Abstract

In increasingly saturated wine markets, firms need to understand the subtle trade-offs consumers make among price, sensory attributes, and contextual cues. Adopting a choice-based conjoint design, this thesis elicits observations from 99 wine drinkers and estimates preference structures with three complementary approaches: classical statistical using the Multinomial logit model, Hierarchical Bayesian model, and Machine Learning models, using regularization and random forest. Results reveal a pronounced preference for moderation: utility peaks at a mid-tier price (€ 12), at mid-level alcohol percentages (7–12 %), and longer aging time, around three to four years. White wine is favoured over red, rosé, and sparkling wine, overturning long-standing assumptions about varietal hierarchy, while gender and regional culture emerge as significant moderators of price sensitivity; Men and Western consumers penalise higher prices more sharply than their counterparts. The Bayesian model confirms coefficient robustness, and SHAP diagnostics reproduce the same attribute ranking in the non-parametric framework, underscoring the stability of the results across methodologies. The findings highlight a market that rewards moderation yet remains segmented by gender and culture, offering actionable guidance for product design, price sensitivity, and cross-market positioning.

Keywords: Choice-based conjoint analysis, Wine preference, Cross-cultural consumer behavior, Multinomial, Hierarchical Bayesian logit, Machine Learning, Regularization, Random Forest

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1 Introduction

Nowadays, technology significantly affects how the industry works and how to gain a competitive advantage within the industry. Ignited by the introduction of Industry 4.0 and followed by the recent development of Artificial Intelligence, firms are now overloaded with data, and the usage of data-driven decision-making has become a necessity and a positive trend within the industry. The current condition prompts firms to create a competitive advantage based on data. One of the ways is to position their product in the market through product differentiation to best serve the consumer. Product differentiation extends beyond basic attributes such as flavor and size to encompass variations in quality, branding, production methods, and sustainability claims (Pomarici & Vecchio, 2014). In industries such as wine production, where offerings range from mass-market to premium selections, understanding consumer preferences is crucial for strategic decision-making (Rinck, 2023). Consumers consider multiple factors when purchasing wine, including price, origin, grape variety, and quality indicators such as aging time and production techniques (Culbert et al., 2017; Goodman et al., 2008). Firms that successfully identify and respond to these preferences can gain a competitive advantage by optimizing product offerings and marketing strategies.

One of the most well-known statistical techniques in marketing for analyzing consumer decision-making is conjoint analysis, a widely used technique for evaluating trade-offs in consumer preferences (Eggers et al., 2021). Conjoint analysis decomposes consumer choices into specific attribute contributions, offering valuable insights into the relative importance of various product features (Maldonado et al., 2015). Traditionally, conjoint studies relied on classical statistical models**,** such as ordinary least squares (OLS), which assume linearity and often struggle to capture nonlinear interactions or high-dimensional relationships between attributes (Maldonado et al., 2015). To overcome these limitations, Bayesian approaches, especially Hierarchical Bayes (HB)**,** have become prominent for their ability to model uncertainty and account for individual-level heterogeneity through structured priors (Gelman et al., 2013). However, Bayesian methods require careful prior specification and can be computationally intensive. As the consumer decision-making processes become more complex, recent advancements in machine learning and optimization offer promising alternatives that can achieve comparable or superior predictive accuracy, often with greater scalability and fewer modeling assumptions (Toubia et al., 2007).

Existing research has identified key wine attributes influencing consumer purchase decisions, including price sensitivity, production methods, and brand reputation (Culbert et al., 2017). Nevertheless, research has yet to provide a comprehensive comparison of different analytical techniques in modeling consumer preferences, particularly in the context of wine selection. As mentioned earlier, each method has its own trade-offs between interpretability, flexibility, and predictive performance, an empirical comparison is needed to assess how these techniques perform in real-world conjoint data, which in this case is specific to consumer wine preference.

This study aims to evaluate which wine attributes most significantly influence consumer choice and to compare the effectiveness of classical statistical models, Bayesian approaches, and machine learning techniques in analyzing consumer preference through conjoint analysis. Specifically, investigates how each modelling method differs in terms of interpretability, predictive accuracy, and ability to capture complex relationships between product attributes. Additionally, the study explores ways to optimize conjoint analysis methodologies to enhance their practical application in marketing and product development. To achieve these objectives, this study seeks to answer the following research question:

“Which wine attributes have the greatest influence on consumer preference based on conjoint analysis through different modeling approaches?"

To answer the research question, this study employs choice-based conjoint (CBC) analysis, which simulates real-world consumer decision-making by presenting respondents with hypothetical product profiles (Eggers et al., 2021). Data were collected through a structured survey in which participants evaluated various wine offerings based on key attributes such as price, wine type, aging time, and alcohol percentage (Rinck, 2023). The resulting dataset is analyzed using three distinct modeling approaches. First, classical statistical methods, specifically multinomial logistic regression, are applied to estimate attribute importance and model consumer choices (Maldonado et al., 2015). Second, Bayesian techniques implement probabilistic frameworks to estimate consumer preferences while accounting for uncertainty (Si et al., 2017). Third, machine learning models, including regularization methods and random forests, are used to enhance predictive performance and uncover complex, nonlinear relationships between attributes (Toubia et al., 2007).

The findings from this study will provide insights into the trade-offs consumers make when selecting wine products and offer actionable recommendations for product positioning, pricing strategies, and new product development in the wine industry. By comparing the strengths and limitations of classical statistical models, Bayesian approaches, and machine learning techniques, this research contributes to both marketing practice and methodology by assessing the effectiveness of different conjoint modeling approaches for consumer preference analysis.

2 Literature review

This chapter presents the theoretical framework and empirical foundations of the study, beginning with key concepts on consumer preferences, conjoint analysis, and wine attributes. Building on this foundation, the chapter then outlines the research hypotheses and introduces the conceptual model guiding the analysis.

2.1 Consumer Preference in Wine Product

Consumer preference refers to the inclination of individuals toward specific product attributes when making purchasing decisions. These preferences, especially in wine products, are shaped by various factors, including past experiences, perceived quality, brand familiarity, cultural influences, and personal taste (Robertson et al, 2018). While the consumer's likelihood to buy a product is measured by purchase intention, consumer preference solely reflects the desirability of certain attributes, which neglects the external purchasing constraints (Mauracher et al., 2019).

In marketing, understanding consumer preferences is essential for firms seeking to maintain a competitive advantage. By identifying the key product attributes that consumers prioritize, companies can develop offerings that more closely align with market demand (Hauser & Urban, 1986). Consumer preference research enables firms to uncover behavioral patterns and design products that reflect evolving customer expectations (Sethuraman & Cole, 1999). It also enhances market segmentation by allowing firms to tailor features and messaging to specific target groups, improving targeting precision and customer satisfaction. Furthermore, according to Mauracher et al. (2019), preference data provides valuable input for pricing strategies by revealing consumers' price sensitivity and willingness to pay, which enables firms to design more competitive and value-based pricing models.

In the food and beverage industry, where taste is highly subjective and culturally embedded, understanding consumer preferences is particularly important. In the case of wine, consumption behavior is shaped by regional culture, social norms, and habitual patterns, making localized market insights a critical factor in business success (Johansen et al., 2006). While consumer preferences heavily influence product desirability, actual purchase decisions are also constrained by factors such as price, availability, and promotional activity (Eggers et al., 2021). For instance, consumers may prefer premium wines but opt for more affordable alternatives due to budget limitations. Additionally, familiarity with product features, such as wine type, alcohol content, and aging, can significantly influence consumer choices, particularly among less experienced drinkers (Goodman et al., 2008; Drennan et al., 2015). These dynamics underscore the complexity of translating consumer preference into real-world purchasing behavior.

This complex relationship between consumer preferences and actual choices can be effectively captured using Choice-Based Conjoint (CBC) analysis. Unlike traditional rating scales or self-reported importance rankings, CBC requires respondents to make realistic trade-offs, thereby capturing preference structures more accurately and reducing hypothetical bias (Louviere et al., 2010). As a result, CBC enables firms not only to identify the most valued product attributes but also to estimate consumers' willingness to pay and simulate market share under various product configurations. These insights are invaluable for guiding product development, optimizing pricing strategies, and forecasting competitive positioning in the market.

