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Revealing Consumer Preference for Wine Products: A Choice-Based Conjoint Analysis Study using Classic Statistical Model, Bayesian Approach, and Machine Learning Methods.

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MARKETING ANALYTICS AND DATA SCIENCE

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Overview

- Introduction
- Hypotheses
- Conceptual Model
- Methodology
- Results
- Summary of Hypothesis Testing
- Discussion
- Managerial Implications & Limitations

Introduction

- In a competitive wine market, understanding consumer trade-offs is crucial for success.
- Firms need to differentiate their products based on what consumers truly value, from price to sensory attributes (Culbert et al., 2017; Goodman et al., 2008).
- Conjoint analysis is a powerful tool to understand preferences (Eggers et al., 2021).
- This thesis provides a comprehensive comparison of classic statistical, Bayesian, and machine learning models to analyze wine preferences, which has not been extensively done before.
- **Research question**: “Which wine attributes have the greatest influence on consumer preference based on conjoint analysis through different modeling approaches?”

Hypotheses

H1: Consumer preference for wine follows an inverted-U shape with respect to price.
(Robertson et al., 2018; Lockshin et al., 2006)

H1a: The effect of price on wine choice is moderated by gender, such that female consumers exhibit greater sensitivity to price than male consumers.
(Forbes & Dean, 2010; Atkin et al., 2007)

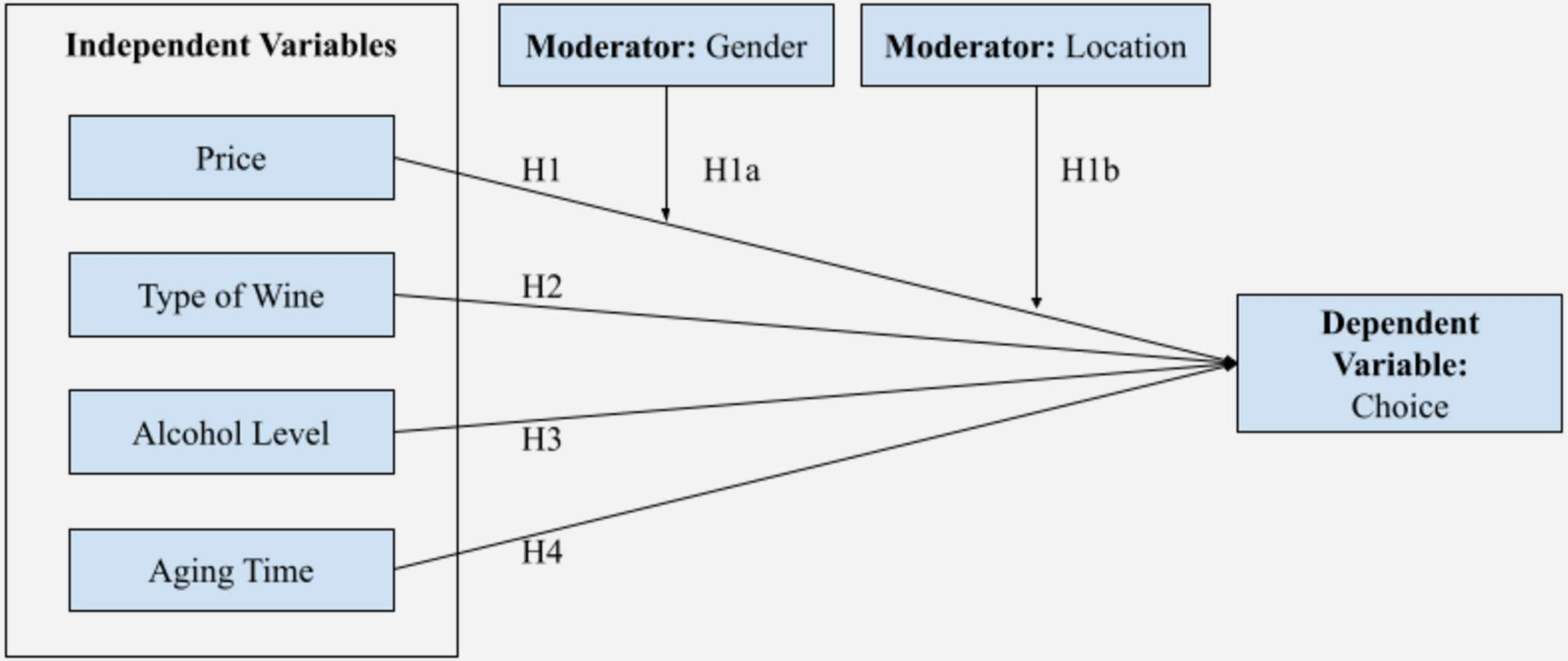
H1b: The effect of price on wine choice is moderated by location, such that consumers in Western countries are more price-sensitive than those in Eastern countries.
(Shavitt & Barnes, 2020; De Mooij & Hofstede, 2011; Agnoli & Begalli, 2016)

H2: Consumers are most likely to prefer red wine over other wine types.
(Goodman et al., 2008)

H3: Consumer preference for wine follows an inverted-U shape concerning alcohol content, with wines with 12% alcohol being most likely to be chosen.
(Schäufele & Hamm, 2017)

H4: Consumer preference for wine aging time follows an inverted-U shape, with moderately aged wines (e.g., 3 years) being preferred over both younger and older alternatives.
(Bruwer et al., 2011)

Conceptual Model



Variables

- Product Attributes: Price, Type of Wine, Alcohol Level, and Aging Time
- Moderators (Price): Gender, and Location
- Control Variables: Age Group, Last Education, Physical Activity, Occupation, Consumption Frequency, Drinking Occasion

Methodology: Conjoint Analysis

This study aim to answer the research question by employing three different types of choice-based conjoint analysis techniques, with the intent to reveal consumer's preference and comparing these techniques in the real-world case.

Conjoint Analysis:

1. Ranking or Rating-based conjoint analysis
2. **Choice-based conjoint analysis,** study from Eggers et al., 2021:
   a. simulates real-world purchasing scenarios
   b. forcing respondents to make realistic trade-offs between product attributes
   c. reveals respondents preferences

Experimental Design: Building the Survey

Analytical Approaches:

1. **Classical Statistical**: Multinomial Logit (MNL) Model
2. **Bayesian Approach**: Hierarchical Bayesian (HB) Model
3. **Machine Learning Methods:** Regularization and Random Forest (RF)

Methodology: Experimental Design

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Survey was independently developed in accordance with academic research standards and structured to simulate realistic wine purchasing decisions. The survey is conducted in May 2025, and distributed globally through social media.

