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Published Version:
Angelini, F., Castellani, M., Ventrucci, M. (2025). Cumulative information on quality and willingness to pay: a study on wine evaluation. JOURNAL OF FOODSERVICE BUSINESS RESEARCH, 28(2), 295-333 [10.1080/15378020.2023.2259315].

Availability:
This version is available at: https://hdl.handle.net/11585/942510 since: 2023-09-21

Published:
DOI: http://doi.org/10.1080/15378020.2023.2259315

Cumulative information on quality and willingness to pay: A study on wine evaluation

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July 22, 2024

Abstract

Availability of information about a good with uncertain quality can influence the way consumers perceive its quality, hence, their willingness to pay (WTP) for it. We present a study to investigate whether and to what extent WTP is impacted by the degree of information available to consumers who are exposed first to extrinsic and then intrinsic information regarding a variety of Italian wines. We implement linear mixed models in a Bayesian framework, which provides a flexible tool to account for different sources of heterogeneity, e.g., correlation within groups of observations and spatial correlation between participants sitting nearby. Based on data collected in Italy, results show that the availability of extrinsic and intrinsic information yields relevant changes in WTP, but this effect also depends on age, gender, drinking habits, wine quality, and connoisseurship of the agents. According to the findings, the analyzed wines cannot be considered search goods, although this might not hold for more experienced consumers.

Keywords: Wine quality, Willingness to pay, Linear mixed model, Information asymmetry, INLA

This is an Accepted Manuscript of an article published by Taylor & Francis in Journal of Foodservice Business Research on September, 21 2023, available at: `https://doi.org/10.1080/15378020.2023.2259315`.

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1 Introduction

Consumers' evaluation of a good's quality heavily relies on the information they have regarding its characteristics.[1] When information is easily accessible and available to everyone, the quality evaluation is more effective. On the other hand, when the seller retains information or the buyer is not able to interpret it (or both), information is incomplete, limited, and asymmetric, making it harder for the consumer to effectively evaluate the quality. Furthermore, the more complex the multi-dimensional quality of goods, the higher the chance that consumer will lack complete information and/or to lack the ability to process it.

Wine fits into this paradigm since it is a complex-quality good and the evaluation of its quality depends on the level of information available to consumers, as well as their ability to use this information. For this reason, wine can be alternatively considered by consumers as a search, experience, or credence good.[2]

Sophisticated or more-informed consumers know the quality of wine they want to consume, and they can in principle evaluate its quality even before consuming it (search good). However, naive or less-informed consumers are not able to assess the quality of wine before they consume it (experience good), and sometimes even after the consumption process ended (credence good). An adverse selection mechanism might be at work in the wine market for the uncertainty about its quality, where wines that have above-average quality may be partially (or totally) driven out of the market by wines whose quality is below average.[3] Since consumers' willingness to pay (WTP) is negatively impacted by their uncertainty about the quality of experience goods, more-informed consumers are more likely to choose high-quality wines, while less-informed are more likely to choose low-quality wines.[4] This reasoning will not apply to wines as search goods, since all the needed information is potentially available to everyone before consumption (Ashton, 2014, 2017). In particular, it might be interesting to understand if wine is a search good and whether this holds for all types of consumers. However, to answer these questions, we have to study how consumers' spending choices change depending on the quantity and the type of information they are exposed to.

As regards the type of information, intrinsic and extrinsic information can also play a role in

[1] Though in literature it is unclear which good characteristics consumers find most relevant to evaluate its quality, consumers' quality perception is modeled within several contexts such as marketing, psychology, business, and economics. For instance, within the economic literature, theoretical foundations of the approach based on the characteristics of the good have been provided by Lancaster (1966), Muth (1966), and Becker (1965), and this approach has been empirically tested in several studies using hedonic techniques (e.g., Muellbauer, 1974).

[2] A search good is a good whose quality can be evaluated by the consumer before its consumption (Stigler, 1961). An experience good is a good whose quality can only be evaluated by the consumer after its consumption (Nelson, 1970). A credence good is a good whose characteristics cannot be evaluated by the consumer even after its consumption, and the evaluation of its quality requires further information that could be costly to obtain and can be collected from experts (Darby and Karni, 1973).

[3] Similar to the market for lemons (Akerlof, 1970), the negative effect of (ex-ante) asymmetric information is due to the adverse selection mechanism, whereby an agent who possesses more information about the quality of the good than others exploits his informational advantage to the detriment of others.

[4] The previous literature has also examined the influence of information on WTP for restaurants. For instance, researchers have explored how consumers may deduce food quality from cues like the physical ambiance and ethnic authenticity, as demonstrated in the work of Lin and Jiang (2022). Similarly, factors such as food presentation can impact perceptions, as illustrated by Kuo and Barber (2014) investigation into the material of dishware used. Also fine-dining products' engrossment and acquaintance play a role in shaping consumers' WTP (Gupta et al., 2022). The presence of uncertainty extends beyond quality and encompasses other facets of the consumption experience, including safety and health considerations. This was underscored by Belarmino and Repetti (2022) study, which identified an effect associated with the usage of masks within restaurant environments during the COVID-19 pandemic.