2.2 Conjoint Analysis

Conjoint analysis is a widely adopted quantitative method in marketing research that enables the evaluation of trade-offs between different product attributes made by consumers. By presenting respondents with systematically varied sets of hypothetical product profiles, researchers can estimate the relative importance of each attribute in shaping consumer choices. This approach is particularly valuable for modeling consumer preferences, simulating choice behavior, and guiding strategic decisions related to product design, positioning, and market segmentation (Eggers et al., 2021). These are four core applications of conjoint analysis that are instrumental in strategic marketing and product management:

1. Consumer Preference Estimation: Conjoint analysis enables the estimation of part-worth utilities, quantifying the value consumers assign to specific levels of product attributes. These utility estimates are derived from choices respondents make when presented with sets of hypothetical product profiles, each varying systematically across multiple attributes. The resulting part-worths reflect the relative importance of each attribute in shaping consumer preferences and allow researchers to decompose overall utility into individual components. This information is instrumental for firms seeking to identify which product features are most influential in consumer decision-making. Recent methodological advances in conjoint analysis, particularly in Choice-Based Conjoint (CBC) frameworks, have improved the precision of utility estimation and enhanced the ability to simulate realistic market scenarios (Eggers et al., 2021).

2. Choice Probabilities: Choice-Based Conjoint (CBC) analysis helps estimate how likely a consumer is to choose one product option over alternative configurations. This is achieved by modeling the likelihood of choice based on the estimated utilities of the product attributes, providing insights into consumer choice behavior under various scenarios. These probabilities are instrumental in simulating market scenarios, forecasting market shares, and informing strategic decisions related to product design and positioning (Eggers et al., 2021).

3. Willingness to Pay (WTP): Conjoint analysis allows researchers to determine how much consumers are willing to pay for different product features. By analyzing the trade-offs consumers make between price and product features, firms can determine the monetary value assigned to each attribute, which can help pricing strategies and product feature enhancements (Gensler et al., 2012).

4. Market Share Simulation: CBC analysis enables the forecasting of market share by aggregating individual-level choice probabilities across a simulated market scenario. Once part-worth utilities have been estimated, these can be used to model consumer preferences for competing product profiles, allowing researchers to simulate consumer decisions under various configurations. This approach provides firms with strategic insights into how different product offerings may perform relative to one another, supporting the evaluation of competitive positioning and aiding in the optimization of product portfolios. By incorporating consumer heterogeneity and realistic decision environments, conjoint-based market simulations help anticipate product success in the marketplace (Eggers et al., 2021).

2.3 Key Attributes for Wine Products

As consumer choice serves as the dependent variable in this study, it is essential to examine the product attributes that shape the selection behavior. While consumer preferences reflect the desirability of individual product features, Choice-Based Conjoint (CBC) analysis captures how these preferences shift when consumers are presented with competing alternatives. By modeling trade-offs in realistic choice scenarios, this study aims to identify which wine attributes exert the greatest influence on consumer decisions and how they differ across consumer segments.

Product attributes refer to specific features or characteristics that distinguish one product from another and influence consumer decision-making. These attributes are commonly classified as intrinsic and extrinsic (Robertson et al., 2018). Intrinsic attributes are inherent to the product and cannot be modified without altering its core nature. In the context of wine, examples include alcohol content, aging time, and type of wine. In contrast, extrinsic attributes are external cues that influence perception and can be altered without changing the product's physical composition, such as price and label information (Goodman et al., 2008). Understanding the relative importance of these attributes is critical for firms aiming to optimize their product offerings. Some consumers may prioritize sensory aspects, such as the type of wine, aging time, and alcohol level, while others may treat price as a heuristic for quality (Mauracher et al., 2019). In the wine industry, where subjective perception and tradition heavily influence purchase decisions, the interaction between intrinsic and extrinsic attributes becomes particularly salient (Drennan et al., 2015).

The remainder of this section introduces the specific attributes selected for this study and justifies their inclusion based on both prior literature and practical relevance in the wine industry.

2.3.1 Price

Price is widely recognized as a fundamental determinant in consumer decision-making and is particularly influential across diverse market segments. It not only reflects economic constraints but also serves as a psychological cue that shapes perceptions of product quality. As Rao (2005) note, consumers frequently rely on price as a heuristic indicator of quality, particularly when other information is scarce or ambiguous. In such contexts, higher prices are typically interpreted as signals of superior craftsmanship, while lower prices suggest accessibility and value (Mauracher et al., 2019). This perception dynamic helps explain why mid-range pricing can appeal to both budget-conscious and quality-seeking consumers, offering a perceived balance between affordability and product quality. Price sensitivity also varies according to demographic and psychological profiles, for instance, some consumers prioritize value for money, while others associate premium prices with prestige, status, or exclusivity. These dynamics underscore the relevance of price as a key attribute in wine-choice modeling.

2.3.2 Type of Wine

Different wine categories offer distinct sensory profiles and consumption experiences. Consumers often develop preferences based on taste, food pairings, and occasion-based consumption, which can influence their choices between red, white, rosé, and sparkling wines (Goodman et al., 2008). Thus, making the type of wine a significant factor influencing consumer preference. Additionally, demographic factors such as age and gender may impact preferences for different wine types, with younger consumers often favoring lighter, fruitier wines and more experienced consumers gravitating toward complex, aged varieties (Johansen et al., 2006). The survey in this study includes four primary wine types: red, white, rosé, and sparkling wine. Thus, allowing an in-depth analysis of how consumers evaluate and trade off these categories when making purchasing decisions.

2.3.3 Alcohol Content

Alcohol content is a key factor influencing consumer wine preferences, though its impact varies depending on cultural drinking norms, individual taste preferences, and consumption occasions. Some consumers associate higher alcohol levels with richer flavors and premium quality, favoring full-bodied wines for celebratory events or special occasions (Johansen et al., 2006). In contrast, others prefer lower-alcohol wines that offer a lighter, more refreshing experience, often selected for casual social settings or as a complement to food pairings. Additionally, health-conscious consumers may gravitate toward wines with reduced alcohol content, as this trend linked to broader wellness preferences and healthier lifestyle choices (Bucher et al., 2018).The dual role of alcohol content as both a sensory and lifestyle-driven attribute makes it a crucial element in consumer decision-making and market positioning.

2.3.4 Aging Time

Longer aging time is often associated with higher quality, complexity, and enhanced flavor development. Many consumers perceive longer aging periods as a marker of superior craftsmanship, believing that older wines exhibit richer and more nuanced taste profiles, which contribute to their premium status in the market (Bruwer et al., 2011). This perception is particularly strong among wine enthusiasts and connoisseurs, who associate aging with refined tannins, depth, and balance. Thus, aging time is an essential feature in wine products.

However, preferences for aging time vary across consumer segments. Less experienced consumers may rely on wine age as a heuristic for quality, assuming that older wines are inherently superior regardless of grape variety or production methods. In contrast, more knowledgeable consumers take a more refined approach, considering vintage conditions, terroir, and storage methods as more significant indicators of quality than aging alone. Additionally, aging preferences may be influenced by regional wine traditions and habitual drinking patterns, where certain markets favor younger, fruitier wines, while others appreciate aged, full-bodied varieties that undergo extensive maturation (Bruwer et al., 2011).

In summary, the four attributes discussed, price, type of wine, alcohol content, and aging time, represent a combination of economic, sensory, lifestyle, and symbolic dimensions that shape consumer decision-making in the wine market. By incorporating these attributes into the choice-based conjoint design, this study aims to capture the complex and multidimensional nature of wine preference, thereby offering deeper insights into how consumers make purchasing decisions under real-world constraints.

2.4 Interaction terms

2.4.1 Gender as a moderator of Price

While product attributes such as price and type of wine directly influence consumer choice, previous research suggests that these effects may vary across different consumer segments. In particular, gender has been shown to moderate how consumers evaluate price in wine purchasing decisions. Atkin et al., (2007) observed that female consumers are more cautious when evaluating wine quality, often relying on extrinsic cues such as medals, labels, and shelf tags to infer value. While these cues are not directly related to price, they highlight a broader tendency among female consumers to engage in value-seeking and risk-averse behavior. Complementing this, Forbes and Dean (2010) found that women tend to spend less per bottle on average, are more responsive to discounts, and exhibit greater sensitivity to numeric prices when purchasing wine. Male consumers, by contrast, were more likely to prioritize prestige or regional attributes, even at higher price points.

Based on these insights, this study incorporates an interaction term between Price and Gender to investigate whether price sensitivity differs by gender group. By doing so, the model accounts for potential heterogeneity in decision-making processes and captures more nuanced patterns in consumer wine preferences.

2.4.2 Location as a moderator of Price

Geographic location plays a significant role in moderating how consumers evaluate price in wine purchasing behavior, encompassing not just physical placement but also cultural and market contexts. In this study, location is operationalized at the country level, allowing for a comparison of consumer behavior between respondents from Western (e.g., the Netherlands) and Eastern (e.g., Indonesia) markets.

