Conjoint Analysis

*(A Study for SONY curve TV in Australia)*

Ayush Pradhananga

Contents

[**Introduction** 1](#_Toc126073667)

[**Literature Review** 1](#_Toc126073668)

[**Methodology** 3](#_Toc126073669)

[**Participants and Design** 3](#_Toc126073670)

[**Data collection** 3](#_Toc126073671)

[**Analysis** 3](#_Toc126073672)

[**Obtaining Part worths** 3](#_Toc126073673)

[**Range and Importance** 4](#_Toc126073674)

[**Utility** 4](#_Toc126073675)

[**Evaluation Technique** 4](#_Toc126073676)

[**Results and interpretation** 5](#_Toc126073677)

[**Conclusion and Recommendations** 8](#_Toc126073678)

[**References** 9](#_Toc126073679)

# **Introduction**

According to Channel News. (2021), Samsung dominates the television market in Australia. A recent study conducted over 21 months showed that Samsung holds 28.1% of the overall TV market, followed by LG with 18.8%, Hisense with 16.2%, Sony with 14.4%, TCL with 5.4%, and Panasonic with 4.5%.

There is a new segment in the television market which is the “Curved TV”. There are two curved tv products available in the market offered by LG and Samsung. SONY is planning to launch a new product in the market. This study is based on the following research question and objective.

**Research Question:** What is the optimal product profile for Sony to introduce in the Australian Curved TV market to maximize overall profit?

**Objective:** To determine the most profitable product profile for Sony in terms of screen size and price, while keeping the resolution at 4000 pixels and refresh rate at 120Hz, based on consumer preferences collected from a fractional factorial design.

For the purposes of this study, conjoint analysis has been used. It is commonly used when launching a new product as it helps companies to understand consumer preferences. Also, it identifies the most important product attributes and how they affect customer preferences and purchase decisions. Through this, SONY can make data-driven decisions as to what feature to include in their new product.

# **Literature Review**

In this section, an attempt is made to review some of the literatures concerning consumer behaviour, marketing strategy, analytics, market share, etc. Various books, journals articles and some previous research work related to this topic and many indirect topics have been reviewed.

According to Rajala and Hantula (2000), Consumer behaviour analysis (CBA) is a field of study that seeks to understand and explain the decision-making processes and actions of consumers. The authors define CBA as the examination of various factors that influence consumer behaviour and how these factors contribute to purchasing decisions.

In general term, “brand competitive clout" (BCC) describes the strength and advantage that a brand has in comparison to its competitors in a market. A study done by Gázquez-Abad et al. (2015) proposed a model to see how three factors consumer price sensitivity, brand market share and consumer brand preferences played their role in BCC formation. The authors findings were:

* Consumer price sensitivity has the strongest influence on brand competitive clout.
* Intrinsic brand preference and market share are not key factors in creating market power.
* Interactions between price sensitivity, intrinsic preference, and market share are crucial to determining a brand's competitive clout.

Overgoor, G., et al. (2019) conducted a study where they utilized CRISP-DM framework to develop AI solutions for marketing problems. The researchers found that it is important for the organization to include all relevant stakeholders to understand the business problem and increase the chances of success. When dealing with images, text and videos, multiple steps of CRISP-DM process is required. Evaluation, such as through calibration, stress tests, case studies and sensitivity analysis, were found to be necessary for validating the model.

Ljepava, N. (2022) conducted a systematic review of research articles from 2020 to 2022, examining the application of AI in the five steps of the marketing process: analysis, strategy, tactics, customer relations, and value proposition creation. The findings of the study were that the early stages of marketing such as understanding and predicting customer behaviour and the tactical stage of creating a marketing mix utilized the majority of AI applications whereas in the latter stages of marketing, the use of AI was negligible. The author has suggested research to be conducted about use of AI in other marketing stages as well.

Zhang, L. et al. (2018) attempted to use data driven approach to find the best product specification. The author’s aim was to identify the best product features using the data collected from the targeted consumers. A customer choice model was developed with two objectives: maximising the Expected marketing cost and minimising the total engineering cost (TEC). This research presented two important results:

* Using information about how satisfied customers are with a product, problems with the traditional way of analysing utility, which often leads to inaccurate results can be solved.
* The new model created in this research could choose the best features for a product based on how satisfied different groups of customers were.