the quality evaluation process.[5] If the good is a search good and the consumer has already been exposed to extrinsic information, such as the information reported on the label, the intrinsic information that is related to the experience *per se* should not impact the evaluation of the good quality. However, the response to information might also be different depending on the consumer's degree of knowledge. Indeed, greater knowledge allows the consumers to better process information and improve their evaluation of complex-quality goods.[6]
Studies of wine attributes are mainly based on the information about wine shared with consumers, and most of the research has focused on the influence of wine labels on consumers' WTP (Charters et al., 1999; Skuras and Vakrou, 2002; Appleby et al., 2008; Barber et al., 2009; Mueller et al., 2010; Thiene et al., 2013). Several scholars have studied the effect of wine tasting versus the availability of wine information on consumers' WTP (e.g., Lecocq et al., 2005; Gustafson et al., 2016). Other researchers have focused on consumers' WTP for local or international wines as the wine quality is related to the geographic wine regions and their terroir (e.g., Boncinelli et al., 2016; Vecchio et al., 2019a). Experimental studies have also been conducted to compare the evaluation of wine between blind tasting sessions and informed sessions, with findings suggesting that label information plays a role in the evaluation (e.g., Klink-Lehmann et al., 2019; Gassler et al., 2019). Many studies investigating consumers' WTP utilize hypothetical methods, including discrete choice analysis and conjoint analysis (McFadden, 1986; Louviere, 1994). However, within the wine experimental literature, non-hypothetical methods such as the Vickrey auction and the Becker-deGroot-Marschak (BDM) mechanism are commonly employed (Vickrey, 1961; Becker et al., 1964).[7]

From such vast literature investigating the effects of different types of information on wine evaluation, one could argue that information can be seen as a multifaceted variable, composed of several parts, each potentially affecting the evaluation process. However, few scholars have studied the impact of cumulative information (or increasing information or sequential information) on consumption choices and on consumers' WTP, and the role played by the type of information remains an open issue (Ay et al., 2017; Ferreira et al., 2021). However, to the best of the authors' knowledge, there have been no studies analysing the relationship between cumulative information and the nature of the good, and most studies assume that the accumulation of information occurs by first accessing intrinsic information and then receiving extrinsic information (or accessing both simultaneously). Therefore, we aim to fill this gap by adopting a different perspective and focusing on how consumers accumulate information and learn from experience when intrinsic information is available subsequent to extrinsic information. Understanding the effect of the former type of information on how the consumers evaluate the quality of the good when they have already been exposed to extrinsic information is key to unravel the nature of the good.
In this paper, we examine the effect of different levels of extrinsic information on consumers' WTP, while also allowing participants to receive intrinsic information through direct wine tasting experience. We consider a heterogeneous group of red and white wines, encompassing variations in prices, quality, wineries, denominations, and grapes. Unlike previous studies, we employ an approach of analysis based on Bayesian linear mixed models. This approach enables

[5]The former is an indivisible part of the product, such as its colour, while the latter is external to the product, such as its brand and its packaging.

[6]Information can originate from various external influences like marketing campaigns, which can subsequently impact consumers' WTP. For instance, Remar et al. (2016) demonstrated that local food marketing plays a significant role in influencing consumers' WTP and, consequently, their purchasing choices for local food products.

[7]Experimental auctions are a form of non-hypothetical valuation, while laboratory and field experiments are the other forms of experimental methods to measure the WTP. See, for example, Lusk (2003), Huffman et al. (2003), Didier and Lucie (2008), and De Groote et al. (2011). For a review of methods for measuring WTP, see Breidert et al. (2006).

us to flexibly estimate the impact of information on WTP and to account for some potential biases arising from the observational nature of the study. This way we can account for possible different sources of correlation between agents that take part in the study, such as spatial correlation among participants seated next to each other. The results highlight the significance of information in the evaluation of complex goods, which aligns with findings from previous studies. Specifically, the paper's findings suggest that for certain individuals – such as frequent wine consumers or those who attended a tasting course in the past – extrinsic information alone may be sufficient for wine evaluation. This implies that wine could be regarded as a search good for these individuals. However, for participants outside of these two groups, the findings indicate that tasting the wine (i.e., intrinsic information) has a generally negative impact on their WTP. Furthermore, we observe that the impact of cumulative information varies depending on other characteristics of the participants, such as age and gender, as well as on wine quality. However, how each cue affects the consumer evaluation of the good quality depends on the consumers' information accumulation process and how they learn from experience when intrinsic information is available subsequently to extrinsic information.[8]

The rest of the paper is organized as follows. Section 2 reviews the wine experiments literature. In Section 3, the data collection process is described in detail. In Section 4, a statistical modeling framework is presented, which provides estimation and uncertainty quantification of the effect of cumulative information on WTP. Section 5 discusses the results and the limitations of the study, and Section 6 concludes.

2 A literature review

One of the pioneering studies in consumer evaluation of wine was conducted by Lange et al. (2002). In this study, two experimental settings were employed: a Vickrey auction and a hedonic model. The aim was to investigate whether participants' evaluations, particularly those by the naive consumers, varied depending on the setting. The settings included blind tasting only, bottle information only, and both bottle and tasting combined. The finding revealed that participants struggled to accurately recognize the quality of wine in the blind tasting experiment. However, when label information was made available, the evaluations aligned more closely to market value.

Other notable studies have also contributed to understanding consumers' WTP for wine. For instance, Lecocq et al. (2005) examined the influence of socio-demographic variables and wine information on WTP using a Vickrey auction. However, instead of specific information treatments, they focused on the presence or absence of information. Another relevant study by Bazoche et al. (2008) utilized the Becker-deGroot-Marschak (BDM) mechanisms to assess the impact of public messages regarding pesticide effects on consumers' WTP for wine. The findings revealed a premium associated with environmentally-friendly wines. Interestingly, the valuation of environmental signals, such as label owners conveying information on environmental actions, varied, while the dissemination of information about the environmental effects of agricultural methods did not significantly affect WTP.