In Western regions, notably Western and Central Europe (e.g., France, Germany, the Netherlands) and North America, wine consumption is widespread and culturally normalized. Wine is typically viewed as a routine grocery product, accessible through competitive retail channels. As a result, consumers in these regions often exhibit higher price sensitivity, assessing wines based on cost-efficiency and value. Agnoli and Begalli (2016) found that in mature markets, consumers are more accustomed to evaluating wine using tangible and economic cues such as price, brand, and quality.

In contrast, Eastern markets, such as China, Indonesia, and Japan, represent more emerging wine economies, where wine is often perceived as a symbolic or aspirational product. In such cultures, price may be a secondary consideration, as consumers place stronger emphasis on relational or status-based cues. A study by Shavitt and Barnes (2020) shows that collectivist cultures prioritize social harmony and contextual appropriateness, leading consumers to consider how a product fits within group expectations or relational meaning, potentially reducing their responsiveness to price.

In Western societies, which tend to be more individualistic, consumers are generally more inclined to make autonomous decisions and prioritize personal benefits, a behaviour that often leads to greater engagement in price comparisons and information search. In contrast, Eastern cultures characterized by collectivism tend to base consumption choices on social expectations and symbolic values rather than purely on economic considerations (De Mooij & Hofstede, 2011).

By including interaction terms between price and gender and location, this study accounts for socio-demographic heterogeneity in consumer behavior. These interactions enhance the model's explanatory power and allow for a more nuanced understanding of how price sensitivity varies across consumer groups.

2.5 Hypotheses Development

Price often plays a pivotal role in consumer decision-making, particularly in categories like wine, where objective quality is difficult to assess. Consumers often rely on price as a heuristic cue for quality, especially when their product knowledge is limited (Robertson et al., 2018). However, the relationship between price and consumer preference is not always linear. While low prices may raise concerns about quality, very high prices can exceed consumers' acceptable value thresholds, making them less attractive despite any premium associations.

Studies using discrete choice experiments on wine have consistently reported that price has a negative effect on utility, indicating that many consumers inherently prefer lower-priced options. For example, Lockshin et al. (2006) found that utility tends to decline as price increases, which is a typical signal of price sensitivity in consumer choice behavior. However, they also observed preference heterogeneity across segments, revealing that certain consumers are willing to pay more when favorable attributes such as brand, origin, or awards are present. These findings support the interpretation that price sensitivity is not strictly linear, and that moderate price levels may be most preferred, offering a perceived balance between quality and affordability.

H1: Consumer preference for wine follows an inverted-U shape with respect to price.

Previous research suggests that gender differences influence how consumers respond to price when making wine purchase decisions. Women are generally more price-sensitive, value-conscious, and value cues such as discounts (Forbes & Dean, 2010). In contrast, men tend to place greater emphasis on prestige or symbolic attributes, even at higher price points (Atkin et al., 2007). These differences imply that the effect of price may not be uniform across gender groups. Incorporating an interaction between price and gender allows us to test whether gender moderates the influence of price on consumer choice. Identifying such variation helps capture preference heterogeneity and improves the explanatory power of the model.

H1a: The effect of price on wine choice is moderated by gender, such that female consumers exhibit greater sensitivity to price than male consumers.

Prior research highlights that consumer sensitivity to price differs across regions due to cultural and market contexts. In Western countries, where wine is widely available and integrated into everyday consumption, consumers tend to be more price-conscious and value-driven (Agnoli & Begalli, 2016). In contrast, Eastern markets often treat wine as a symbolic or status-related product, where price plays a less central role. Consumers in these collectivist cultures are more likely to base their choices on social meaning and appropriateness rather than economic utility (Shavitt & Barnes, 2020; De Mooij & Hofstede, 2011). Including location as a moderator of price allows this study to test whether regional cultural factors moderate price sensitivity, helping capture cross-market preference heterogeneity.

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.

The type of wine, encompassing sensory attributes such as body, flavor, and style, plays a critical role in shaping consumer preferences. Research has shown that wine type is an essential factor in choice behavior, with individuals showing strong preferences for sparkling wine over red, white, or rosé in contexts related to celebration, freshness, and novelty (Goodman et al., 2008). Such preferences are also influenced by demographic and lifestyle factors, where red wine often appeals to younger or more socially driven consumers. Based on these patterns, we hypothesize:

H2: Consumers are most likely to prefer red wine over other wine types.

Alcohol content influences consumer wine preferences by shaping perceptions of taste, strength, and overall quality. While some consumers associate higher alcohol levels with richer flavors and greater complexity, others prefer moderate alcohol content for its balance, drinkability, and compatibility with food. Empirical evidence suggests that wines with moderate alcohol levels, typically around 12% are more favorably evaluated than those with lower or higher alcohol content, indicating a non-linear, inverted-U-shaped relationship between alcohol level and consumer utility. Using a conjoint-based approach, Lockshin et al., (2006) found that consumers tended to avoid wines at the extremes of alcohol content, favoring mid-range levels. Similarly, Schäufele and Hamm (2017) reported that wines with approximately 12% alcohol were evaluated most positively, especially among health-conscious consumers, reflecting a growing preference for balance over intensity. This leads to the following hypothesis:

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

Lastly, aging time is often perceived as a cue for wine quality, with longer aging traditionally associated with complexity and refinement. However, evidence indicates that consumer preference does not linearly increase with age. While some consumers value older wines, others prefer moderately aged wines due to their balance of flavor development and accessibility. Consumer preferences for wine aging vary by demographic and regional factors, suggesting that certain segments may favor moderately aged wines, while others prefer either younger or more mature profiles (Bruwer et al., 2011). Therefore, we hypothesize:

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.

This study seeks to quantify how consumers prioritize different wine attributes and what trade-offs they make when selecting a bottle of wine by testing these hypotheses through choice-based conjoint (CBC) analysis.

2.6 Conceptual Model

This section presents the visualization and explanation of the conceptual model, which defines the scope of the study. The model is structured to analyze the relationship between wine attributes and consumer choice, incorporating various methodological approaches for comparative analysis.

The dependent variable in this study is consumer choice, representing the selected wine product based on a combination of attributes. The independent variables include key wine attributes: price, type of wine, alcohol level, and aging time, which are hypothesized to influence consumer decision-making. Gender and Location are used as moderators for Price. Location, in this case, indicates which country the respondents reside in. Furthermore, consumer demographic factors are included as the control variables, namely age, education, and occupation. Additionally, behavior variables such as physical activity, consumption frequency, and drinking occasion are also collected.. Those factors serve as extraneous influences that may affect consumer choice but are not the primary focus of the study.

In summary, the conceptual model not only outlines the relationship between key wine attributes and consumer choice, but also provides a framework for comparative analysis across multiple methodological approaches. By applying classical statistical techniques, Bayesian modeling, and machine learning methods, the study enables a deeper and more nuanced interpretation of consumer preferences. This multi-method design enriches our understanding by highlighting how different analytical lenses can yield complementary insights into wine selection behavior.

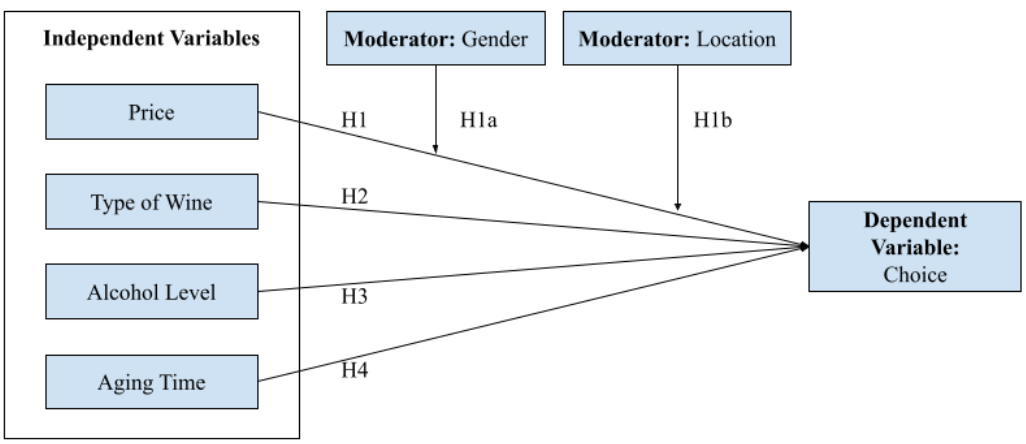

Figure 1 - Conceptual Model using Choice as DV

3 Research Methodology

This chapter presents the methodological framework to investigate consumer wine preferences in across regions. This study is based on a primary data collection effort using a CBC experiment, which simulates real-world purchasing scenarios by asking respondents to choose from sets of hypothetical wine profiles. Each profile varies systematically across key product attributes, allowing for the estimation of consumer utilities and the trade-offs they make.