The authors suggested that Further research could enhance product design by incorporating operating data with additional sources such as online reviews and social data to gain a more thorough understanding of user profiles.

A study was conducted by Menon et al. (2015) to examine the role of social media in consumer purchasing decisions. The research was conducted in partnership with a fashion retailer that uses Facebook for promotion and sales. Conjoint analysis was used to compare consumer preferences for different marketing elements such as delivery method, product size, photos, charitable donations, and guarantees. The research was based on the Behavioural Perspective Model of consumer choice. The findings, with a high correlation coefficient of 0.998 and a significant p-value of less than 0.05, demonstrated that as prices increased, consumer satisfaction decreased. This inverse relationship was also observed for other factors such as shipping cost.

Luan, Y.J. and Sudhir, K. (2010) published a journal article on “Forecasting Marketing-Mix Responsiveness for New Products”. This study aimed to tackle the difficulty in estimating demand response to marketing-mix variables in preparation for a new product launch. It focused on the "slope endogeneity" problem, which refers to the influence of private information possessed by managers on observed decisions. To address the bias, the authors devised a control function approach capable of handling multiple interdependent variables and the impact of marketing mix factors that persist over time. The approach was utilized to predict the impact of advertising on sales in the U.S. DVD market. The findings indicated that the response to advertising varied greatly among different DVD titles and that neglecting the slope endogeneity issue could lead to incorrect calculations of marketing mix sensitivity. The findings of the research were significant for researchers and managers involved in entertainment marketing, providing insights into the impact of private information on observed decisions and the importance of considering slope endogeneity when estimating demand responseTop of Form

# **Methodology**

## **Participants and Design**

The participants for the analysis included individuals from the population of 200,000 TV consumers in Australia. 20 consumers were selected at random. Four attributes and their levels were identified (as seen in Table 1).

|  |  |
| --- | --- |
| Attribute | Levels |
| Brand | Samsung/SONY/LG |
| Screen Size | 65/75/85 inches |
| Refresh Rate | 120/240 Hz |
| Resolution | 2160/4000 pixels |
| Price | $4000/$6000/$9000 |

Table 1: Attributes and level

The five attributes and their respective levels would result in (3x3x2x2x3=108) product profiles which is not practical to rank. Hence, a fractional factorial design of 18 different product profiles were provided to the respondents for ranking their preference on a 7-point scale where 7 meant ‘Most favourite’ and 1 meant ‘Least favourite’.

## **Data collection**

Although there are other ways to collect data such as pairwise comparison and rating scale evaluation, SONY has opted to use Ranking order method.

## **Analysis**

### **Obtaining Part worths**

For analysing the responses of participants, firstly part-worths of each attribute and their corresponding levels were obtained. This was done through linear regression. However, the responses (although looks like numeric) were categorical in nature. To overcome this issue, dummy variable coding was a way through which categorical variables could be converted into numeric. For each category of the variable, a new binary variable was created with a value of 1 or 0 indicating the presence or absence of that category respectively. This allowed the model to consider the effect of these categorical variables on the preference ranking. Part-worths for each attribute and level was obtained through running regression for all the respondents.

The following levels were chosen as base or reference level.

* Brand: LG
* Screen size: 85 inch
* Refresh rate: 240 Hz
* Resolution: 2160 pixels
* Price: $9000

Regression Model:

Y = Constant + b(65 inches) D(65 inches) + b(75 inches) D(75 inches) + b (Samsung) D(Samsung) + b(SONY) D(SONY) + b(120 Hz) D(120 Hz) + b(4000 pixels) D(4000 pixels) +b($4000) D($4000) + b($6,000) D($6000)

Where,

D represents dummy variables set to 1 when the level is present otherwise 0.

b represents the respective coefficients which is the part-worth of each level.

### **Range and Importance**

After obtaining the part-worths, range of part-worths was calculated by subtracting lowest part-worth of each attribute level by the highest part-worth of each attribute level. **It is to be noted that part-worth for base levels are 0**. This was followed by the calculation of relative importance of each attribute. This determines the how much influence a particular attribute has when making a buying decision. The range of part-worths for each attribute was divided by total of all part-worths to get the relative importance of attribute. Average relative importance was then calculated by taking a mean of all respondents.

