is assigned to 2, and "augmented reality" is assigned to 3. Under the Product Performance attribute, "safety" is assigned to 1, "reduction of shutdown" to 2, and "improve overall equipment efficiency" to 3. Under the Training attribute, "online" is assigned to 1, "in-house" is assigned to 2, and "on-site" to 3.

4. Simulated data

For this paper, customer responses have been simulated through the *sample()* command in R. The sample command takes a sample of a specified size n, which is set to 2400, from the elements of x, which is set to 10. The replacement parameter is set to TRUE. Next, the *dim()* function is used to set the dimensions of the 2400 sampled responses to a 300 x 8 matrix. This results in 300 rows and 8 columns, where each row represents one respondent, and each column is associated with one of the service bundles. The number of respondents is set to 300 to ensure credibility (4). The simulated matrix consists of ratings for the eight service bundles on a scale ranging from 1 to 10, with 10 representing the highest degree of preference. Figure 4 shows the first customer's responses to the eight questions.

Respondent	q1	q2	q3	q4	q5	q6	q7	q8
1	8	8	10	8	9	10	5	5

Figure 4: *Layout of the simulated response data*

5. Analysis and Results

The R output using the *Conjoint()* command provides utility values and bar charts displaying the attribute importance as shown below.

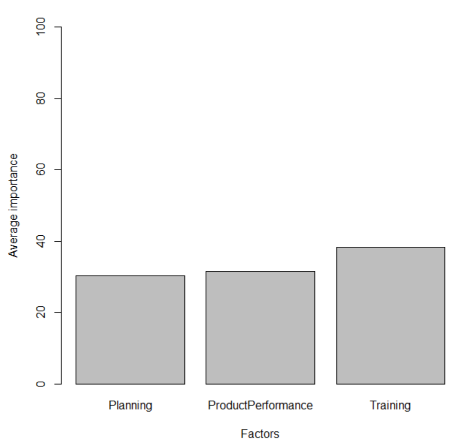

Figure 5:*Bar chart comparing the attribute utility values*

Figure 6: *Bar chart comparing the training utility values*

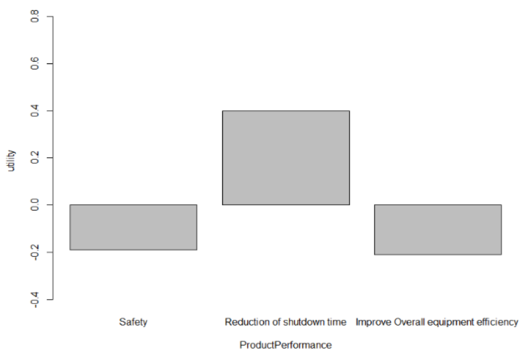

***Figure 7**: Bar chart comparing the product performance utility values*

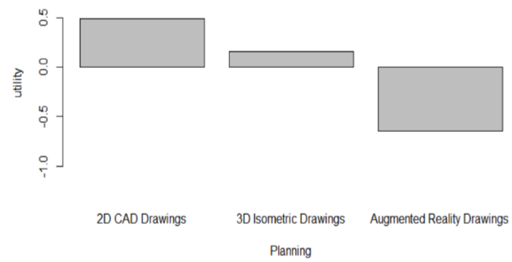

***Figure 8**: Bar chart comparing the planning utility values*

Firstly, from the bar charts above, we can see that customers prefer Training over Product Performance and Planning. Thus, during the implementation of a project, Layher must focus more on training the customers on its equipment. Within the Training attribute, online training seems to be the preferred option. Layher typically offers in-house training as the default option, which is more expensive than the online option since flight tickets must be paid for. Additionally, an employee must set aside some time to train the customer and answer their questions. Thus, implementing online training will save resources. Several online training videos can be created covering the different aspects of the equipment and can be used by the entire customer base. Under Product Performance, customers value reduction of shutdown time over safety and the improvement of equipment efficiency. Layher's marketing team can use this information to promote their services efficiently, emphasizing the reduction of shutdown time. Layher already promotes reduction in shutdown time, as can be seen from the Layher website (9) in Figure 9, however, the conjoint analysis confirms that it is the strategic choice, and it can be promoted similarly on other platforms.

- All these solutions are geared towards a safer scaffold project that also meets an ever more critical schedule to reduce shutdown times.

The name Layher is synonymous with unsurpassed versatility, flexibility, and safety, offering a range of products for the cement industry. We have become the world's leading scaffold solution provider for industrial applications because of this. After 75 years in business, our mission continues to be to combine world-class engineering service, innovative scaffold solutions, and implementation of training—all of that to reduce shutdown times and increase scaffold productivity for industrial applications.

Having a scaffold of all metal components reduces the need for consumables and custom build, increasing productivity while simultaneously reducing costs. Moreover having an all metal scaffold reduces the burn rate, thus improving safety. This leads to the customer benefit of shutdown time reduction.The following are just a few of the ways we've managed to increase scaffold productivity and reduce shutdown times in the cement industry.