To analyze consumer choice behavior, this study applies three modeling techniques: classical statistical methods, specifically the Multinomial Logit (MNL) model; a Bayesian estimation approach using hierarchical modeling; and machine learning (ML) methods**,** which offer a flexible, data-driven alternative to traditional utility-based models. This multi-method approach enables a robust assessment of model performance, predictive power, and interpretability.

Each method contributes distinct strengths. The MNL model offers a clear economic interpretation and closed-form probability expressions. The Bayesian approach incorporates individual-level heterogeneity and provides uncertainty quantification (Eggers et al., 2021). Machine learning models such as random forests and regularization algorithms are designed for predictive accuracy but are less interpretable in economic terms (Volk et al., 2015).

The remainder of this chapter outlines the experimental design, data preparation, model fit and validation, and estimation techniques, followed by the results and discussion of post-estimation analyses, including willingness to pay (WTP) and market share simulation**.**

3.1 Choice-Based Conjoint Analysis

This study aims to reveal consumer preferences in the context of wine selection by employing CBC analysis**.** In this context, consumer choice serves as the appropriate dependent variable, as it captures the decision-making process by which individuals select a product from a set of alternatives based on their preferences for different product attributes (Eggers et al., 2021). To model this complexity, CBC is adopted as the core method. CBC is a widely used stated preference technique in marketing research, designed to replicate real-world purchasing scenarios by asking respondents to select one alternative from a set of alternatives with different profiles rather than rating or ranking them in isolation (Louviere et al., 2010). This task structure mirrors the way consumers make actual market decisions, ensuring that preferences are revealed through concrete trade-offs rather than hypothetical evaluations. By analyzing these observed choices across multiple tasks, CBC enables the estimation of part-worth utilities, which serve as numerical indicators of the relative desirability of specific attribute levels.

This approach facilitates a deeper understanding of consumer preferences by capturing the nuances of trade-offs between competing product features. It allows researchers to evaluate which product attributes are most influential in driving choice, how individuals weigh various product features, and whether preference structures vary across demographic or contextual segments. For instance, CBC supports the inclusion of interaction terms, such as the moderating effect of gender on price sensitivity, enabling the identification of preference heterogeneity**.**

In this study, the CBC design is constructed based on a careful review of existing literature on wine consumer behavior. Key attributes and levels are selected to ensure both theoretical relevance and empirical realism, allowing for the robust modeling of consumer utility and the prediction of choice behavior under varying product configurations (Ben-Akiva et al, 2019; Toubia et al., 2007).

3.2 Experimental Design for Conjoint Survey

This study employs a Choice-Based Conjoint (CBC) experimental design, implemented through a self-administered survey conducted in May 2025. The survey was independently developed in accordance with academic research standards and structured to simulate realistic wine purchasing decisions. It includes four attributes, each with four levels, following best practices which recommend 2 to 4 levels to balance model accuracy with respondent burden (Orme, 2010). Attributes with too many levels tend to increase cognitive complexity without proportional gains in predictive precision.

A full factorial design based on these specifications would produce $4^4 = 256$ unique product profiles. Presenting all combinations to each respondent would be infeasible and cognitively overwhelming. Therefore, an efficient fractional factorial design was used to ensure sufficient attribute-level variation while maintaining feasibility and respondent engagement.

Each task presents four product alternatives, including a "no-choice" option, which reflects real-life decision-making more accurately. Incorporating such an opt-out option is widely recommended to capture realistic consumer behavior, where abstaining from a purchase is often a valid outcome (Louviere et al., 2000).

To ensure statistical validity while minimizing respondent fatigue, the number of tasks per respondent was carefully considered. While prior literature commonly recommends 8 to 12 tasks per respondent (Orme, 2010; Chandukala et al., 2007), this study adopts a more conservative design with 7 tasks per respondent. This decision is supported by emerging research on declining digital attention spans, which shows that shorter, more focused online tasks lead to improved participation and response quality (Galesic & Bosnjak, 2009; Revilla & Ochoa, 2017). Each respondent thus evaluates 21 product profiles (7 tasks × 3 alternatives).

To determine the minimum required sample size**,** this study applies the Johnson-Orme rule-of-thumb (Orme, 2010), which ensures that each attribute level appears at least 500 times across all respondents. The formula is:

$$n \geq \frac{500 \cdot c}{t \cdot a} \qquad (1)$$

Where:

- n is the number of the required respondents
- c is the largest number of levels for any attribute c = 4
- t is the number of tasks (choice sets) t = 10
- a is the number of alternatives per task a = 3 (not including the “no-choice” option)

Substituting the values:

$$n \geq \frac{500 \cdot 4}{7 \cdot 3} = \frac{2000}{21} \approx 95.24 \Rightarrow \lceil 96 \rceil$$

Thus, the minimum sample size required for this design is 96 respondents, ensuring sufficient statistical coverage of all attribute levels.

3.2.1 Creating the Survey

The product profiles and choice alternatives were generated using the idefix package in R**,** applying the Coordinated Exchange Algorithm to construct an efficient fractional factorial design. This method ensures statistical efficiency through key properties such as orthogonality**,** attribute-level balance, and minimal overlap. In the context of conjoint analysis, orthogonality means that attribute levels are varied independently across choice tasks, allowing the unbiased and unconfounded estimation of each attribute's effect on utility (Louviere et al., 2000). Maintaining orthogonality is essential to prevent multicollinearity, improve model efficiency, and support clear interpretation of part-worth utilities (Kuhfeld, 2010).

The full design produced 12 unique tasks (i.e., questions). During the survey, respondents were randomly assigned to 7 of these 12 unique tasks, and each task or question consisted of 4 alternatives (including a no-choice option). This blocked design balances the need for broad attribute coverage across the sample with the cognitive limitations of individual respondents.

Respondents were asked to make discrete choices, which involved selecting the most preferred option in each task, rather than providing ratings or rankings. This forced-choice format better mirrors real-world purchase decisions and aligns with the foundations of CBC methodology (Louviere et al., 2010).

In addition to choice tasks, the survey collected basic background information such as age group, location, gender, last education, occupation, physical activity, wine consumption frequency**,** and drinking occasions. These variables may be used for descriptive analysis, exploratory subgroup comparisons, or validation of segmentation logic.

An example of the choice task interface is provided below:

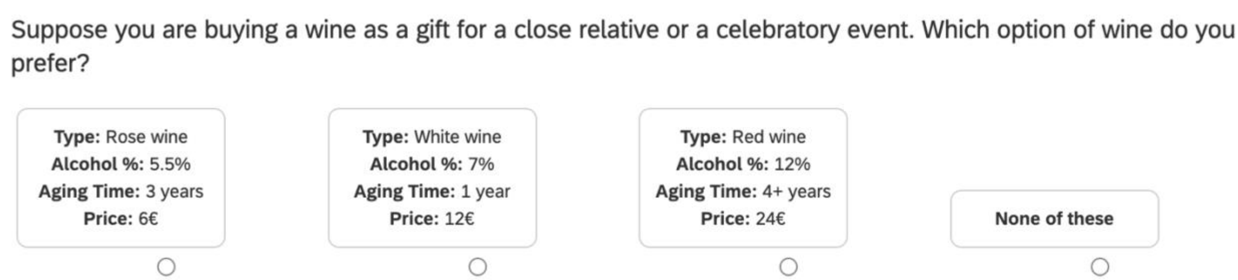

Figure 2 - Example of a Task

3.3 Variable Description

The table below summarizes the variables collected from the conjoint survey, including the additional demographic questions. It outlines the variable types, names, and the corresponding values used in subsequent modeling and analysis.

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

3.4 Data Preparation

Before conducting the analysis, data preprocessing and transformation were carried out to ensure consistency, compatibility, and analytical integrity across all modeling approaches. The original dataset, exported from Qualtrics in wide format, was reshaped into long format using Excel to align with the requirements of Choice-Based Conjoint (CBC) modeling, where each row represents a single alternative within a choice task.

Upon import into R, categorical variables were initially stored as character types. These were converted into factors to enable correct treatment in modeling. Numerical variables such as Price were preserved in their native numeric form for models using continuous specifications, and also transformed into factors to enable categorical treatments in alternative model configurations.

To capture respondent choices accurately, a "No Choice" variable (NC) was introduced to identify when respondents opted not to select any product. This binary indicator was coded as 1 if the respondent selected the opt-out alternative and 0 otherwise. The inclusion of this variable allows the models to reflect real-world decision-making behavior where abstaining from purchase is a valid outcome.