Product Attributes

- Price: €6, €12, €18, and €24.
- Type of Wine: Red, White, Rose, and Sparkling
- Alcohol Level: 5.5%, 7%, 12%, 18%
- Aging Time: 1 year, 2 years, 3 years, 4 years+

Questionnaire Design

- Number of Attributes: 4
- Attribute Levels: 4 Levels for each
- Number of Alternatives: 3 (+ 1 No Choice)
- Number of Tasks per Respondent: 7
- Number of Unique Question: 12
- Fractional Factorial Design created using idefix
- Required respondents: ~96 (Orme, 2010)

Demographic Information

- Age Group
- Gender
- Location
- Employment Status
- Academic Background
- Physical Activities
- Consumption Frequency – Sanity Check
- Drinking Occasion

Example of a Task

Suppose you are buying a wine as a gift for a close relative or a celebratory event. Which option of wine do you prefer?

Type: Rose wine **Alcohol %:** 5.5% **Aging Time:** 3 years **Price:** 6€	**Type:** White wine **Alcohol %:** 7% **Aging Time:** 1 year **Price:** 12€	**Type:** Red wine **Alcohol %:** 12% **Aging Time:** 4+ years **Price:** 24€	**None of these**

Methodology: Classical Statistical

Model

Using Multinomial Logit (MNL) Model.
MNL model:

1. Discrete choice data
2. Allow more than 2 alternatives in the choice set
3. Assume the probability of choosing an alternative
4. Allow estimation of part-worth utilities from the observed choices
5. Type of Model: Vector, Ideal Point, Part-worth

Formula

Baseline model utility formula (dummy-coded):

Model 1: Vector Model
$U_{ij} = \beta_1 \cdot \text{Price}_{ij} + \beta_2 \cdot \text{Alcohol}_{ij} + \beta_3 \cdot \text{Age}_{ij} + \beta_4 \cdot \text{Red}_{ij} + \beta_5 \cdot \text{Rosé}_{ij} + \beta_6 \cdot \text{White}_{ij} + \varepsilon_{ij}$

Model 2: Vector Model + Interactions
Model 3: Part-worth Model
Model 4: Part-worth Model + Interactions

Model Fit

1. McFadden's Pseudo R^2
2. Likelihood Ratio Test
3. VIF
4. AIC
5. Hit Rate

Interpretation

1. Utilities
2. Willingness-to-Pay (WTP)
3. Market Share

Formula: WTP

$$\text{WTP}_{\text{Attribute}} = \frac{\beta_{\text{Attribute}}}{-\beta_{\text{Price}}}$$

Formula: Market Share

$$P_{ij} = \frac{\exp(U_{ij})}{\sum_{k=1}^{J} \exp(U_{ik})} \qquad \text{Market Share}_j = \frac{1}{N}\sum_{i=1}^{N} P_{ij}$$

Methodology: Bayesian Approach

The main advantage of this method is its ability to capture individual-level differences and quantify the uncertainty around our estimates, which provides much richer insights.

Concept

Hierarchial Bayesian (HB) Multinomial Logit model

1. Estimated a unique set of preferences for each respondent
2. Learning the overall patterns in the data

Bayesian Approach Steps:

1. Set priors: initial
2. Define likelihood: MNL Formula
3. Combine priors and the data: posterior distribution

Posterior distribution: give a full range of plausible values for each utility, not only a single number

Model Fit

1. Posterior Predictive Check
2. WAIC
3. Hit Rate

Interpretation

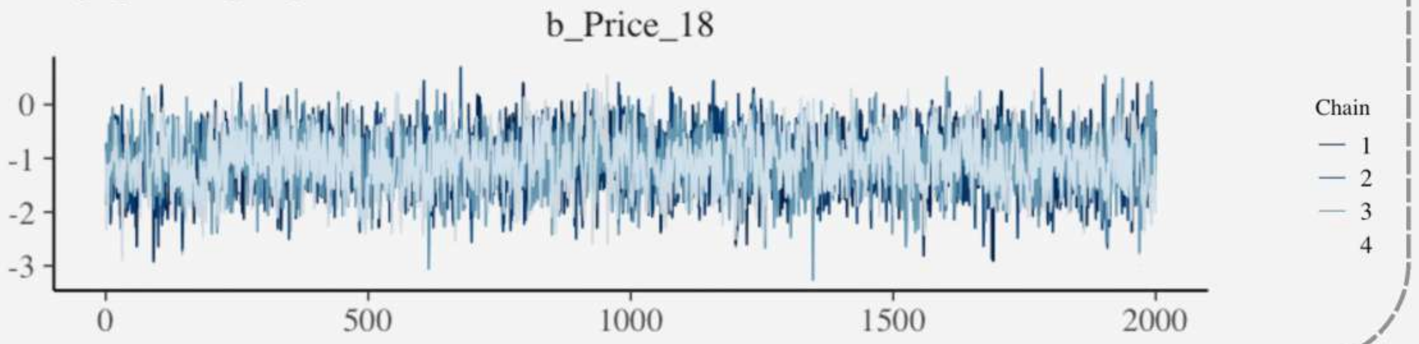
1. Utilities
2. Willingness-to-Pay
3. Market Share

Utilities

ATTRIBUTE	ESTIMATE	2.5 %	97.5 %	SIGNIF.
INTERCEPT	–2.53	–3.33	–1.76	Yes
NO CHOICE	–0.75	–1.71	0.20	No
PRICE LEVELS				
€ 12	0.51	–0.23	1.25	No
€ 18	–1.06	–2.07	–0.07	Yes
€ 24	–0.79	–2.11	0.53	No

Posterior Distribution

Trace Plots



Methodology: Machine Learning Methods

Improve predictive performance, model robustness, and interpretability.
Performed using 5-fold Cross Validation techniques to mitigate overfitting and ensure model performance.

Regularization

Reduce model complexity by shrinking less relevant coefficients to 0.

Techniques:

- Lasso, α = 1
- Ridge, α = 0
- Elastic Net, α = 0.5

Model Fit: Hit Rate

Interpretation: which parameters retained

Random Forest

Capture non linear relationships and interactions without the need of manual specification.

