The Analysis of Customer Preferences for Ray-Ban Meta Smart Glasses

Analysis progress reports 1B Part 1

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1. Executive Summary

This report presents key insights from a conjoint analysis of Ray-Ban Meta smart glasses consumer preferences. Data was collected from 43 valid respondents, selected from a total of 68 respondents via a screening question on AR interest. We estimated individual-level part-worth utilities by using dummy-coded profiles and regression modelling in Python.

Results show a strong preference for mid-tier pricing, ***$450***, and the ***AI Assistant & Hands-Free Control*** feature. Indoor attributes were most influential overall. However, their upgraded levels were not always favoured. These findings offer valuable direction for feature prioritisation, pricing, and market positioning of Ray-Ban Meta smart glasses.

2. Introduction

As wearable technology advances, understanding feature-level preferences becomes vital for customer-centric product design. This study applies conjoint analysis to quantify the value users place on specific features in AI-powered Ray-Ban Meta smart glasses. By analysing part-worth utilities and attribute importance, we aim to inform product development and pricing strategies that align with user expectations.

The analysis was conducted using survey responses from 43 qualified participants. Dummy-coded design matrices were prepared in Excel, and regression modelling was performed in Python. To ensure reliable estimates, we used rating data instead of rankings, as many ranking responses showed minimal variation. Both the Python code and the corresponding Excel outputs are provided in Appendices 1 and 2.

3. Average Part-Worth Utilities

The resulting part-worth matrix included utilities for each respondent and feature level. We calculated **average utilities** across all respondents to understand preferred features.

Attribute	Level	Average Part-Worth Utility
Price	Price $450	**0.47**
Price	Price $550	**0.14**
Indoor	Smart Adaptive Display	**(0.20)**
Indoor	AI-Optimized Vision	**(0.27)**
Outdoor	Advanced GPS & Live Mapping	**0.25**
Outdoor	AR Navigation & Real-Time Environmental Data	**0.03**
Professional	Smart Voice Commands & Reminders	**0.23**
Professional	AI Assistant & Hands-Free Control	**0.45**
Health&Fitness	Heart Rate & Workout Insights	**(0.17)**

Table 1: Average Part-Worth Utilities by Attribute Level

The part-worth results show that **Price at $450** was preferred over the $350 baseline. This suggests that users saw better value in the mid-range price point, possibly because it came with more useful features. ***AI Assistant & Hands-Free Control*** and ***Advanced GPS & Live Mapping*** were also highly preferred compared to their basic versions. This highlights that users are interested in smart, hands-free, and real-time features that improve daily use.

Conversely, some upgraded features were rated lower than their base versions. ***Smart Adaptive Display*** and ***AI-Optimized Vision*** (Indoor) received negative scores, as did ***Heart Rate Insights*** in Health & Fitness, implying users preferred simpler options.

Interestingly, ***AR Navigation & Real-Time Environmental Data*** had a near-neutral utility score of 0.03, suggesting users were indifferent to this feature. This means users had mixed feelings about this feature as it didn't add or reduce value overall. In summary, while smart assistive functions and mid-range pricing are well-received, not all advanced upgrades are perceived as added value.

4. Model Evaluation

While the overall model fit was strong (average $R^2 = 0.96$), we observed that two respondents (3 and 17) had R^2 values of 1.00 with only an estimated intercept term.

This suggests that these individuals may have provided uniform ratings across all profiles, resulting in no meaningful variation to estimate part-worth utilities. These responses were retained in Part 1 for completeness but will be excluded in Part 2 analysis to maintain data quality.

5. Relative Importance Analysis

We computed **Relative Importance (%)** for each attribute by calculating the utility range for each attribute per respondent, then aggregating these proportions across all respondents.