Categorical variables in this study, including Type of Wine, Gender, and Location, were dummy-coded, with one level of each variable used as the reference category. This approach was chosen over effect coding to facilitate interpretation in classical statistical models and ensure compatibility with machine learning algorithms. For the Location variable, countries with fewer than five observations were consolidated under an "Other" category to mitigate data sparsity and enhance statistical reliability. In models such as Random Forest, all dummy variables were retained, including those corresponding to reference levels, to meet the requirement of complete binary input representations.

In addition to the above, while Price, Alcohol Level, and Aging Time were already included in their continuous form to enable linear model specifications, dummy variables were also created for these attributes to support the estimation of part-worth utilities in models treating them as categorical. This dual representation allows for direct comparison between linear and non-linear effects in later analyses. Furthermore, interaction terms were manually constructed to enable moderator analysis. These included categorical interactions (e.g., Price_12_Male, Price_12_Germany) and Continuous interactions (e.g., Price_Male, Price_Germany). These additions were essential for exploring heterogeneous preferences across gender and country-based subgroups, especially within Multinomial Logit (MNL) and Hierarchical Bayesian (HB) frameworks.

Although several control variables (e.g., Age Group, Education, and Drinking Occasion) were collected through the survey for exploratory segmentation, they were not included in the final model estimation. This exclusion is due to the limited theoretical relevance of these variables to the primary utility functions and the potential inflation of model complexity. Including such controls would substantially increase the number of estimated parameters, which may lead to overfitting, reduced model performance, and decreased generalizability. Their use is limited to descriptive statistics and sanity checks.

Through this rigorous data preparation process, the dataset was optimized for reliable and interpretable model estimation across classical, Bayesian, and machine learning frameworks.

3.5 Classical Statistical Methods

This study first applies the Multinomial Logit (MNL) model, the most commonly used parametric approach in choice modeling, to establish a statistical foundation for estimating consumer preferences. The MNL model estimates the probability that a consumer selects a given profile from a choice set alternatives based on the utility derived from product attributes. In the context of CBC analysis, this method allows the estimation of part-worth utilities from observed choices, providing interpretable coefficients for each attribute level (Train, 2009).

Unlike simpler approaches such as Ordinary Least Squares (OLS)**,** which are traditionally used in rating- or ranking-based conjoint tasks, MNL is tailored for discrete choice data, making it suitable for CBC experiments where respondents choose one alternative per task. The model assumes that the probability of choosing an alternative is a function of the exponential of its utility, relative to the sum of exponentiated utilities across all options in the choice set. The utility specification used for the MNL estimation follows the baseline model presented later in Section 3.8, where utility is defined as a linear function of the wine attributes and their associated part-worth coefficients.

The MNL model serves as a benchmark for comparison with the more flexible Bayesian and machine learning approaches introduced later in the study. In its baseline specification, the MNL treats Price, Alcohol Content, and Aging Time as continuous variables, assuming a linear effect on utility. However, alternative specifications explore categorical (dummy-coded) representations of these variables to estimate part-worth utilities. Interaction effects, such as Price × Gender and Price × Location, are also included to account for heterogeneity in price sensitivity across consumer subgroups. These extensions enhance the model's ability to capture variation in preferences across different consumer segments.

Despite its interpretability and closed-form estimation, the MNL model is limited by two key assumptions. First, it assumes preference homogeneity, meaning that the same utility function applies to all individuals, which fails to capture individual-level variation (Train, 2009). Second, it relies on the Independence of Irrelevant Alternatives (IIA) property, which assumes that the relative odds of choosing between any two alternatives remain constant regardless of the presence or absence of other alternatives (Ben-Akiva & Lerman, 1985).

These limitations motivate the inclusion of more advanced techniques in subsequent sections. Nevertheless, the MNL model provides a transparent and theoretically grounded baseline for estimating consumer preferences and deriving Willingness to Pay (WTP) and market share predictions in the wine selection context.

3.6 Bayesian Approach

The Bayesian framework enhances traditional conjoint analysis by incorporating probabilistic modelling. This allows for flexible estimation of consumer preferences while capturing individual-level heterogeneity and uncertainty. Unlike classical regression-based models that yield point estimates for part-worth utilities, Bayesian models generate full posterior distributions. This provides richer insights into consumer preferences, which is particularly valuable when dealing with small samples or complex hierarchical structures (Hein et al., 2020).

The Bayesian estimation process begins with the specification of prior distributions. In this study, weakly informative normal priors are assigned to all coefficients to allow for continuous variation in preferences, while avoiding overly restrictive assumptions. These priors represent initial beliefs before observing the actual choice data. Next, the likelihood function is defined. This study uses a Multinomial Logit (MNL) likelihood, which models the probability of each alternative being chosen as a function of the utility derived from its attributes. This step connects the observed choice data to the underlying part-worth utilities being estimated (Train, 2009).

Posterior inference is then performed by integrating the priors and the likelihood using Hamiltonian Monte Carlo (HMC)**,** as implemented via the brms package in R. HMC is a gradient-based sampling method that offers faster convergence and more efficient exploration of posterior distributions compared to traditional MCMC, especially in hierarchical models. HMC is particularly well-suited for this study's structure and sample size, enabling the inclusion of random effects at the respondent level and complex interaction terms without prohibitive computational cost (Bürkner, 2017).

The resulting posterior distributions provide estimates of central tendency (e.g., means, medians) and credible intervals for each part-worth utility, offering a probabilistic interpretation of consumer preferences. These outputs allow for robust inference and more nuanced interpretation of the relative importance of product attributes and individual-level variation, enhancing model interpretability and predictive performance.

3.7 Machine Learning Methods

Machine learning enhances conjoint analysis by capturing complex attribute interactions and nonlinear relationships, offering a flexible and data-driven approach to modeling consumer preferences. Unlike traditional statistical methods, which rely on predefined functional forms and assume linear relationships between attributes, machine learning algorithms autonomously learn patterns from the data, making them particularly effective in high-dimensional conjoint settings (Volk et al., 2015). This flexibility is especially valuable when interactions between attributes are unknown or when individual-level heterogeneity must be considered.

In this study, Regularized Logistic Regression and Random Forest (RF) from machine learning methods are applied to improve the predictive performance, model robustness, and interpretability of the conjoint analysis. Regularization techniques, such as Lasso, Ridge, and Elastic Net, are employed to prevent overfitting and improve model generalizability. These methods apply a penalty to model complexity by shrinking less relevant coefficients toward zero, thereby simplifying the model and enhancing interpretability (Tibshirani, 1996). Regularization is especially useful in conjoint analysis for identifying the most influential attributes among many for prediction purposes, particularly in the presence of multicollinearity or sparse data.

Random Forest (RF), on the other hand, is selected for its ability to capture nonlinear relationships and attribute interactions without the need for manual specification. RF constructs multiple decision trees on bootstrapped samples and aggregates their predictions, which enhances robustness and reduces variance. Furthermore, RF provides feature importance scores, enabling a transparent understanding of which product attributes most strongly influence consumer choices.

The implementation of machine learning in this conjoint framework follows a structured process. First, the dataset is pre-processed to ensure proper formatting for analysis. This includes encoding for both explanatory and latent variables to the requirements of the methods. Next, feature importance analysis is conducted using either the regularized coefficients or RF-based importance scores to assess the relative influence of each attribute. Also, K-Fold Cross-Validation is applied to assess model performance and mitigate overfitting. The data is split into multiple folds, and the model is iteratively trained and validated to estimate its generalization ability on unseen data.

By incorporating these machine learning techniques into the conjoint analysis, this study aims to improve the accuracy and robustness of consumer preference estimation. Regularized models aid in variable selection and robustness, while Random Forest supports the detection of nonlinear relationships and interaction effects. Together, these approaches address key limitations of classical models and offer a more scalable and precise framework for understanding complex consumer choice behavior.

3.8 Part-Worth Utilities, Willingness to Pay, and Market Share Simulation

Upon estimating the utility model, the resulting part-worth utilities (β coefficients) form the basis for interpreting consumer preferences. These values represent the marginal contribution of each attribute level to the overall utility assigned to a product profile. The baseline utility model, consistent with the choice modeling framework described earlier, is defined as follows:

$$U_{ij} = \beta_1 \cdot \text{Price}_{ij} + \beta_2 \cdot \text{Alcohol}_{ij} + \beta_3 \cdot \text{Age}_{ij} + \beta_4 \cdot \text{Red}_{ij} + \beta_5 \cdot \text{Rosé}_{ij} + \beta_6 \cdot \text{White}_{ij} + \varepsilon_{ij} \quad (2)$$

In this formulation, Wine type is treated as a categorical variable using dummy coding, with "Sparkling" wine serving as the reference category. Its influence is thus embedded in the model intercept and interpreted relative to the other wine types. Price, Alcohol Content, and Aging Time are modeled as continuous variables, assuming linear effects. However, in subsequent models, these attributes will also be analyzed as categorical variables to capture potential non-linearities or threshold effects, allowing for more flexible modeling of preference structures. Additionally, interaction terms will be introduced, particularly between Price and Gender, and Price and Location, to explore how price sensitivity varies across demographic groups. These model enhancements facilitate a more nuanced understanding of consumer heterogeneity and provide deeper insights into how demographic and contextual factors influence choice behavior.