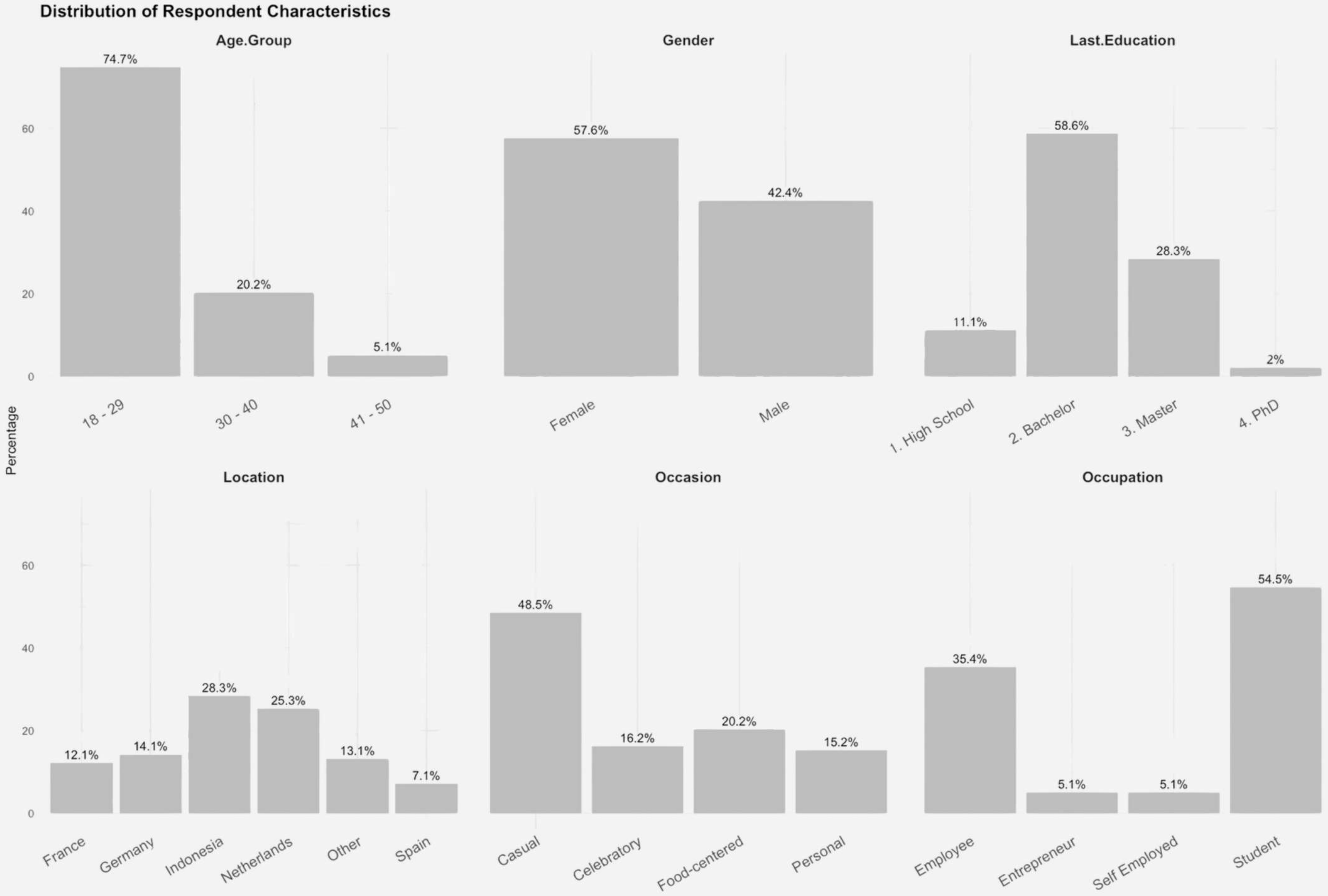
It works by building hundreds of decision trees and aggregating their predictions, which makes the model very robust.

Model Fit: Hit Rate

Interpretation: Feature Importance

Unlocking the “black box” using Shapley Additive Explanations (SHAP)

Results: Descriptive Statistics



Final sample is 99 out of 144 respondents.
Exclusions are due to:

1. Non-wine Consumers
2. Incomplete Survey
3. No-choice > 5 out of 7

Location:
The 'Other' category was created for model stability by grouping countries with fewer than 5 respondents (e.g., Taiwan, China, Canada, USA).

Results: Classical Statistical

Model Fit

LR Test

MODEL	DESCRIPTION	DF	LL	ΔDF	LR CHI-SQUARE	P-VALUE	SIGNIF.
0	Null model	3	-648.85	–	–	–	–
1	Linear model	7	-622.85	4	51.995	1.38e-10	***
2	Linear + Interaction terms	13	-604.26	6	37.180	1.62e-06	***
3	Part-worth model	13	-618.59	0	28.655	< 2.2e-16	***
4	Part-worth model + Interaction terms	31	-585.88	18	65.412	2.66e-07	***

AIC

NAME	MODEL DESCRIPTION	LOG-LIKELIHOOD	PARAMETERS	AIC
MODEL 1	Linear (Baseline)	-622.85	7	1259.70
MODEL 2	Linear + Interactions Terms	-604.26	13	1234.52
MODEL 3	Part-worth model	-618.59	13	1263.17
MODEL 4	Part-worth model + Interactions Terms	-585.88	31	1233.76

VIF for Model 4: NC: 5.03 & Price_24 5.09

Hit Rate

NAME	MODEL DESCRIPTION	IN-SAMPLE HIT RATE (%)	OUT-OF-SAMPLE HIT RATE (%)
MODEL 1	Linear (Baseline)	41.4	38.0
MODEL 2	Linear + Interactions	47.3	41.5
MODEL 3	Categorical (Non-linear)	41.8	35.1
MODEL 4	Categorical + Interactions	49.8	40.9

Model 4 is used for further analysis, as it the model has the best overall fit and also highest McFadden's (~0.1).

Interpretation

Findings based on attribute importance from Model 4

Type of Wine: White Wine > Red Wine > Rosé > Sparkling
H2: Red wine is most preferred **– Not Supported**

Price: Positive and significant at €12 price point
H1: Price Inverted-U – **Supported**
H1a: Women are more price sensitive – **Not Supported**
H1b: Western consumers are more price sensitive – **Supported**, for instance: The Netherlands

Aging Time: Positive and Significant at 2*, 3 and 4+ years
H4: Aging Time Inverted-U – **Partially Supported**