Experimental auctions have been widely used to investigate consumers' WTP for wine, yielding valuable insights. For instance, Schmit et al. (2013) conducted a lab experiment employing a combined sensory and monetary evaluation framework. They explored the asymmetric order effects on consumers' WTP for environmental attributes of semi-dry Riesling wines. Interestingly, they found that sensory effects played a dominant role compared to extrinsic environmental attributes. In a similar vein, Vecchio (2013) employed an experimental auction to examine the

[8]To understand the nature of wine and whether it is a search good or not, in Appendix A we formally represent a theoretical framework to conceptualize this process.

effect of environmental labeling on WTP for three sustainable wines. The study revealed that female and older subjects tend to bid higher for sustainable wines. Furthermore, knowledge of specific information labels increased WTP. However, it is worth noting that the author acknowledged the limitations of their sample, as it was not representative of the broader wine consumer population due to its restriction to undergraduate students. Boncinelli et al. (2016) estimated consumers' WTP for wines with different proportions of international grape varieties through an experimental auction. Their results indicated a preference for wines produced from autochthonous grape varieties, as consumers exhibited a greater WTP for wines with typical blends compared to those with international blends. However, they observed a significant decrease in the premium price for autochthonous grapes varieties in the auction experiment with blind tasting for the examined wines. Another noteworthy study by Gustafson et al. (2016) integrated data from an auction experiment with participants' wine knowledge. Their findings provided evidence that knowledge and preference are separable, and differences in preference for wines were primarily driven by sensory information among consumers with low and high wine knowledge.

Several more recent papers have further advanced the analysis of consumers' WTP for wine. Ay et al. (2017) conducted a study examining the influence of increasing information on the impact of agricultural practices at global and local scales on WTP for wine. Their experiment, utilizing the BDM procedure, revealed that an organic premium significantly increased with the provision of information, and this effect depended on the spatial distance between vineyards and consumers. Pomarici et al. (2018) investigated young consumers' preferences for water-saving wines and the determinants of WTP for these wines using data collected from an experimental auction. The results indicated that young consumers and those with environmentally friendly attitudes were willing to pay higher prices for wines labeled as water-saving. Klink-Lehmann et al. (2019) examined consumers' WTP for different sustainability labels and one award label on German Riesling through an incentive-compatible auction and tasting experiment. They found that providing information about the product or process quality of the wine, compared to a blind tasting, influenced more strongly consumers' WTP. Additionally, gender and income were identified as important determinants of consumers' decisions regarding wine. Eustice et al. (2019) studied the impact of different product messages on wine tourists' WTP using a non-hypothetical experiment. The findings revealed that messages emphasizing sensory information about the wines had no impact on WTP. However, messages about awards labels and medals generated the highest levels of the WTP. Furthermore, messages highlighting local production of the wines led to modest increases in WTP. Gassler et al. (2019) combined experimental auctions with a blind tasting experiment to investigate the effect of organic labeling on German consumers' WTP for wine. Their study aimed to separate the environmental information effect from the taste and quality perception effect of an organic label on WTP. The results indicated that organic wines were perceived as tastier and of higher quality and value. Moreover, the organic labeling effect was stronger for committed organic consumers. The findings confirmed that perceptions of wine quality are the main mediator through which organic labeling affects WTP for this type of consumers. Vecchio et al. (2019a) examined whether consumers' WTP differed in a non-hypothetical experimental auction on Sangiovese-based wines at varying levels of price points (basic, medium, and high). They also explored the effect of denominations of origin on preferences by comparing evaluations from a blind tasting and an informed tasting. Vecchio et al. (2019b) analyzed the effect on WTP of the production process and information about sparkling wines produced following the Champenoise and Charmat method. Their study combined a quantitative descriptive sensory analysis (hedonic rating) with a non-hypothetical auction under three different information steps: blind tasting, information only, and information with tasting. The findings revealed that both sensory and non-sensory attributes of sparkling wines influenced consumers' WTP. Additionally, the information about the production process strongly impacted quality expectations of the consumers but did not affect their hedonic liking. Ribeiro et al. (2020) developed a discrete choice experiment to investigate how consumers' WTP changes as quantitative information (such as experts' rating of the wine) and qualitative information (related to the description of wine's characteristics) are shared with them. The study demonstrates that both types of information had a positive impact on WTP. Ferreira et al. (2021) conducted a blind taste experiment with two settings: one where extrinsic information was shared after blind tasting, and another where all the information was available at once. The study found that disclosing all the information at once led to higher WTP among participants. Finally, Lerro et al. (2021) performed a non-hypothetical economic experiment in Italy and Germany, employing three information treatments to assess consumers' WTP for conventional wine and wine differentiated by sustainable certifications. The study specifically examined the moderating effects of consumers' psychographic characteristics, such as subjective knowledge, wine involvement, and sustainability, on their preferences for wine with different credence attributes related to sustainability.

In Table 1, we provide a summary of the key empirical studies on wine auctions that have been published in academic journals over the past 20 years. This study stands out from these previous analyses in that it examines the impact of cumulative information on consumers' WTP for wine. Specifically, we investigate the effects of exposing consumers to extrinsic information followed by intrinsic information, employing Bayesian linear mixed models. However, it is important to note that this study does not employ an experimental setting, as we will explain further in the subsequent sections.

[Table 1 about here.]

3 Data collection

We collected the data from 38 subjects who took part in a public event held during the University of Bologna's Rimini Campus European Researchers' night (Rimini, Emilia-Romagna, Italy) on September 27, 2019. The event was promoted through various channels, including the University of Bologna - Rimini Campus's website as well as on local newspapers, and social networks. To attend the event, participants were required to reserve a seat in advance through the University of Bologna - Rimini Campus's website. Both the booking and participation in the event were free of charge.[9] The data collection process started at 6.30 pm and lasted approximately two hours. Six Italian wines were analyzed, starting from three white wines of different vintages (Verdicchio 2018, Malvasia 2017, Chardonnay 2016), followed by three red wines of the same vintage (Nebbiolo 2016, Sangiovese 2016, Brunello 2016). For simplicity, we use the labels listed in Table 2 (e.g., Verdicchio) instead of the full denominations (e.g., Verdicchio dei Castelli di Jesi DOC) in order to enhance readability. Table 2 provides the details of the wine labels used in this paper, including the denomination, the alcohol by volume (ABV), the indication of whether it was bottled in the estate, the website of the winery, and additional logos, information, and text present on the label.