From the estimated part-worth utilities, willingness-to-pay (WTP) can be expressed as the monetary value consumers attach to improvements in specific product attributes. In many conjoint studies where price is specified as a continuous predictor, WTP is calculated by dividing an attribute's utility by the marginalutility of price (Train, 2009):

$$\text{WTP}_{\text{Attribute}} = \frac{\beta_{\text{Attribute}}}{-\beta_{\text{Price}}} \qquad (3)$$

Equation (3) converts utilities into interpretable euro values, making it possible to gauge the economic importance of each feature and to run market-share simulations for hypothetical product profiles. In this study, both linear and categorical (part-worth) price specifications were estimated using the multinomial logit model. Accordingly, two different approaches to WTP estimation were applied: the marginal rate of substitution formula (Equation 3) when price is modeled as continuous, and utility differences relative to a reference level when price is treated as a categorical variable.

For the MNL and Bayesian models, market shares are calculated using predicted choice probabilities. First, the probability that individual i selects alternative j from a set of J options is given by

$$P_{ij} = \frac{\exp(U_{ij})}{\sum_{k=1}^{J} \exp(U_{ik})} \qquad (4)$$

These probabilities are then averaged across all respondents to simulate the expected market share of alternative j:

$$\text{Market Share}_j = \frac{1}{N}\sum_{i=1}^{N} P_{ij} \quad (5)$$

These aggregated probabilities allow the simulation of consumer behavior across hypothetical market scenarios, helping firms anticipate the performance of new or modified products.

However, these post-estimation outputs come with model-specific limitations. In the MNL model**,** WTP estimation is straightforward, but the model assumes homogeneous preferences and independence of irrelevant alternatives (IIA), which may oversimplify real behavior. The Bayesian approach accounts for preference heterogeneity and produces distributions of WTP at the individual level. In practical terms, WTP is computed for each posterior draw by dividing the draw of the attribute coefficient by the corresponding draw of the price coefficient, yielding a distribution that reflects both individual variation and uncertainty. In contrast, machine learning models, in this case, can generate accurate market share predictions based on predicted probabilities but do not estimate utility coefficients**.** As a result, WTP cannot be meaningfully derived from ML models, since they do not rely on linear, interpretable structures.

3.9 Validation

To ensure the robustness and predictive accuracy of our models, we employed validation techniques tailored to each methodological approach: Multinomial Logit (MNL), Bayesian inference, and Regularization and Random Forest for the Machine learning methods.

3.9.1 Validation for Multinomial Logit (MNL) Models

To assess the robustness and predictive accuracy of the Multinomial Logit (MNL) model, a combination of model fit statistics and predictive validation metrics is employed. First, the Log-Likelihood is used to measure how well the model explains the observed choices. A higher log-likelihood value suggests a better model fit. Complementing this, McFadden's Pseudo R^2 compares the log-likelihood of the estimated model with that of a null model (one without predictors). While values above 0.2 are considered relatively strong for discrete choice models (McFadden, 1974), its primary function is comparative rather than absolute.

The Likelihood Ratio Test (LRT) is used to determine whether the inclusion of independent variables significantly improves model fit over the null model. The LRT follows a chi-square distribution, with degrees of freedom equal to the difference in the number of parameters between the two models (Hosmer et al., 2013). In this study, the LRT is derived from the difference in model deviance statistics, automatically reported during logistic model estimation in R.

To detect potential multicollinearity among predictors, the Variance Inflation Factor (VIF) is calculated for each explanatory variable. VIF quantifies how much the variance of an estimated regression coefficient increases due to multicollinearity. When VIF values are below the commonly accepted threshold of 5, they indicate no severe multicollinearity and support the reliability and interpretability of the coefficient estimates (O'Brien, 2007).

For evaluating model parsimony, the Akaike Information Criterion (AIC) is reported. This metrics penalize for model complexity and are particularly useful when comparing the performance of the MNL with alternative modeling approaches such as Bayesian logistic regression or regularized machine learning models. Lower AIC values indicate a better trade-off between goodness-of-fit and simplicity.

Finally, to assess predictive accuracy, the dataset was first split into training and test sets, ensuring that all three modeling approaches, Multinomial Logit (MNL), Bayesian inference, and machine learning, were evaluated on the same data partitions. This allows for a consistent comparison of in-sample and out-of-sample performance across methods. The MNL model is trained on the training set and evaluated on the hold-out set using a standard hit rate metric, defined as the proportion of times the model correctly predicts the chosen alternative. This train-test split validation ensures that predictive performance is not overstated due to overfitting and provides a realistic measure of model effectiveness in unseen data scenarios.

3.9.2 Validation for Bayesian Inference Models

To evaluate the performance of the Bayesian approach, multiple validation techniques are employed to assess both model fit and predictive capability. These procedures ensure that the Bayesian model accurately captures consumer preferences and generalizes beyond the training data.

First, Posterior Predictive Checks (PPCs) are conducted to evaluate how well the model reproduces observed choice patterns. PPCs involve generating synthetic data from the posterior distribution and comparing it to the actual observations using visual diagnostics or summary statistics. A well-fitting model should exhibit minimal discrepancy between the simulated and observed data, suggesting that the model adequately captures the underlying data-generating process (Gelman et al., 2013).

To compare model fit while accounting for complexity, the Widely Applicable Information Criterion (WAIC) is reported. WAIC is a fully Bayesian metric that estimates out-of-sample prediction error using the entire posterior distribution (Gelman et al., 2014). Lower values indicate a more favorable trade-off between model fit and parsimony, and are especially useful when comparing alternative model specifications (Vehtari et al., 2017).

For predictive validation, the Bayesian model is evaluated using the same train-test split introduced earlier to ensure consistency across model comparisons. The hit rate, defined as the proportion of times the model correctly predicts the chosen alternative based on the highest posterior probability, is computed for both training and hold-out sets. This approach enables a robust assessment of the model's generalizability and predictive accuracy.

Finally, the credible intervals surrounding the posterior distributions of the model parameters are analyzed. These intervals reflect estimation uncertainty and help assess the stability and robustness of inferred consumer preferences. Narrow credible intervals suggest strong certainty around the estimates, while wider intervals may indicate preference heterogeneity or sparse data.

3.9.3 Validation for Machine Learning Models: Regularization and Random Forest

To evaluate the machine learning models, specifically regularized logistic regression (Ridge, Lasso, and Elastic Net) and Random Forest, a combination of cross-validation and interpretability diagnostics was applied. While performance was assessed using Five-Fold Cross-Validation to suit the characteristics of these models, the same underlying data split was preserved to maintain comparability with the classical and Bayesian approaches. In this procedure, the data was divided into five equal folds: each fold served once as the validation set while the remaining four were used for training. Model performance was then averaged across folds to mitigate overfitting and provide robust generalizability estimates.

For both Lasso and Elastic Net models, binomial deviance was monitored across the validation folds to determine the optimal regularization parameter (λ). The one-standard-error rule was also applied to select a more parsimonious model without sacrificing much predictive accuracy. These models improve interpretability by shrinking less informative coefficients toward zero, aiding in variable selection (Tibshirani, 1996).

To further enhance model interpretability, Shapley Additive Explanations (SHAP) were employed. SHAP values provide a unified measure of feature contribution by decomposing each prediction into additive attributions, showing the marginal impact of each feature while accounting for interaction effects (Lundberg & Lee, 2017). This method allows for both global interpretability and local explanation of individual predictions, making it particularly useful in choice modeling contexts where transparency is critical.

3.10 The Use of GenAI for this thesis

In accordance with the guidelines set by the University of Groningen on the ethical use of generative AI tools in academic work, this thesis made use of ChatGPT in a responsible and transparent manner. The tool was primarily used as a cognitive aid to support conceptual understanding of statistical methods, assist in interpreting model outputs, and refine the clarity and coherence of academic writing. It functioned as a “second brain” during the research and writing process, such as providing explanations, rephrasing complex arguments, and offering structural suggestions, while ensuring that all content, interpretations, and final decisions written in this thesis remained under the author.

4 Results

4.1 Descriptive Statistics

This section presents an overview of the demographic and behavioral characteristics of the sample after data cleaning procedures. Out of the 144 participants who initially completed the survey, 99 respondents were deemed eligible for analysis. The exclusion of 45 participants was based on three main criteria: indicating that they never consumed wine, completing fewer than four choice tasks, or selecting the "no-choice" option in more than five out of the seven tasks. These cleaning steps were taken to ensure that the final dataset was reliable, interpretable, and suitable for modeling.