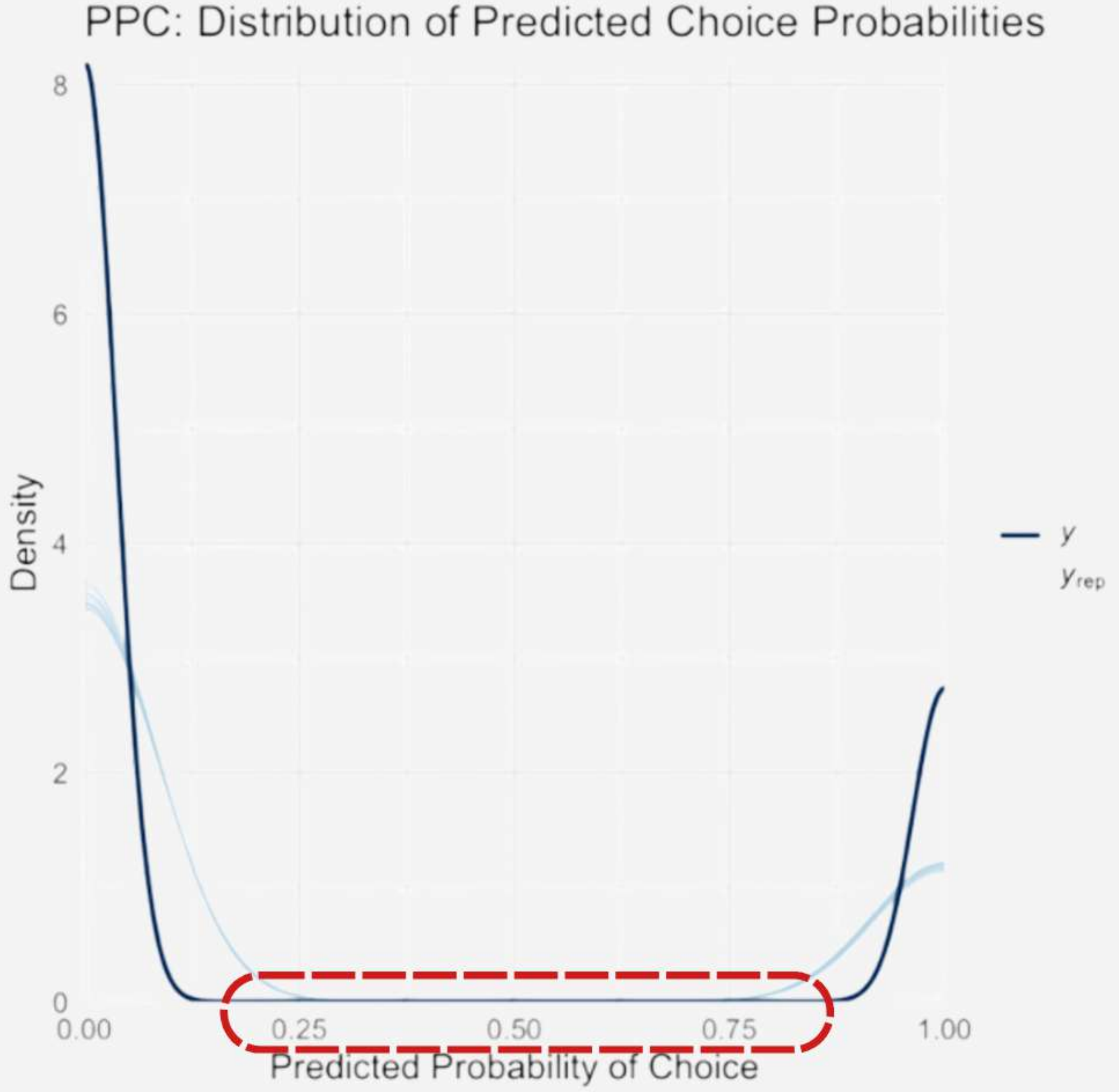
Alcohol Level: Positive and Significant at 12% and 18%*
H3: Alcohol Level Inverted-U – **Supported**

Note: *Marginal

Results: Hierarchical Bayesian Approach

Model Fit

Posterior Predictive Check



Hit Rate

MODEL	IN-SAMPLE (%)	OUT-OF-SAMPLE (%)
MODEL 1	70.7	69.8
MODEL 2	70.5	68.4
MODEL 3	71.6	69.3
MODEL 4	72.7	69.8

WAIC

MODEL	WAIC	STANDARD ERROR (SE)
MODEL 1	1,685.2	51.7
MODEL 2	1,695.2	52.7
MODEL 3	1,685.8	52.3
MODEL 4	1,678.2	54.5

Interpretation

Findings based on attribute importance from Model 4

Type of Wine: Positive and Significant for White
H2: Red wine is most preferred **– Not Supported**

Price: Positive and significant at €18 price point
H1: Price Inverted-U – **Supported**
H1a: Women are more price sensitive – **Not Supported**
H1b: Western consumers are more price sensitive – **Supported**, for instance: The Netherlands

Aging Time: Positive and Significant at 3 & 4+ years
H4: Aging Time Inverted-U – **Partially Supported**

Alcohol Level: Positive and Significant at 7%
H3: Alcohol Level Inverted-U – **Partially Supported**

Results: Machine Learning Methods

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Hit Rate: Regularization

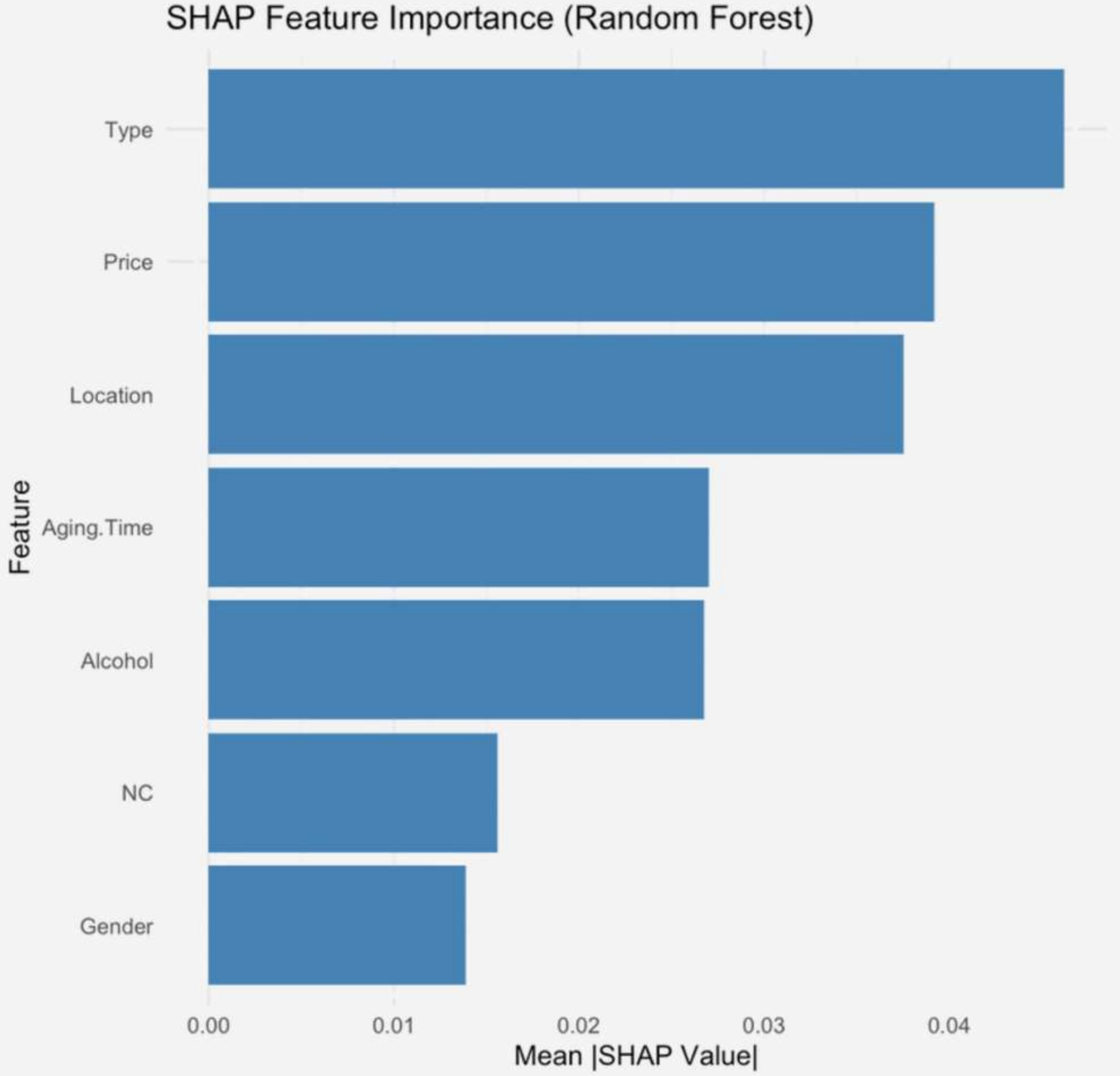
MODEL	NON ZERO COEFF.	IN-SAMPLE HIT RATE (%)	OUT-OF-SAMPLE HIT RATE (%)	OVERFIT GAP (PP)
M1: MNL	**7**	**41.4**	**38.0**	**3.4**
M1: LASSO	7	41.4	38.0	3.4
M1: RIDGE	7	41.4	38.0	3.4
M1: EL NET	7	41.4	38.0	3.4
M2: MNL	**13**	**47.3**	**41.5**	**5.8**
M2: LASSO	12	42.6	39.2	3.4
M2: RIDGE	13	44.4	40.4	4.0
M2: EL NET	12	43.2	39.2	4.0
M3: MNL	**13**	**41.8**	**35.1**	**6.7**
M3: LASSO	12	41.8	35.7	6.1
M3: RIDGE	13	43.0	35.1	7.9
M3: EL NET	12	41.8	35.7	6.1
M4: MNL	**31**	**49.8**	**40.9**	**8.9**
M4: LASSO	26	46.3	38.0	8.3
M4: RIDGE	31	46.7	38.6	8.1
M4: EL NET	26	46.1	38.0	8.1