Figure 9*: Snippet from the Layher website (9)*

Lastly, under Planning, customers seem to prefer 2D CAD drawings. Production of a 2D CAD drawing is simpler than that of a 3D isometric drawing and augmented reality drawing since the last two options require expertise and are costlier and more time-consuming.

```
[1] "Part worths (utilities) of levels (model parameters for whole sample):"
                                levnms    utls
1                            intercept  6,3056
2                      2D CAD Drawings  0,9278
3                3D Isometric Drawings -0,1778
4             Augmented Reality Drawings   -0,75
5                               Safety -0,3611
6              Reduction of shutdown time  0,9444
7  Improve Overall equipment efficiency -0,5833
8                   Online Class Training  1,1833
9                      In-House Training -1,1611
10   On-Site Training and Field Support -0,0222
[1] "Average importance of factors (attributes):"
[1] 31,43 28,45 40,12
[1] Sum of average importance:  100
[1] "Chart of average factors importance"
```

Figure 10*: R output displaying the utility values*

Figure 10 above displays the utility values. The utilities are scaled to add up to zero within the attributes. Utility values greater than 0 are favored over average, and similarly, utility values less than zero are preferred below average. Pair-wise independence of attributes is assumed in conjoint analysis. The idea is that consumers evaluate the desirability of a service bundle based on the separate, yet conjoint parts. The desirability of a bundle is considered additive according to pair-wise independence (10). To calculate the desirability of our bundles, we can add up the utility values presented in Figure 10, and the results are as follows.

Preference	Bundle	Utility value
1	Bundle 3(2D CAD Drawings, Improve overall equipment efficiency, Online)	1.53
2	Bundle 2(Augmented Reality, Reduction of Shutdown time, Online):	1.37
3	Bundle 5(2D CAD Drawings, Reduction of Shutdown time, In-House):	0.712
4	Bundle 1(3D Isometric Drawings, Safety, Online):	0.65
5	Bundle 7(2D CAD Drawings, Safety, On-Site):	0.55
6	Bundle 8(Augmented Reality, Improve overall equipment efficiency, On-Site):	-1.35
7	Bundle 6(3D Isometric Drawings, Improve overall equipment efficiency, In-House):	-1.92
8	Bundle 4(Augmented Reality, Safety, In-House Training):	-2.27

From these calculations, we conclude that Bundle 3, which is the combination of 2D CAD drawings, improve overall efficiency and online class training is the most preferred service bundle. Bundle 4, which is the combination of augmented reality, safety , and in-house training is the least preferred service bundle. However, we can assume that the combination of 2D CAD drawings, reduction of shutdown time and online class training would outperform Bundle 3 since the aforementioned levels have the highest utility value within their respective attributes.

```
Coefficients:
                               Estimate Std. Error t value Pr(>|t|)
(Intercept)                      6,3056     0,1582  39,854  < 2e-16 ***
factor(x$Planning)1              0,9278     0,2043   4,542 8,94e-06 ***
factor(x$Planning)2             -0,1778     0,2584  -0,688 0,492089
factor(x$ProductPerformance)1  -0,3611     0,2043  -1,768 0,078385 .
factor(x$ProductPerformance)2   0,9444     0,2584   3,655 0,000317 ***
factor(x$Training)1              1,1833     0,2043   5,793 2,22e-08 ***
factor(x$Training)2             -1,1611     0,2043  -5,685 3,90e-08 ***
---
Signif. codes:  0 '***' 0,001 '**' 0,01 '*' 0,05 '.' 0,1 ' ' 1

Residual standard error: 2,123 on 2393 degrees of freedom
Multiple R-squared:  0,3148,    Adjusted R-squared:  0,2971
F-statistic: 17,84 on 6 and 2393 DF, p-value: < 2,2e-16
```

Figure 11*: R output displaying the regression coefficients*

The *conjoint* function also provides a regression output as shown above in figure 11. The regression estimates are the same as the utility values displayed in Figure 10. The output also provides t values. A t-test is used to determine whether there is a significant difference between the two groups. From the R output, we can see that a few levels fail the statistical significance test as indicated by the t values. However, due to the scaling of utilities within each attribute, relying on the standard interpretation of the t-value produces misleading results. The scaling causes levels with moderate preference to have estimated utilities close to zero, thus producing artificially low t-values, which in turn causes a failure of statistical significance. Therefore, the utility values and bar charts discussed earlier are sufficient for analysis.

6. Discussion

Conjoint analysis allows customers to make decisions in the marketplace and replicates trade-off behavior, where customers can pick from several options. It also serves as a useful experimentation medium for different features before a new product launch. Additionally, it can also be used as a strategy for pricing decisions (11). Conjoint analysis assumes that a customer's purchase behavior mimics the compensative model, i.e., the utility can simply be summed together as a higher preference of one attribute will compensate for lower preference of another. This is considered a drawback because this behavior may lead to an exaggerated compensative model but Green and Srinivasan concluded that the predictive validity of the conjoint analysis methodology is still high despite customers following decision rules that are different than compensative (12). Another shortcoming of the conjoint study is that only a limited number of product attributes can be analyzed effectively, resulting in the underestimation of a product. To overcome this, Hauser suggested using a bridging technique, which involves creating several service bundles with different attributes linked to a common “anchor attribute” in each bundle to make the utilities comparable (13) .

In the future, Layher could experiment with clustering the customers, which is a function available in the conjoint analysis package in R. The customers can be clustered by similarity of their preference and analyzed within subgroups for better understanding of their decisions.

7. Conclusion

As mentioned, this project was performed on simulated data to test the performance of the conjoint analysis methodology for Layher. The research conducted in the paper serves as a proof of concept that can be applied to the real customer responses. Based on the simulated responses, Layher was able to identify Planning to be the most important stage of a project’s implementation. The average customer prefers 2D CAD drawings, reduction of shutdown time, and online training. Through the conjoint analysis, a solid foundation was created for making reasonable decisions about Layher’s marketing strategy and resource management.

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