[Table 2 about here.]

[9]The event had a total of 40 available seats for participants. At the time of booking their seats, all participants were informed about the data collection process, the presence of an expert, and the tasting experience. They could leave whenever they wanted, but all 38 participants remained until the end of the event. The characteristics of the participants, including their demographic information and past experience, are detailed in Table 3.

The wines were chosen by a expert sommelier, who selected three white wines and three red wines of different price levels. It should be noted that the price of the wines is associated with their quality and is influenced by factors such as the reputation of the winery, the grape variety, and the denomination.[10] In our case, we ensured that the price levels of the low-level wines (both red and white) were comparable, as were the price levels of the two medium-priced wines and the two high-price wines, as indicated in Table 5. This allowed us to maintain consistency and comparability within each price category during the study. All six wines possess a denomination, either DOC (controlled designation of origin), DOCG (controlled and guaranteed designation of origin), or DOP (protected designation of origin). These wines originate from different wineries and wine regions, which are outlined in Table 2. Notably, two of the wineries hold international recognition, namely Les Cretes in the Valle d'Aosta region and Vie di Romans in the Friuli Venezia Giulia region. Additionally, two wineries are renowned at the national level, Vietti in the Piemonte region and Capanna in the Toscana region, while the remaining two enjoy local prominence, namely Villa Otto Lune in the Emilia-Romagna region and Tenuta dell'Ugolino in the Marche region. Furthermore, the grapes varieties used in the wines carry international appeal (Chardonnay and Brunello), national recognition (Nebbiolo and Malvasia), and local significance (Sangiovese and Verdicchio). In the paper, we categorize the wines as either local (Verdicchio and Sangiovese) or non-local (Malvasia, Chardonnay, Nebbiolo, and Brunello).[11] The participants in this study were not provided with information about the price ranking of the wines. This decision was made based on previous research that highlights how disclosing the reference price can influence participants' evaluations (e.g., Lusk and Fox, 2003). By omitting this information, our aim was to ensure that participants' evaluations were solely based on the information already available to them due to their previous experience, as well as the information we provided, without introducing any biases related to price considerations.
At the beginning of the data collection process, each participant received a questionnaire in Italian, which we reported in Appendix C. During each round (i.e., for each of the six wines), three steps were performed. In the first step, all participants were shown the wine label containing extrinsic information, such as denomination, the Italian region of origin, and winery name.[12] We call this the 'label step'. After seeing the label, participants were asked to declare their WTP for a bottle of the wine. In the second step, called the 'expert step', an expert sommelier (not the same expert who selected the wines) presented the characteristics of the wine, the winery, and the geographic area it comes from. The expert's speech, which lasted approximately two minutes for each step, focused on the wine and winery reputation, as well as information about

[10] Table 5 in Appendix B provides the prices of the wines obtained from a restaurant wine list, as well as the ranking of the quality of each wine. To ensure the accuracy of the rankings, we cross-referenced the expert ratings from several renowned Italian wine guides. The rankings aligns consistently with these sources. For instance, when considering the expert ratings as an indicator of quality, Chardonnay and Brunello receive the highest scores according to Gardini Notes Wine Ranking by Luca Gardini. On the other hand, Verdicchio and Sangiovese receive the lowest scores according to Sensorial Synesthetic Wheel by Luca Maroni. Nebbiolo and Malvasia receive intermediate ratings according to Bibenda by Fondazione Italiana Sommelier. By consulting multiple sources and comparing our rankings, we ensured the reliability and validity of our assessments of wine quality.

[11] The concept of 'local' in this paper does not refer to the region of origin but rather to the proximity of the production location and Rimini in the Emilia-Romagna region. While the Verdicchio wine that is part of this study is produced in the Jesi area of the Marche region, it is located less than 80km in a straight line from Rimini. The other wines in this study are produced at greater distances from Rimini, as we reported in Table 5 in Appendix B. Concerning distance and its relationship with consumers' WTP for wines, Ay et al. (2017) find that the premium associated with organic wines decreases as the distance between the consumer's home and the vineyard increases, suggesting a role of proximity in the evaluation of wine. The contribution of local products to shaping consumers' WTP has also been investigated in the context of restaurants and foodservice (e.g., Shin et al., 2018; Remar et al., 2016).

[12] Table 2 provides information on the content of each label.

the wine's origin, without mentioning its quality or price. The expert discussed the winery's story, described the *terroir* of the wine, and provided an overview of the vinification techniques used. This step reflects extrinsic information as well. After the expert's speech, participants had the opportunity to update their WTP based on the additional information provided. In the third step, called the 'sensorial step', participants were given a sample of wine, approximately 2 cl, to taste. They were then asked to update their WTP, if desired. Information accumulated during this step is intrinsic because it depends on the intrinsic characteristics of the wine, and also on the tasting ability of each subject.
Throughout the data collection process, additional subject-specific data were collected, including gender, age, occupation, wine-drinking habits, wine-tasting experience, and wine-buying habits. These data aimed to capture possible variations in abilities and preferences among participants.[13]

In this study's design, the 'label step', the 'expert step', and the 'sensorial step' can be considered as levels of an ordinal factor representing *cumulative information*. Each step builds upon the previous one, with the 'expert step' including the information from the 'label step', and the 'sensorial step' incorporating both the 'label step' and 'expert step' information. This cumulative information framework allows for the examination of how the accumulation of information influences participants' WTP.