Model 4
Lasso and Elastic-Net removed:
Price_24, Price_18_Germany, Price_24_Spain, Price_18_Male, Alcohol_18

Hit Rate: Random Forest

MODEL	IN-SAMPLE HIT RATE (%)	OUT-SAMPLE HIT RATE (%)	OVERFIT GAP (PP)
MODEL 1	43.4	38.6	4.8
MODEL 2	59.9	43.3	17.2
MODEL 3	43.4	38.7	6.5
MODEL 4	60.9	42.7	16.1

Feature Importance: Random Forest



Summary of Hypothesis Testing

H1: Price preference follows an inverted-U shape.
Result: **Supported**. Both models show preference peaks at a moderate price (€12) before declining.

H1a: Women are more price-sensitive.
Result: **Not Supported.** The opposite was found; men showed greater price sensitivity, but specifically at lower price points.

H1b: Western consumers are more price-sensitive.
Result: **Supported.** Respondents from Western countries, especially the Netherlands, showed a strong aversion to higher prices.

H2: Red wine is the most preferred type.
Result: **Not Supported.** White wine was consistently ranked as more preferred than red wine across the models.

H3: Alcohol Level preferences follow an inverted-U shape.
Result: **Partially Supported.** The preference for both alcohol peaked in the moderate ranges (7-12%), which aligns with the hypothesized pattern.

H4: Aging Time preferences follow an inverted-U shape.
Result: **Partially Supported**. The preference for aging time peaked in the moderate ranges (3-4 years), which aligns with the hypothesized pattern.

Discussion

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Market rewards moderation
Results showed consistent inverted-U shape for price, alcohol, and aging time, with consumer utility peaking at moderate levels for each.

Preferences are not universal
Price sensitivity varies significantly by **gender** and **location**, with men and Western consumers showing greater price aversion.

The findings are robust
These core results were consistent across the Classical Statistical Techniques, Bayesian Approach, and Machine Learning Methods, which gives us strong confidence in their reliability.

Bayesian approach offered the best overall performance
Providing a superior balance of predictive accuracy and rich, interpretable insights.

Hit Rate	MNL Model		HB Model		RF Model	
Model	**In Sample (%)**	**Out Sample (%)**	**In Sample (%)**	**Out Sample (%)**	**In Sample (%)**	**Out Sample (%)**
Model 1	41.4	38	70.7	69.8	43.4	38.6
Model 2	47.3	41.5	70.5	68.4	59.9	43.3
Model 3	41.8	35.1	71.6	69.3	43.4	38.7
Model 4	49.8	40.9	72.7	69.8	60.9	42.7

Managerial Implications

Focus on the Mid-Tier products
Wineries should strategically position a 'core' line of products around the €12 price point, as this represents the sweet spot for the broadest segment of consumers.

Elevate White Wine
Given its high preference, white wine should be given greater weight in inventory and promotions, positioned as a versatile flagship product.

Communicate 'Balance'
Marketing should highlight cues like 'balanced 11.5% ABV' or 'aged 36 months' on labels to signal the moderate qualities that consumers prefer.

Targeted Promotions
Pricing and discount strategies should be tailored by gender and region. For example, be cautious with price hikes in Western Europe, and use prestige cues more in Eastern markets.

Limitations & Future Research

The sample was modest in size and was primarily composed of Western European respondents, which means we should be cautious when generalizing the cross-cultural findings.

The machine learning models are exploratory. The dataset was not large enough to unlock the full predictive potential of these advanced methods.

Q&A Session

Thank you for listening!

BACK TO OVERVIEW

Conjoint Analysis: Revealing Consumer Preferences

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Key Finding:

Bayesian approach offered the best overall performance
Providing a superior balance of predictive accuracy and rich, interpretable insights. Bayesian models delivered the best performance, achieving ~70% out-of-sample predictive accuracy.