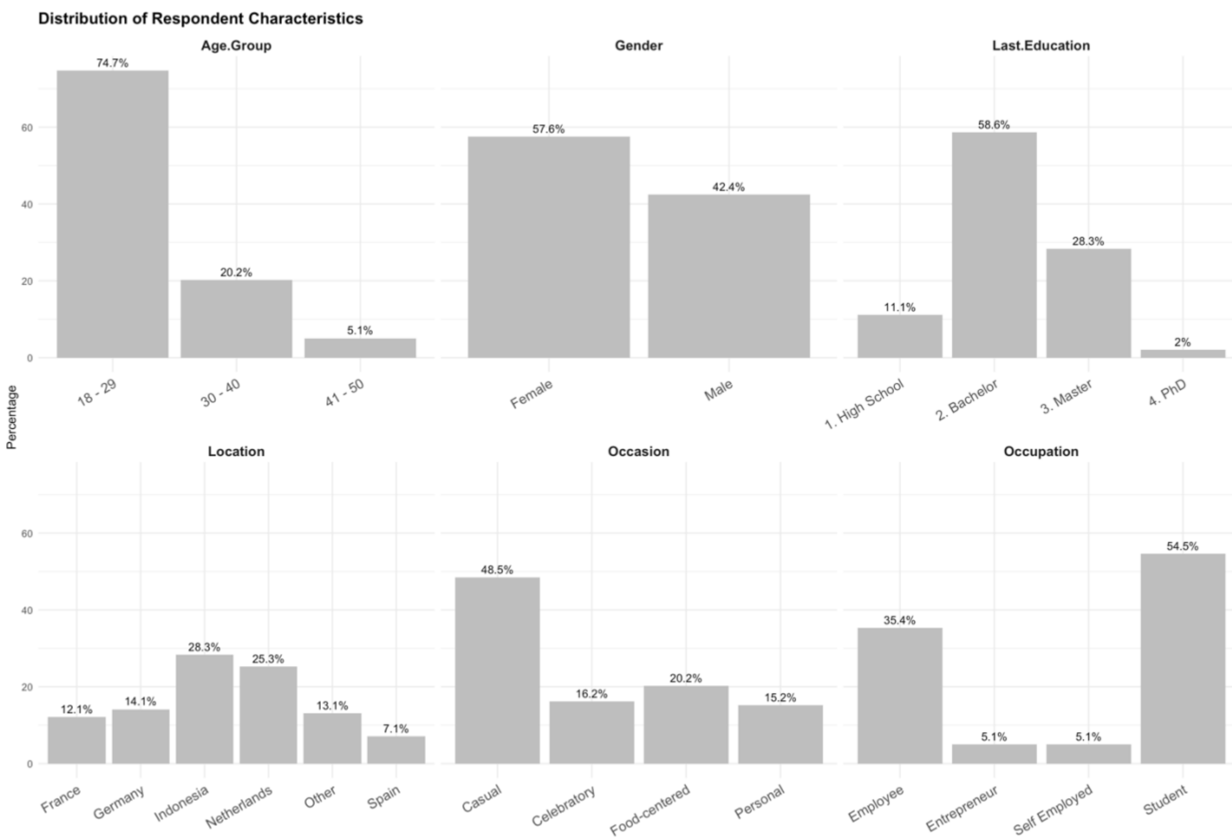

Figure 3 - Distributions of Respondents

The age distribution of the eligible respondents is heavily skewed toward younger individuals. The majority of participants (74 out of 99) fall within the 18 to 29 age group. This is followed by 20 respondents in the 30 to 40 range and only 5 in the 41 to 50 group. No respondents aged above 50 were retained after the cleaning process. Gender representation is relatively balanced, though slightly female-dominated, with 57 female respondents and 42 male respondents.

In terms of educational attainment, most respondents hold a bachelor's degree, accounting for 58 individuals in the sample. A further 28 participants reported having completed a master's degree, while 11 respondents listed high school as their highest level of education. Only two individuals reported holding a PhD. Occupational data shows that more than half of the respondents are students, with 54 individuals currently in education. Another 35 respondents are employed, while smaller numbers reported being self-employed or entrepreneurs, each with 5 individuals.

Geographically, the sample reflects a broad international background. The largest national groups are from Indonesia (28 respondents) and the Netherlands (25 respondents), followed by Germany (14), France (12), and Spain (7). Additionally, there were smaller representations from Taiwan (4), China (3), Canada (3), and the USA (3). For modeling purposes, countries with fewer than five observations, namely Taiwan, China, Canada, and the USA, were grouped into a single "Other" category to mitigate statistical sparsity while preserving model stability.

Wine consumption frequency also varied across the sample; 32 respondents reported drinking wine at least once per month, 31 consumed wine at least once per year, 25 indicated they drank wine once every three months, and 11 reported a weekly consumption habit. Importantly, no respondents in the final dataset indicated that they never consumed wine, as such cases were filtered out during data cleaning.

Regarding wine-drinking occasions, the majority of participants (48) reported consuming wine in casual settings. Other contexts included food-centered occasions (20 respondents), celebratory events (16), and personal moments (15). Lastly, in terms of physical activity, most respondents described their activity level as moderate (58), followed by low activity (23), and high activity (18). No respondent selected "none" for this variable. Altogether, these descriptive statistics provide a clear demographic and behavioral portrait of the sample and serve as the basis for subsequent analyses of wine preference modeling.

4.2 Multinomial Logit Model on Wine Preferences

This section presents a series of Multinomial Logit (MNL) models to estimate consumer preferences based on observed wine choice behavior. Starting with a baseline specification of product attributes, the models are progressively extended to incorporate interaction effects and non-linear treatments of key predictors. This stepwise approach allows for detailed exploration of how wine attributes and respondent characteristics influence choice, while also offering statistical comparison of model performance and insights into consumer trade-offs and preference heterogeneity.

Model 1 is the baseline model, which includes the main product attributes as continuous variables: Price, Alcohol content, Aging Time, and Wine Type (with Sparkling as the reference category), along with the no-choice (NC) alternative. The formula for the Model can be found in Equation (2). Next is Model 2, to assess how price sensitivity varies across subgroups, this model includes interaction terms between Price and Gender, and Price and the respondent's Location. The model captures heterogeneity in price preferences and is specified as:

$$U_{ij} = \beta_1 \cdot Price_{ij} + \beta_2 \cdot Alcohol_{ij} + \beta_3 \cdot Age_{ij} + \beta_4 \cdot Red_{ij} + \beta_5 \cdot Rosé_{ij} + \beta_6 \cdot White_{ij} + \beta_7 \cdot NC_{ij} + \gamma_1 \cdot Price_{ij} \cdot GenderMale_i + \sum_c \gamma_c \cdot Price_{ij} \cdot Location_{ic} + \varepsilon_{ij} \quad (4)$$

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Appendix I - Multinomial Model

ATTRIBUTE	LEVEL OR INTERACTION	ESTIMATE	STD. ERROR	P-VALUE	SIGNIF.
PRICE	Per unit increase	-0.031	0.008	0.000	***
ALCOHOL	Per % increase	-0.009	0.013	0.467	
AGING TIME	Per unit increase	0.100	0.055	0.071	.
WINE TYPE	Red	0.882	0.197	<0.001	***
	White	0.878	0.187	<0.001	***
	Rosé	0.428	0.199	0.031	*
NO-CHOICE OPTION	None	-1.249	0.333	<0.001	***

Table 19 - MNL Model 1 Estimation Result

ATTRIBUTE	LEVEL OR INTERACTION	ESTIMATE	STD. ERROR	P-VALUE	SIGNIF.
PRICE	Per unit increase	0.021	0.016	0.187	
ALCOHOL	Per % increase	–0.008	0.013	0.557	
AGING TIME	Per unit increase	0.081	0.056	0.152	
WINE TYPE	Red	0.906	0.199	<0.001	***
	White	0.924	0.190	<0.001	***
	Rosé	0.443	0.202	0.028	*
NO-CHOICE OPTION	None	–1.400	0.342	<0.001	***
PRICE × GENDER	Male	–0.006	0.015	0.710	
PRICE × COUNTRY	Netherlands	–0.115	0.021	<0.001	***
	Germany	–0.060	0.023	0.010	**
	France	–0.076	0.024	0.001	**
	Spain	–0.010	0.028	0.722	
	Other	–0.051	0.025	0.038	*