### **Utility**

Kotler, P., & Keller, K. L. (2016) stated that the utility of a product bundle is the value or satisfaction that a customer derives from purchasing and using the combination of products included in the bundle. Considering SONY’s decision, apart from the 18 product profiles that respondents ranked, 9 new combinations were created for simulation. To determine the overall utility of a product, the part-worth utilities for each attribute level were summed. This was done for the existing products in the market as well.

### **Evaluation Technique**

This study has used the **Multinomial Logit Model (MNL)** which estimates the probabilities of customers choosing one product over another based on the attributes and levels of the product, Train, K. (2003). MNL model represented below:

Purchase prob. (Pk) = exp (Utility of Pk)/  
(exp (Utility of Pk) + exp (Utility of LG 65 in 120 HZ 4000 Pixels $4000) + exp (Utility of Samsung 85 in 120 HZ 4000 Pixels $9000)

Where Pk is the purchase probability of product k compared to the existing products in the market in this case.

**Market share** for each product was predicted by averaging the purchase probabilities of all respondents. Finally, profits for potential products were evaluated using the following equation.

Profit = Sales \* (Price – total variable cost) – fixed cost.

# **Results and interpretation**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Attributes** | **Levels** | **Average Part-worths**  **(Reg Coeff)** | **Average Range of Part-worths** | **Average Relative importance** |
| **Brand** | **Samsung** | -0.69 | 1.19 | 17% |
| **SONY** | -0.25 |
| **LG** | 0 |
| **Screen Size** | **65 inches** | -0.27 | 1.01 | 15% |
| **75 inches** | 0.23 |
| **85 inches** | 0 |
| **Refresh Rate** | **120 Hz** | 1 | 1.21 | 19% |
| **240 Hz** | 0 |
| **Resolution** | **2160 pixels** | 0 | 0.64 | 10% |
| **4000 pixels** | -0.20 |
| **Price** | **$4000** | 2.63 | 2.71 | 38% |
| **$6000** | 1.36 |
| **$9000** | 0 |

Table 2: Analysis and Results

Price is the most important attribute, accounting for 38% of the average relative importance. The results show that $4000 is the most preferred price, with a part-worth of 2.63. $6000 is slightly less preferred with a part-worth of 1.36, while $9000 is the least preferred with a part-worth of 0. This suggests that consumers are not willing to pay a higher price for televisions. It has an average range of part-worths of 2.71 which means that the variability in the preferences is the most for level of prices.

Refresh rate is the second most important attribute, accounting for 19% of the mean relative importance. The results show that 120 Hz is the most preferred refresh rate with a part-worth of 1 while 240 Hz is less preferred, with a part-worth of 0. This shows that higher refresh rate is not necessarily preferred over 240 Hz.

Brand is the third most important attribute with 17% average relative importance. Samsung is the least preferred brand among the three options (Samsung, SONY, and LG) with an average part-worth of -0.69. On the other hand, SONY is slightly preferred over Samsung with a part-worth of -0.25 Currently, LG is the market leader which is most preferred by the consumers.

The next important attribute is screen size which has 15% relative mean importance. The result shows that 75-inch TV is most preferred with part-worth of 0.23, followed by 85-inch TV with part-worth of 0. 65-inch TV is the least preferred size with average part-worth of -0.27.

Resolution is the least important attribute having only 10% relative importance. 2160 pixels is more preferred a part-worth of 0, while 4000 pixels is slightly less preferred with a part-worth of -0.20.

Figure 1: Average Relative importance of attributes

The result (Figure 2) also shows that there is positive linear relation between average range of part-worths and average relative importance of attribute. This means that the variability in preference for different levels of attribute is higher for more important attributes.

Figure 2: Relation between part-worth range and relative importance

Using the MNL model, purchase probability for each product profiles were calculated, which was then averaged to predict the market share of the profiles. The product profile with the highest preference among consumers (potential market share) was Sony 75-inch, 120 HZ, 4000 Pixels $4000.This product can capture 50% of market. On the other hand, the product profile with the least predicted market share of just 9% was Sony 65-inch, 120 HZ, 4000 Pixels, $9000.