Hit Rate	MNL Model		HB Model		RF Model	
Model	In Sample (%)	Out Sample (%)	In Sample (%)	Out Sample (%)	In Sample (%)	Out Sample (%)
Model 1	41.4	38	70.7	69.8	43.4	38.6
Model 2	47.3	41.5	70.5	68.4	59.9	43.3
Model 3	41.8	35.1	71.6	69.3	43.4	38.7
Model 4	49.8	40.9	72.7	69.8	60.9	42.7

Appendix – Variables description

NO	TYPE	VARIABLE NAME	VALUES
1	Dependent	Consumer Choice	0 = Not Chosen, 1 = Chosen
2	Independent	Price	€6, €12, €18, €24
3	Independent	Type of Wine	White, Red, Rosé, Sparkling
4	Independent	Alcohol Content	5.5%, 7%, 12%, 18%
5	Independent	Aging Time	1 year, 2 years, 3 years, 4+ years
6	Moderator for Price	Gender	Male, Female
7	Moderator for Price	Location	Indonesia, The Netherlands, Spain, Germany, France, Taiwan, China, Canada, USA, Taiwan, Philippine
8	Control	Age Group	18 - 29, 30 - 40, 41 - 50, 51 - 60, 60+
9	Control	Last Education	High School, Bachelor, Master, PhD
10	Control	Physical Activity	None, Moderate, Low, High
11	Control	Occupation	Student, Employee, Entrepreneur, Self-employed
12	Control	Consumption Frequency	One bottle per week, one bottle per month, one bottle per 3 months, one bottle per year, never
13	Control	Drinking Occasion	Casual, Food-centered, Celebratory, Personal

Table 1 - Summary of the Variables

Appendix – Reason for using 7 tasks

Methodology

Severe

Predicted duration

Our data indicates that surveys longer than 9 minutes start to see substantial levels of respondent break-off on mobile devices - sometimes long surveys are necessary, but in order to increase your survey completion rate we'd suggest that you make sure this is one of those rare cases.

Learn more about recommended survey durations

33.9 Mins
Goal: 7.0

Show Block: Wine Preference - Celebratory (12 Questions) Toggle Questions
Add Below Move Duplicate Delete

Show Block: Wine Preference - Casual (12 Questions) Toggle Questions
Add Below Move Duplicate Delete

Show Block: Wine Preference - Food (12 Questions) Toggle Questions
Add Below Move Duplicate Delete

Show Block: Wine Preference - Personal (12 Questions) Toggle Questions
Add Below Move Duplicate Delete

Appendix – Ideal Point

```
Call:
mlogit(formula = Choice ~ Price^2 + Alcohol^2 + Aging.Time^2 +
    Type_Red + Type_White + Type_Rose + NC | 0, data = mlogit_data_train,
    reflevel = "A", method = "nr")

Frequencies of alternatives:choice
       A        B        C     None
0.293774 0.328794 0.315175 0.062257

nr method
5 iterations, 0h:0m:0s
g'(-H)^-1g = 0.000699
successive function values within tolerance limits

Coefficients :
             Estimate Std. Error z-value  Pr(>|z|)
Price      -0.0311315  0.0080694 -3.8580 0.0001143 ***
Alcohol    -0.0092846  0.0127681 -0.7272 0.4671173
Aging.Time  0.1000644  0.0554999  1.8030 0.0713936 .
Type_Red    0.8819677  0.1966603  4.4847 7.301e-06 ***
Type_White  0.8784719  0.1865186  4.7098 2.479e-06 ***
Type_Rose   0.4281984  0.1988829  2.1530 0.0313173 *
NC         -1.2490189  0.3329773 -3.7511 0.0001761 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log-Likelihood: -622.85
```

```
Call:
mlogit(formula = Choice ~ Price_12^2 + Price_18^2 + Price_24^2 +
    Alcohol_7^2 + Alcohol_12^2 + Alcohol_18^2 + Aging_2^2 + Aging_3^2 +
    Aging_4^2 + Type_Red + Type_White + Type_Rose + NC | 0, data = mlogit_data_train,
    reflevel = "A", method = "nr")

Frequencies of alternatives:choice
       A        B        C     None
0.293774 0.328794 0.315175 0.062257

nr method
5 iterations, 0h:0m:0s
g'(-H)^-1g = 0.000679
successive function values within tolerance limits

Coefficients :
            Estimate Std. Error z-value  Pr(>|z|)
Price_12     0.009793   0.126112  0.0777 0.9381040
Price_18    -0.276015   0.155297 -1.7773 0.0755121 .
Price_24    -0.681935   0.180360 -3.7810 0.0001562 ***
Alcohol_7    0.280051   0.148620  1.8843 0.0595190 .
Alcohol_12   0.248554   0.147965  1.6798 0.0929931 .
Alcohol_18  -0.111734   0.183776 -0.6080 0.5431933
Aging_2      0.304786   0.163008  1.8698 0.0615170 .
Aging_3      0.347693   0.171931  2.0223 0.0431475 *
Aging_4      0.467270   0.187310  2.4946 0.0126086 *
Type_Red     0.905198   0.213199  4.2458 2.178e-05 ***
Type_White   0.931564   0.203702  4.5732 4.804e-06 ***
Type_Rose    0.482374   0.214120  2.2528 0.0242707 *
NC          -0.718819   0.316314 -2.2725 0.0230569 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log-Likelihood: -618.59
```

Appendix – MNL Interpretation

ATTRIBUTE	LEVEL OR INTERACTION	ESTIMATE	STD. ERROR	P-VALUE	SIGNIF.
PRICE	€12	0.589	0.270	0.029	*
	€18	0.273	0.331	0.410	
	€24	0.439	0.365	0.230	
PRICE × COUNTRY	€12 × France	–0.071	0.379	0.851	
	€18 × France	–0.932	0.525	0.076	.
	€24 × France	–1.406	0.546	0.010	*
	€12 × Germany	–0.283	0.378	0.454	
	€18 × Germany	–0.297	0.473	0.530	
	€24 × Germany	–1.566	0.545	0.004	**
	€12 × Netherlands	–0.967	0.321	0.003	**
	€18 × Netherlands	–1.586	0.436	<0.001	***
	€24 × Netherlands	–2.427	0.507	<0.001	***
	€12 × Spain	0.093	0.473	0.844	
	€18 × Spain	–0.182	0.619	0.769	
	€24 × Spain	–0.320	0.621	0.606	
	€12 × Other	–0.162	0.399	0.685	
	€18 × Other	0.263	0.477	0.581	
	€24 × Other	–2.079	0.722	0.004	**
PRICE × GENDER	€12 × Male	–0.646	0.241	0.007	**
	€18 × Male	–0.130	0.311	0.677	
	€24 × Male	0.028	0.357	0.938	
WINE TYPE	Red	0.978	0.221	<0.001	***
	White	1.038	0.213	<0.001	***
	Rosé	0.532	0.222	0.017	*
ALCOHOL CONTENT	7%	0.334	0.154	0.030	*
	12%	0.286	0.153	0.061	.
	18%	–0.067	0.190	0.723	
AGING TIME	2 years	0.299	0.168	0.075	.
	3 years	0.359	0.180	0.046	*
	4 years	0.459	0.195	0.019	*
NO-CHOICE OPTION	None	–0.642	0.325	0.048	*