4 Statistical modeling and data analysis

In the following, we present the descriptive statistics of the data collected via questionnaires (Section 4.1). We then introduce standard linear regression (Section 4.2), showing its limitations with the data at hand, and discuss more flexible frameworks such as linear mixed models (4.3). Also, we describe the Bayesian approach and how to interpret the posterior estimation obtained from the INLA R package (4.4). Model assessment is documented in Section 4.5.

4.1 Descriptive statistics

The data about WTP collected in this study exhibit a distinctive feature: the presence of correlation within subjects. WTP measures tend to be more similar within the same subject than between subjects.[14] This suggests that information may play a role in determining participants' WTP.
Table 3 reports descriptive statistics regarding the socio-economic characteristics of the participants. The majority of participants are women (55%) and are not employed (66%). There is a high percentage of participants in the $(23, 30]$ years age interval. Approximately 40% of participants have a drink once or less than once per week, while around 37% have two to four drinks on average per week. Nearly all the participants (94.7%) do not usually drink alone. Participants are used to purchase wine in various ways, from a restaurant (92.1%), wine shops (81.6%), and directly from the winery (63.2%). These figures suggest that the participants are wine enthusiasts but not necessarily experts, which is further supported by the low percentage

[13] All the participants were involved in all six rounds of the study, meaning that the information accumulation process was consistent for all wines and participants. As a reward for the participation, a final lottery was conducted, where six prizes, each consisting of a bottle of wine, were awarded. In the first round of the lottery, one of the participants was randomly selected as the winner. This winner was then removed from the list of potential winners for the remaining rounds. This ensured that each participant had the opportunity to win up to one bottle of wine as reward for their participation.

[14] From Figure 8 in Appendix D it can be noticed that all six wines present variability in the declared WTP at the three information levels (the lines are rarely stable throughout the three steps), often showing growing or inverted U-shaped dynamics.

of participants who read specialized magazines about wine (5%), have taken a tasting course in the past (around 16%), and use digital tools to obtain information about wine (around 29%).[15]

[Table 3 about here.]

4.2 Linear model

Ordinary least square regression is a useful statistical framework to evaluate the effect of cumulative information on WTP. A simple linear regression where cumulative information is the explanatory variable and WTP the response variable provides estimates of the average WTP for the three information levels (*label*, *expert*, *sensorial*). Uncertainty quantification is straightforward through the calculation of standard errors of the regression coefficients, which enables us to make inference on the differential WTP across the three cumulative information levels.

Assuming the response y_{ij} is the log of the WTP for subject $i = 1, \ldots, 38$ and wine $j = 1, \ldots, 6$, the model is:

$$y_{ij} = \alpha + \boldsymbol{x}_{ij}^T \boldsymbol{\beta} + \epsilon_{ij} \quad \forall i, j, \tag{1}$$

where α is the model intercept and $\boldsymbol{x}_{ij}^T = (x_{1,ij}, \ldots, x_{p,ij})^T$ is a vector of p covariates observed at subject i and wine j. We assume the first three covariates in vector $\boldsymbol{x}_{ij}^T$ as the dummy variables associated with the three levels of the factor *cumulative information.* Thus, $\boldsymbol{\beta} = (\beta_1, \beta_2, \beta_3)^T$ are the regression coefficients measuring the effect of cumulative information on WTP. We find convenient to fit model (1) (and the models presented below) by applying the constraint $\beta_1 + \beta_2 + \beta_3 = 0$. This way, $\beta_1, \beta_2, \beta_3$ can be interpreted as differences relative to an average, overall information levels, WTP; for instance, β_1 quantifies how much WTP at the label step differs from average.[16]

The properties of the ordinary least square estimator rely on independent and identically distributed (i.i.d.) errors $\epsilon_{ij} \sim \mathcal{N}(0, \sigma_\epsilon^2)$. If this assumption does not hold, then the standard errors associated with the estimated $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$ from model (1) will be biased, potentially causing misleading conclusions.[17] To overcome this issue we use linear mixed models in a Bayesian framework (Gelman and Hill, 2007).

4.3 Linear mixed models

A linear mixed model is an extension of linear regression where the variability of the response variable (WTP) is modelled by a mix of so-called *fixed* and *random* effects. Typically, the fixed effects are the regression coefficients associated with the observed covariates and measure the change in the response associated with a unit increase in the covariate. The random effects capture heterogeneity in the data mainly associated with unobserved variables or missing covariates (*unobserved heterogeneity*). This heterogeneity is typically reflected by the presence of structure in the residuals of the model. Data from this study are strongly correlated within subjects/wines (i.e., WTP observations from the same subject/wine will be more similar than WTP observations taken at different subjects/wines) and possibly spatially correlated in the

[15] The sample of participants in this study appears to be heterogeneous, although it is not representative of the entire population, which includes individuals who do not drink wine. It is important to note that non-drinkers were unable to participate in the event as one of the steps involved tasting the wines. Additionally, it is likely that non-drinkers would not have had the inclination to participate in the study, since the participants had to voluntarily enroll in the study. Therefore, the sample primarily consists of individuals who have an interest in wine and are willing to engage in wine-related activities, and the results will reflect this type of consumers' behaviour.

[16] This constraint does not change the model, but it is only applied to facilitate interpretation of the results.

[17] For instance, from Figure 8 we see that WTP measurements taken on a single subject are correlated, thus we need to deal with not i.i.d. errors.

sense that observations from participants sitting nearby will likely be more similar than observations from people sitting far apart. So, we expect to find a structure in the data in this sense.