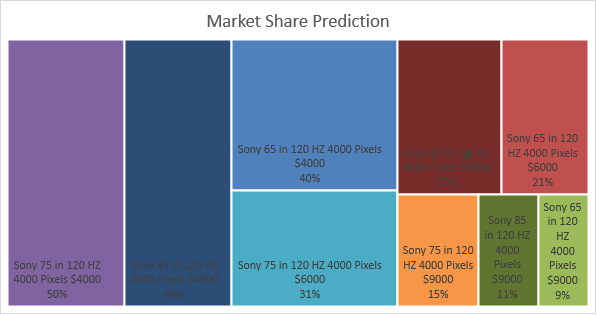


Figure 3: Estimated Market Share

From profitability point of view (Figure 4), Sony 75 in 120 HZ 4000 Pixels $6000 was the profile which could result in the highest profit of about $281 Million. Sony 65 in 120 HZ 4000 Pixels $9000 would result in the least profit.

Figure 4: Profitability Analysis

# **Conclusion and Recommendations**

The highest market share could be achieved by Sony 75-inch, 120 HZ, 4000 Pixels $4000 capturing 50% of the market. Sony 75 in 120 HZ 4000 Pixels $6000 could result in the highest profit of about $281 Million. The aim for SONY should be to get the optimal market share and profit. It is also important to consider the preference and importance of consumers on the attributes of TV before launching the product in the market. Based on the results, 75 inch is the most preferred and $4000 price point is the most preferred. Considering, SONY is new to the Australian curved TV market, it is important to capture a sizeable market share while still generating high profits. Based on all these conditions, **SONY is recommended to launch the (Sony 75 in 120 HZ 4000 Pixels $4000) in the market.** This satisfies the most preferred price point and screen size. Also, it could generate the second most profit of about $258 Million and capture about 40% of the market.

Analysing the competitors, the only serious competition for SONY is LG. It offers the TV in most preferred price point and refresh rate. Samsung on the other hand, offers big screen size with higher price point which is not preferred by the consumers.

# **References**

Channel News. (2021, June 7). TV Market Share Revealed: Samsung Dominates. Retrieved from <https://www.channelnews.com.au/tv-market-share-revealed-samsung-dominates/>

Gázquez-Abad, J.C. and Martínez-López, F.J. (2015) “Increasing a brand’s competitive clout: The Role of Market Share, consumer preference, and price sensitivity,” Journal of Marketing Management, 32(1-2), pp. 71–99. Available at: [https://doi.org/10.1080/0267257x.2015.1089307.](https://doi.org/10.1080/0267257x.2015.1089307)

Kotler, P., & Keller, K. L. (2016). Marketing management. Pearson. p.

Ljepava, N. (2022) “AI-enabled marketing solutions in Marketing Decision making: AI application in different stages of marketing process,” *TEM Journal*, pp. 1308–1315. Available at: [https://doi.org/10.18421/tem113-40.](https://doi.org/10.18421/tem113-40.%20)

Luan, Y.J. and Sudhir, K. (2010) “Forecasting marketing-mix responsiveness for new products,” *Journal of Marketing Research*, 47(3), pp. 444–457. Available at: [https://doi.org/10.1509/jmkr.47.3.444.](https://doi.org/10.1509/jmkr.47.3.444.%20)

Menon, R.G. and Sigurdsson, V. (2015) “Conjoint Analysis for social media marketing experimentation: Choice, utility estimates and preference ranking,” *Managerial and Decision Economics*, 37(4-5), pp. 345–359. Available at: [https://doi.org/10.1002/mde.2721.](https://doi.org/10.1002/mde.2721.%20)

Overgoor, G., et al. (2019). "Letting the computers take over: Using AI to solve marketing problems." California Management Review, 61(4), 156-185. [https://doi.org/10.1177/0008125619859318.](https://doi.org/10.1177/0008125619859318" \t "_new)

Rajala, A., & Hantula, D. A. (2000).” Consumer behavior analysis.” Journal of Consumer Research, 27(3), 279-288.

Train, K. (2003). Discrete choice methods with simulation. Cambridge university press.

Zhang, L. *et al.* (2018) “A data-driven approach for the optimisation of product specifications,” *International Journal of Production Research*, 57(3), pp. 703–721. Available at[: https://doi.org/10.1080/00207543.2018.1480843.](:%20https:/doi.org/10.1080/00207543.2018.1480843.%20)