ATTRIBUTE	WTP (€)
RED WINE	1.66
WHITE WINE	1.76
ROSÉ WINE	0.90
ALCOHOL 7%	0.57
ALCOHOL 12%	0.49
ALCOHOL 18%	–0.11
AGING 2 YEARS	0.51
AGING 3 YEARS	0.61
AGING 4 YEARS	0.78

PROFILE	PRICE	WINE TYPE	ALCOHOL CONTENT	AGING TIME	MARKET SHARE
PROFILE 1	€12	Red	12%	4 years	49.1%
PROFILE 2	€18	White	18%	2 years	22.7%
PROFILE 3	€24	Rosé	7%	3 years	25.7%
NO-CHOICE	-	-	-	-	2.6%

Appendix – HB Interpretation (1)

ATTRIBUTE	ESTIMATE	2.5 %	97.5 %	SIGNIF.
INTERCEPT	–2.53	–3.33	–1.76	Yes
NO CHOICE	–0.75	–1.71	0.20	No
PRICE LEVELS				
€ 12	0.51	–0.23	1.25	No
€ 18	–1.06	–2.07	–0.07	Yes
€ 24	–0.79	–2.11	0.53	No
ALCOHOL LEVEL				
7 %	0.59	0.12	1.06	Yes
12 %	0.38	–0.12	0.89	No
18 %	–0.04	–0.75	0.64	No
AGING TIME				
2 YEARS	0.52	0.01	1.05	Yes
3 YEARS	0.82	0.28	1.38	Yes
4 YEARS	0.88	0.30	1.48	Yes
WINE TYPE				
RED	0.92	–0.03	1.82	No
WHITE	1.33	0.58	2.08	Yes
ROSÉ	0.10	–0.64	0.82	No

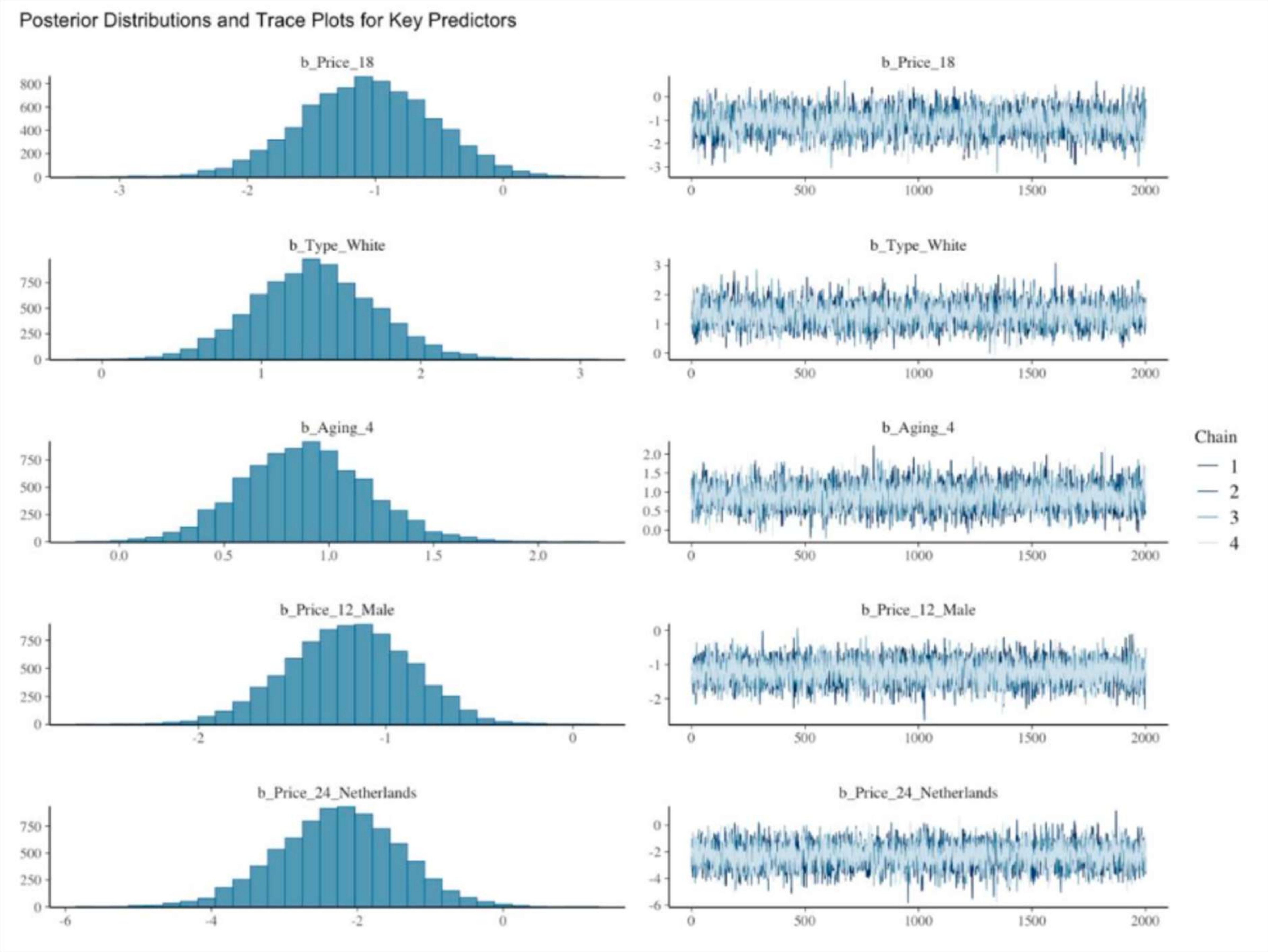
INTERACTION TERM	ESTIMATE	2.5%	97.5%	SIGNIF.
PRICE_12_FRANCE	0.80	–0.11	1.73	No
PRICE_18_FRANCE	–0.65	–2.18	0.78	No
PRICE_24_FRANCE	–1.62	–3.40	0.10	No
PRICE_12_GERMANY	0.23	–0.72	1.16	No
PRICE_18_GERMANY	0.51	–0.78	1.81	No
PRICE_24_GERMANY	–1.88	–3.84	–0.08	Yes
PRICE_12_NETHERLANDS	–0.27	–1.09	0.58	No
PRICE_18_NETHERLANDS	–0.54	–1.69	0.64	No
PRICE_24_NETHERLANDS	–2.25	–4.01	–0.64	Yes
PRICE_12_SPAIN	0.45	–0.87	1.72	No
PRICE_18_SPAIN	0.07	–1.73	1.80	No
PRICE_24_SPAIN	0.71	–1.44	2.89	No
PRICE_12_OTHER	–0.02	–1.03	1.00	No
PRICE_18_OTHER	1.03	–0.32	2.38	No
PRICE_24_OTHER	–2.16	–4.57	–0.02	Yes
PRICE_12_MALE	–1.20	–1.84	–0.57	Yes
PRICE_18_MALE	0.19	–0.67	1.02	No
PRICE_24_MALE	0.88	–0.31	2.06	No