Attribute	Relative Importance (%)
Indoor Features	26.92%
Price	20.97%
Health & Fitness	19.25%
Outdoor Features	17.45%
Professional Use	15.41%

Table 2: Relative Importance of Attributes in Smart Glasses Preferences

Indoor Features were the most influential attribute, contributing over 26.92% to decision-making. This was followed by Price (20.97%) and Health & Fitness (19.25%), indicating a strong preference for functionality and affordability. Outdoor features (17.45%) and Professional use (15.41%) were less impactful but still played a role in shaping user preferences.

6. Summary Insights

The analysis shows that users favor assistive features and mid-range pricing. Price at ***$450*** and ***AI Assistant & Hands-Free Control*** were the most preferred levels, suggesting users are willing to pay more for valuable functionalities.

Attribute	Top-Rated Feature Level	Relative Importance (%)	Average Utility	Baseline Feature Level
Price	Price $450	20.97%	0.47	L1 Price $350
Indoor Features	None (Below baseline)	26.92%	–0.20 to –0.27	L2 Auto-Brightness Adjustment
Health & Fitness	None (Below baseline)	19.25%	-0.17	L1 Step & Calorie Tracking / L3 Full Biometric Analysis & AI Coaching
Outdoor Features	Advanced GPS & Live Mapping	17.45%	0.25	L1 Basic GPS & Weather Updates
Professional Use	AI Assistant & Hands-Free Control	15.41%	0.45	L1 Distraction-Free Alerts

Table 3: Highest-Performing Attribute Levels with Corresponding Relative Importance and Average Utility

Although Indoor features were the most important attribute overall, their upgraded feature levels were rated below the baseline. Similarly, Health & Fitness features underperformed despite moderate importance. In contrast, Outdoor Features and Professional Use had lower importance but included high-utility features, highlighting that users prioritise practical and assistive upgrades over complex enhancements. Baseline features like Auto-Brightness Adjustment and Step & Calorie Tracking remained more favourable than advanced alternatives.

[Words count: 668]

Appendix 1: Python Code

This code was used to automate the process of running regressions for each of the 67 responses that had been collected.

```
import pandas as pd
from sklearn.linear_model import LinearRegression

excel_file = 'RayBan_Meta_Dummy_with_responses.xlsx'
sheet_name = '3. Respondent_summary_Rating'
x_df = pd.read_excel(excel_file, sheet_name=sheet_name, usecols="B:K", skiprows=1, nrows=12)
y_df = pd.read_excel(excel_file, sheet_name=sheet_name, usecols="AE:BU", skiprows=1, nrows=12)


x_df = x_df.dropna()
y_df = y_df.dropna()

x_df.columns = x_df.columns.astype(str)

partworths = []
r2_values = []
option_names = []

for col in y_df.columns:
    y = y_df[col].values
    model = LinearRegression()
    model.fit(x_df, y)
    coeffs = [model.intercept_] + list(model.coef_)
    r2 = model.score(x_df, y)

    partworths.append(coeffs)
    r2_values.append(r2)
    option_names.append(col)

attribute_labels = ['Intercept'] + x_df.columns.tolist()
partworths_df = pd.DataFrame(partworths, columns=attribute_labels, index=option_names)
partworths_df['R_squared'] = r2_values
partworths_df.index.name = 'Option'

output_file = 'partworths_analysis_table.xlsx'
partworths_df.to_excel(output_file)

print(f"Partworths Analysis Table with R² values saved to: {output_file}")
```

Appendix 2: Excel Output Analysis

The Excel file contains the following sheets:

Pathworths_Analysis_
RayBan.xlsx

Sheet Name	Description
Output_partworths & R2	This sheet contains the regression output generated from Python code.
T1_Avg. partworth	Summarises the average part-worth utilities for each feature level across all respondents.
T2_Relative Importance Analysis	Summarises the relative importance (%) of each attribute for each respondent.
T3_Summary Insight	Provides consolidated insights derived from the conjoint analysis.
T4_Cluster Analysis	Provides insight into the Cluster Segmentation and Demand for each product tier