The linear mixed model framework can account for structure in the residuals by using Gaussian random effects with specific covariance; as a result, these models return an accurate estimation of the uncertainty associated with the parameters of interest β_1, β_2, and β_3, leading to reliable conclusions on the effect of cumulative information on WTP. In the following, we will consider two different types of mixed models, both being extensions of model (1).

The first mixed model we assume uses random effects to model correlation within wines and subjects. In this first model, correlation has no spatial structure among subjects.[18] The model is as follows:

$$y_{ij} = \alpha + \boldsymbol{x}_{ij}^T \boldsymbol{\beta} + \delta_j + \gamma_i + \epsilon_{ij} \quad \forall i, j, \tag{2}$$

where vectors $\boldsymbol{\delta} = (\delta_1, \ldots, \delta_6)^T$ and $\boldsymbol{\gamma} = (\gamma_1, \ldots, \gamma_{38})^T$ contain wine-level and subject-level random effects, respectively, with Gaussian distributions:

$$\boldsymbol{\delta} \sim \mathcal{N}(0, \sigma_\delta^2 \boldsymbol{I}) \qquad ; \qquad \boldsymbol{\gamma} \sim \mathcal{N}(0, \sigma_\gamma^2 \boldsymbol{I}). \tag{3}$$

If there is no correlation within subjects (i.e., no clustering) the variance component σ_γ^2 will be zero, meaning that $\gamma_i = 0, \forall i$, and all subjects have the same (log) WTP in average (overall mean). Instead, if correlation within subjects is the case (i.e., the observations are clustered) σ_γ^2 will be larger than 0 and the subject-specific γ_i's deviate from the overall mean. The same interpretation holds for the wine-level random effects.

A common interpretation is that random effects capture the effect of unobserved factors or missing covariates. The key idea behind this interpretation is that correlation within subjects is driven by subject-level variables that were not measured, like for instance income, which may have an effect on WTP or may be considered as a confounding variable, i.e. associated with both WTP and information level. Therefore, adding random effects at the subject level can produce the desired adjustment for unobserved income levels. Also, correlation among WTP observations referred to the same wine is anticipated in this study (each wine is likely to be perceived differently regarding quality and prestige), hence adding random effects for wine also seems reasonable.

In the second class of mixed models that we consider, the subject-level random effects $\boldsymbol{\gamma}$ are not assumed as i.i.d.; instead, they follow a Gaussian with a spatial covariance structure. This allows adjusting the uncertainty estimates for $\boldsymbol{\beta}$ for the presence of spatially correlated residuals. In our case, spatial correlation in the residuals may be induced, for instance, by people sitting next to each other in the audience that might have similar tastes and or share ideas on a particular wine. We have considered the following popular spatial models.
The first spatial model is the Besag model (Besag, 1974), where we assume:

$$\boldsymbol{\gamma} \sim \mathcal{N}(0, \sigma_\gamma^2 \boldsymbol{R}^{-1}), \tag{4}$$

which is a Gaussian distribution with covariance depending on a matrix $\boldsymbol{R}$, denoted as *structure matrix*, which is defined upon a graph, i.e. a collection of nodes and edges reflecting neighbouring relationships between participants[19]. Figure 1 displays two graphs that have been used in the analysis: graph (a) assumes correlation only between subjects sitting next to each other, while graph (b) assumes a correlation between people sitting in the same line. Note that each graph

[18]The existence of a spatial structure might be observed when participants that are near one another are part of the same social group (e.g., a group of friends or family).

[19]The matrix $\boldsymbol{R}$ is rank-deficient and the notation $\boldsymbol{R}^{-1}$ in Eq. (4) indicates the generalized inverse; the model by Besag (1974) is denoted in the statistical literature as intrinsic conditional autoregression (ICAR).

consists of disconnected sub-graphs, which requires extra care when implementing the Besag model in INLA (Freni-Sterrantino et al., 2018).

The second spatial model we consider is a modification of Besag denoted as BYM (Besag et al., 1991; Riebler et al., 2016), with:

$$\boldsymbol{\gamma} \sim \mathcal{N}\left(0, \sigma_\gamma^2\left[(1-\lambda)\boldsymbol{I} + \lambda \boldsymbol{R}^{-1}\right]\right). \tag{5}$$

The BYM is a convex combination of a spatially correlated random effect (with covariance structure $\boldsymbol{R}$) and an i.i.d. random effect (with covariance structure $\boldsymbol{I}$); $\lambda \in (0,1)$ is a mixing parameter that quantifies the proportion of total variance σ_γ^2 explained by the spatial component, hence $1-\lambda$ will be the proportion of variance attributed to the i.i.d. term.

Finally, all the models that we analyzed include covariates at an individual level: gender, occupation, drinking behavior, and age. Gender, occupation, and drinking behavior show no effect on WTP (results not reported here). The effect of age on WTP was flexibly modelled using a spline (Lindgren and Rue, 2008).[20]

[Figure 1 about here.]