Appendix – HB Interpretation (2)

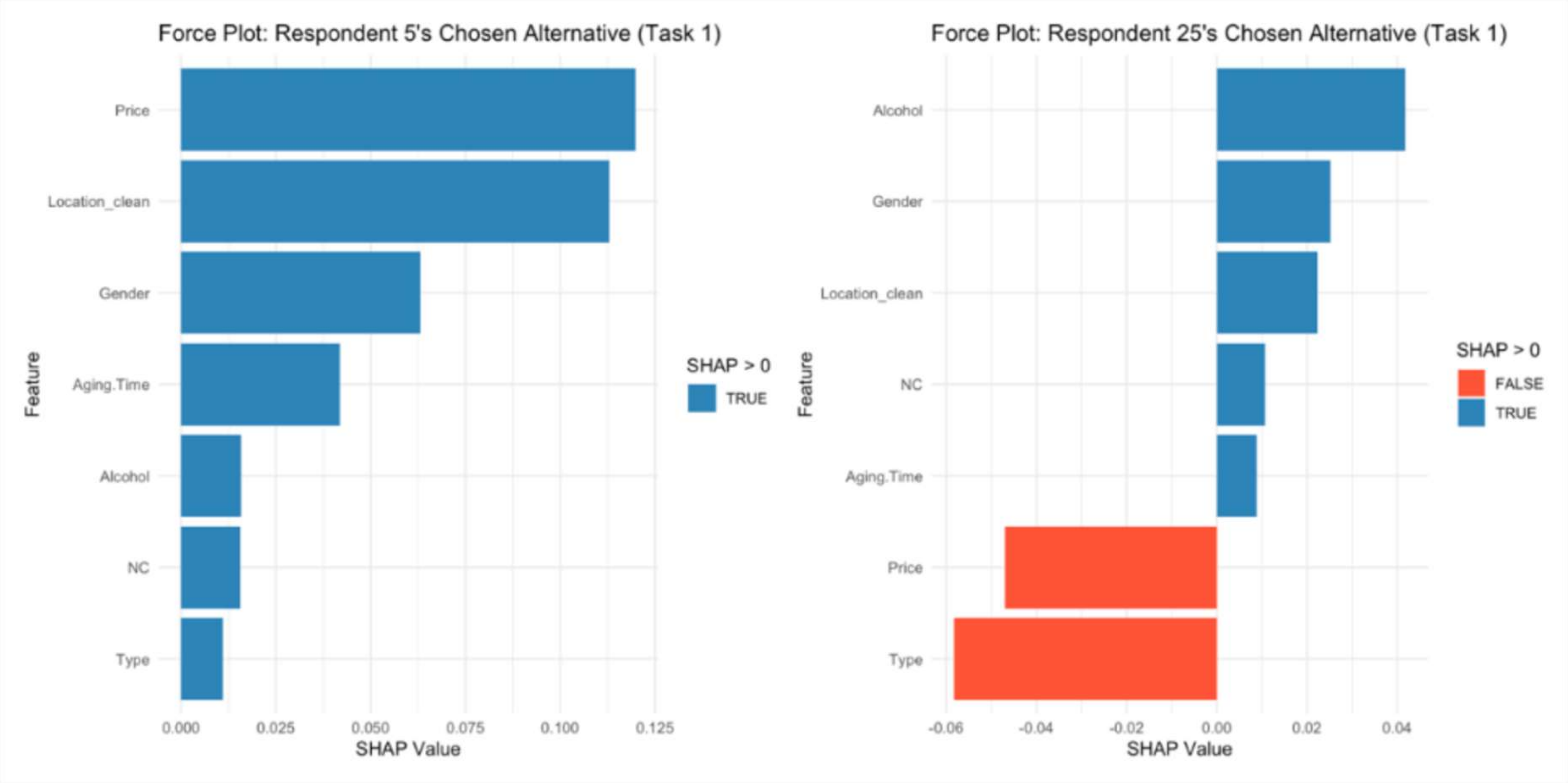
ATTRIBUTE	MEDIAN WTP	2.5% CI	97.5% CI	SIGNIF.
WHITE WINE	-1.24	-6.44	-0.36	Yes
RED WINE	-0.85	-4.93	0.24	No
ROSÉ WINE	-0.09	-1.58	1.17	No
ALCOHOL 7%	-0.55	-2.80	0.00	Yes
ALCOHOL 12%	-0.35	-1.99	0.25	No
ALCOHOL 18%	0.03	-1.08	1.53	No
AGING 2 YEARS	-0.48	-2.64	0.11	No
AGING 3 YEARS	-0.76	-3.84	-0.14	Yes
AGING 4 YEARS	-0.82	-4.45	-0.13	Yes

PROFILE	PRICE	WINE TYPE	ALCOHOL CONTENT	AGING TIME	MARKET SHARE
PROFILE 1	€12	Red	12%	4 years	76.0%
PROFILE 2	€18	White	18%	2 years	10.9%
PROFILE 3	€24	Rosé	7%	3 years	10.6%
NO-CHOICE	–	–	–	–	2.4%

Appendix – Bayesian PDs and TCs



Appendix – Force Plot



Appendix – Hypothesis Testing

HYPOTHESIS	MNL MODEL	BAYESIAN MODEL
H1: Preference for wine follows an inverted-u shape with respect to price.	**Supported** ($p=0.03$ for €12; pattern matches hypothesis)	**Supported** (Price_18: 95% CI excl. 0, negative effect)
H1a: Price × Gender (female exhibit greater price sensitivity).	**Not Supported** (only €12_Male significant and negative)	**Not Supported** (only €12_Male and negative, 95% CI excl. 0)
H1b: Price × Location (western > eastern price sensitivity).	**Supported** (all NL price interactions strongly negative, $p<0.01$)	**Supported** (NL × Price_24: 95% CI excludes 0, negative)
H2: Red wine is most preferred.	**Not Supported** (White > Red, both significant and positive)	**Not Supported** (White > Red; 95% CI includes 0, positive)
H3: Preference for alcohol content follows an inverted-u shape (12% most likely chosen).	**Supported** (Alcohol_7, Alcohol_12 significant and positive)	**Partially Supported** (Alcohol_7: 95% CI [0.12, 1.06], positive)
H4: Preference for aging time follows an inverted-u shape (3 years preferred).	**Partially Supported** (Aging_3, Aging_4 significant and positive)	**Partially Supported** (Aging_3 and Aging_4: 95% CIs exclude 0, positive)