Table 20 – MNL Model 2 Estimation Result

ATTRIBUTE	LEVEL OR INTERACTION	ESTIMATE	STD. ERROR	P-VALUE	SIGNIF.
PRICE	€12	0.010	0.126	0.938	
	€18	-0.276	0.155	0.076	.
	€24	-0.682	0.180	0.000	***
ALCOHOL	7%	0.280	0.149	0.060	.
	12%	0.249	0.148	0.093	.
	18%	-0.112	0.184	0.543	
AGING TIME	2 years	0.305	0.163	0.062	.
	3 years	0.348	0.172	0.043	*
	4 years	0.467	0.187	0.013	*
WINE TYPE	Red	0.905	0.213	<0.001	***
	White	0.932	0.204	<0.001	***
	Rosé	0.482	0.214	0.024	*
NO-CHOICE OPTION	None	-0.719	0.316	0.023	*

Table 21 - MNL Model 3 Estimation Result

ATTRIBUTE	RANGE	RELATIVE IMPORTANCE (%)
WINE TYPE	1.038	33.0%
PRICE	0.589	18.7%
ALCOHOL CONTENT	0.401	12.8%
AGING TIME	0.459	14.6%
NO-CHOICE OPTION	0.642	20.4%
TOTAL	3.129	100%

Table 22 - Relative Importance MNL Model 4

Appendix II - Hierarchical Bayesian Model

PARAMETER	ESTIMATE	STD. ERROR	2.5% CI	97.5% CI	SIGNIF.
INTERCEPT	-1.23	0.39	-1.97	-0.48	Yes
NC	-1.95	0.46	-2.88	-1.07	Yes
PRICE	-0.07	0.02	-0.11	-0.03	Yes
ALCOHOL	-0.01	0.02	-0.06	0.03	No
AGING.TIME	0.18	0.08	0.02	0.34	Yes
TYPE_RED	0.81	0.42	-0.04	1.63	No
TYPE_WHITE	1.11	0.34	0.46	1.78	Yes
TYPE_ROSE	0.03	0.34	-0.64	0.73	No

Table 23 - Bayesian Model 1 Estimation Results

PARAMETER	ESTIMATE	STD. ERROR	2.5% CI	97.5% CI	SIGNIF.
INTERCEPT	-1.94	0.54	-3.01	-0.90	Yes
NC	-2.09	0.47	-3.03	-1.20	Yes
PRICE	-0.02	0.04	-0.09	0.05	No
ALCOHOL	-0.01	0.02	-0.06	0.04	No
AGING.TIME	0.18	0.08	0.02	0.34	Yes
TYPE_RED	0.86	0.43	0.00	1.70	Yes
TYPE_WHITE	1.19	0.34	0.54	1.87	Yes
TYPE_ROSE	0.05	0.35	-0.65	0.74	No
GENDER_MALE	0.05	0.37	-0.67	0.77	No
NL	1.56	0.53	0.55	2.65	Yes
GERMANY	0.54	0.63	-0.72	1.77	No
FRANCE	1.23	0.60	0.09	2.42	Yes
SPAIN	-0.77	0.90	-2.58	0.97	No
OTHER	0.42	0.67	-0.92	1.75	No

Table 24 - Bayesian Model 2 Main Effects

PARAMETER	ESTIMATE	STD. ERROR	2.5% CI	97.5% CI	SIGNIF.
PRICE:GENDER_MALE	-0.02	0.03	-0.07	0.04	No
PRICE:NL	-0.14	0.04	-0.22	-0.05	Yes
PRICE:GERMANY	-0.04	0.05	-0.14	0.05	No
PRICE:FRANCE	-0.10	0.05	-0.19	-0.00	Yes
PRICE:SPAIN	0.07	0.07	-0.06	0.21	No
PRICE:OTHER	-0.03	0.05	-0.14	0.07	No

Table 25 - Bayesian Model 2 Interaction Effects

PARAMETER	ESTIMATE	STD. ERROR	2.5% CI	97.5% CI	SIGNIF.
INTERCEPT	-2.20	0.37	-2.94	-1.49	Yes
NC	-1.00	0.45	-1.91	-0.12	Yes
PRICE_12	0.13	0.23	-0.33	0.59	No
PRICE_18	-0.89	0.31	-1.51	-0.30	Yes
PRICE_24	-1.33	0.40	-2.14	-0.57	Yes
ALCOHOL_7	0.42	0.23	-0.04	0.87	No
ALCOHOL_12	0.32	0.24	-0.16	0.80	No
ALCOHOL_18	-0.01	0.33	-0.67	0.62	No
AGING_2	0.48	0.24	0.01	0.95	Yes
AGING_3	0.69	0.25	0.20	1.20	Yes
AGING_4	0.72	0.28	0.19	1.28	Yes
TYPE_RED	0.78	0.43	-0.07	1.61	No
TYPE_WHITE	1.08	0.34	0.41	1.75	Yes
TYPE_ROSE	0.06	0.35	-0.63	0.75	No

Table 26 - Bayesian Model 3 Estimation Result

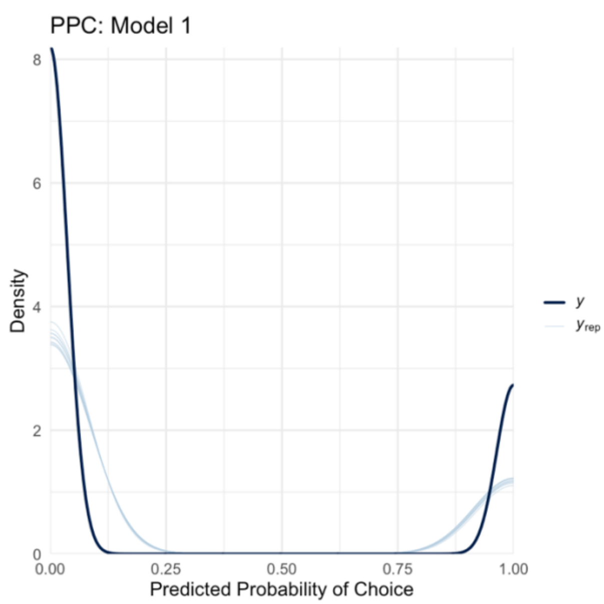

Figure 8 - PPC: Bayesian Model 1

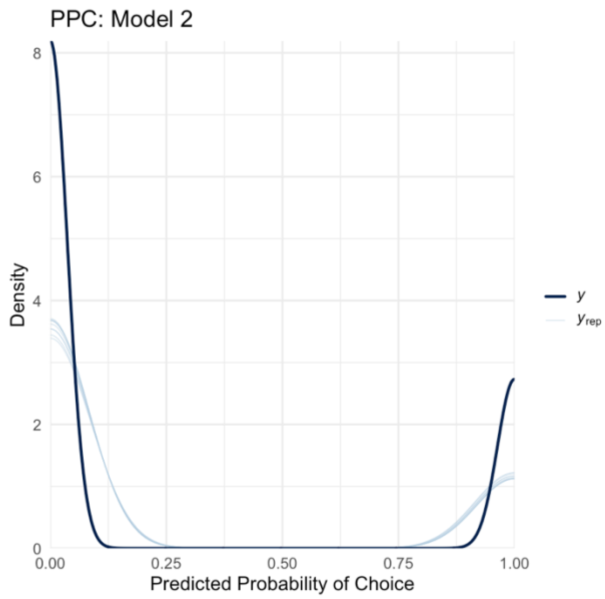

Figure 9 – PPC: Bayesian Model 2

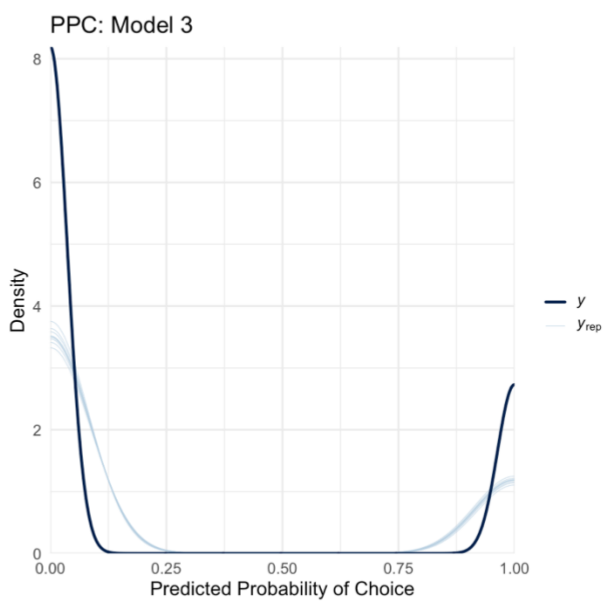

Figure 10 - PPC: Bayesian Model 3