4.4 Bayesian hierarchical models

In this paper, we adopt a Bayesian approach to statistical inference. The mixed models presented above can be considered special cases of Bayesian hierarchical (or multilevel) models (Gelman et al., 2004; Gelman and Hill, 2007). Hierarchical Bayesian models are very popular because they can easily incorporate different sources of heterogeneity in the data. The fundamental aspect of a Bayesian framework is that uncertainty regarding all model parameters can be introduced in the model through prior distributions and then propagated to the model posterior distribution, that is the conditional distribution of all model parameters given the observed data. From the model posterior distribution, any summary (mean, median, mode, quantiles) can be computed regarding any unknown parameters of interest (or a function of these), which allows calculating credible intervals for such unknown quantities. For instance, a 95% credible interval is given by the estimated lower (2.5) and upper (97.5) quantile of the posterior distribution. Essentially, by looking at the posterior distribution we obtain a full account of the uncertainty associated with each estimated model parameter. For a comprehensive presentation of the Bayesian hierarchical approach to inference, see Gelman et al. (2004).[21]

4.5 Model assessment

Table 4 reports model assessment results based on two criteria. The first one is a measure of goodness of fit accounting for model complexity, denoted as DIC (Spiegelhalter et al., 2002); the smallest DIC value points to the best model. The second is a measure of predictive performance, denoted as conditional predictive ordinates (CPO) (Pettit, 1990). The value CPO_i can be computed at each observation y_i as the probability to observe y_i under the model fit using all data but y_i. The summary $\mathrm{CPO} = -\left(\sum_i \log \mathrm{CPO}_i\right)$ is usually taken as a measure of predictive performance; the smallest CPO points to the best model. Results reported in Table 4 refer to all models described in Section 4.3 plus other models including interaction terms which will be discussed later in Section 5.2.

[20] See Figure 9 in Appendix D, displaying the estimated smooth effect of age on WTP, where a decreasing (almost linear) trend can be observed, however suggesting there is no clear relation between WTP and age.

[21] We estimated all models using the R package INLA (Rue et al., 2017). In Appendix E, we present the main advantages of using INLA.

The first thing to notice is that model 1, containing only the fixed effects, is worse compared to all other models, both according to DIC and CPO. Models 2 to 6 achieve very similar DIC and CPO values. Also, the estimates for β_1, β_2, β_3, and associated uncertainty (here not shown) are unchanged under models from 2 to 6. In Section 5 we will report result from models 2, 7, 8, and 9 only, for space constraints.

All the spatial models (3:6) perform roughly similarly to model 2, which does not include spatial random effects, in terms of both DIC and CPO. Even though spatial models do not provide a clear increase in predictive performance, we have evidence that spatial correlation drives some of the heterogeneity in the data. In particular, for model 3 the estimated mixing parameter λ in Eq. (5) is about 0.5, indicating that half of the residual variability (after accounting for the covariates and the wine-level random effect) can be attributed to spatial correlation, possibly due to interaction across people sitting next to each other.

[Table 4 about here.]

5 Discussion

We present a discussion of the main results obtained in this study, focusing firstly on the impact of cumulative information on WTP and, secondly, on possible interactions with particular characteristics of the participants or the wines.

5.1 The impact of cumulative information on WTP

Figure 2 illustrates the impact of cumulative information on WTP: vertical lines represent the 95% credible intervals for the regression coefficients β_1 (*label*), β_2 (*expert*) and β_3 (*sensorial*) from models (1) and (2).[22] Note that the coefficients $(\beta_1, \beta_2, \beta_3)$ sums to 0 by construction, thus these estimates are to be interpreted as relative effects compared to the global average. By examining the size of the credible intervals, it is evident that the mixed model provides more precise estimates. Notably, the three intervals do not overlap, suggesting that the factor 'cumulative information' has a significant impact on WTP [23]. Specifically, the expert talk leads to a significant increase in WTP compared to the WTP observed at the label step. This can be observed from the non-overlapping 95% CI for label and expert steps, with the WTP associated with the expert step being notably higher than the WTP associated to the label step. After the sensorial step, the WTP experience a significant decrease, although it remains significantly higher than the WTP observed at the label step. In conclusion, the results provide evidence that the availability of both extrinsic (e.g., expert) and intrinsic (e.g., sensorial) information leads to significant changes in WTP. Furthermore, considering that customers have access to additional information at each step, it appears that in the market for goods with complex quality, such as wine, the increase in available information does not always results in an increase in WTP for these goods.

[22] A credible interval summarizes the posterior distribution of a parameter and is the main inferential output of a Bayesian analysis.

[23] For the sake of simplicity and given the exploratory purpose of the work we avoid formal hypothesis testing and look at the posterior credible intervals of the estimated effects to detect "statistically significant" results. For instance, we denote a change between WTP at different cumulative information levels, e.g., $\beta_2 - \beta_1$, as significant if the 95% credible intervals of β_2 and β_1 do not overlap; when the intervals partly overlap we refer it to poor evidence of a significant change. Thus, we use the words "statistically significant" in a loose sense here. Commenting the credible intervals in this way is safe and practical way to interpret the Bayesian model output without incurring overstatements (i.e. statements that are not supported by the data). A formal Bayesian testing procedure would be possible by computing the posterior probability that $\beta_2 > \beta_1$ and rejecting $H_0 : \beta_1 = \beta_2$ if this probability exceeds some pre-defined threshold.

[Figure 2 about here.]

If we consider the different levels of quality as reported in Table 5, we can further examine how cumulative information influences WTP for each tier of wines. Figure 3 displays the credible intervals of the declared WTP for each wine tier. It can be observed that all the wines show an increase in the WTP from the label step to the expert step. However, the impact of cumulative information from the expert to the sensorial step varies across different quality tiers. For low-quality wines, there is a significant drop in WTP after the sensorial step, bringing it close to the WTP level observed after the label step. In the case of medium-quality wines, there is still a decrease in the WTP from the expert to the sensorial step, but with less evidence of a significant change. Conversely, for high-quality wines, the WTP levels observed in the expert and the sensorial step are similar, suggesting that the extrinsic information provided during the label and the expert steps might already be sufficient for evaluating these types of wine.

The question whether wine can be categorized as a search good can be approached by checking whether consumers choose to update their WTP after tasting the wine (see Appendix A). Considering the obtained results, which suggest consumers' WTP being influenced by both extrinsic and intrinsic cues, our conclusion is that the data we collected does not support the hypothesis that wine is a search good. This conclusion is strengthened by the use of mixed models to adjust the estimates. However, it is important to note that further investigations are needed, considering the limitations of the study we report in Section 5.3. Nevertheless, in the upcoming section, we will explore the role of drinking habits, which suggests that experienced consumers may perceive wine as a search good.

Investigating whether the wine is an experience good or a credence good would be an important further step to develop. However, in the current study, we are unable to determine which category the wine falls into. Nonetheless, the distinct responses observed among participants regarding medium-quality and high-quality wines suggest that consumers may need to personally experience the wine to fully appreciate its quality characteristics. Regardless, this finding indicates that experiential factors play a significant role in shaping consumers' perceptions of wine quality.

[Figure 3 about here.]

5.2 Interactions

The data contain information regarding some of the characteristics which have been found, in previous research, to influence how wine is evaluated, such as gender (Lange et al., 2002; Almenberg and Dreber, 2011) and knowledge and experience in the consumption of wine (Gustafson et al., 2016). This allows us to investigate possible interactions between cumulative information and factors such as age, drinking habits, and gender. We introduce an interaction by allowing β_1, β_2, and β_3 to vary according to another factor referred to as a modifier (e.g., age), which can be seen as a special case of varying coefficients models (Hastie and Tibshirani, 1993). We implement these models within INLA, following the approach by Franco-Villoria et al. (2019), which provides advantages in terms of avoiding the risk of over-fitting. From Table 4, all the models that include an interaction term (7:9) show fairly similar performance in terms of DIC and CPO, albeit slightly inferior to the corresponding model without the interaction (model 2). Models 2 and 7, in particular, exhibit comparable predictive power and are both substantially supported by the data. Due to the discrepancies in the performance criteria, we believe we can draw reliable conclusions from the interaction models, thus we present some comments in what follows.

[Figure 4 about here.]

Figure 4 displays the effect of cumulative information on WTP for different age classes, allowing us to investigate the strength of the interaction between cumulative information and age. The vertical lines represents the 95% credible intervals for the regression coefficients β_1, β_2, and β_3 from model (2). It is important to note that, for comparison purposes, the coefficients reported in Figure 2 for the mixed model are replicated in Figure 4 (and subsequent figures) and denoted as marginal (i.e., overall age classes).
From Figure 4, we can see that the change in WTP between the label and expert steps is consistent across age classes. However, the interaction between cumulative information and age becomes apparent when considering the tasting: the WTP associated with the sensorial step tends to increase with age. After tasting, young participants (i.e., 18–23) tend to declare similar WTP as in the label step, whereas older individuals (i.e., 30–45 and 45–77) maintain a WTP level similar to what was previously declared at the expert step. This suggests a potential difference in the elasticity of WTP to cumulative information, which could be attributed to different ways to process information depending on the participants' personal characteristics. Alternatively, this finding could indicate that younger consumers may have a lower ability to process intrinsic information or that they are particularly influenced by extrinsic information, particularly that provided by experts.

[Figure 5 about here.]

Considering the interaction between cumulative information and the gender of the participant, we can observe from Figure 5 that the impact of extrinsic information provided by the expert is positive and significant, with a relatively stronger effect for women. Additionally, we note a difference in how intrinsic information is processed between the two genders: while the sensorial step does not lead to a significant change in the WTP declared by male participants, women declared a significantly lower WTP after the intrinsic information is made available through the sensorial step. These findings align with the asymmetry in the reaction to information reported by Lange et al. (2002) and Almenberg and Dreber (2011).

[Figure 6 about here.]

We also examined the interaction between cumulative information and drinking habits, and the results are presented in Figure 6. An interesting pattern emerges from the analysis: similar to previous findings, the expert step shows a larger WTP compared to the label step. The difference is significant for participants who reported consuming less than one drink per week or between two and four drinks per week on average. For those who usually consume more than four drinks per week there is still evidence of a change, as reported by the partial overlap of credible intervals in Figure 6, but the size of it is reduced. The effect of the sensorial step also differs among the three groups. For participants who usually consume less than one drink per week or more than four, there is no evidence of a significant change. But, for those who consume between two and four drinks per week on average, the intrinsic information does significantly influence WTP. Furthermore, looking at Figure 6 and contrasting the sensorial and label steps, we see that the impact of cumulative information is not significant with respect to the label step in participants with a higher frequency of drinks per week, possibly indicating that they might already be able to evaluate WTP during the label step without additional information from the expert or the wine tasting. In contrast, participants with moderate drinking habits (two to four drinks per week) are influenced by both extrinsic and intrinsic information, suggesting a lower ability to extract information from the label alone. However, their ability is likely higher than that of the low-frequency drinkers, who are solely influenced by the expert speeches and maintain the same evaluation even after tasting the wine. This result is in line with the study by Lange et al. (2002), indicating that naive consumers may struggle to recognize quality without the presence of extrinsic information. Here, what we find additionally suggests that they might need different types of extrinsic information to evaluate the good. Furthermore, the results suggest that more experienced consumers might not require additional information beyond what is provided on the label. This implies that, for them, wine could be considered a search good. However, further investigation is needed to confirm this intuition.

Finally, Figure 7 reports the results regarding the interaction between cumulative information and the participants' attendance of wine-tasting courses. The findings indicate that the effect of cumulative information varies depending on the group of participants under consideration.[24] For participants who attended at least one wine-tasting course, the valuation remains stable across the expert and the sensorial steps. In contrast, participants who have never attended a course declare a lower WTP in the sensorial step compared to the expert step. However, it is important to note that even after all three steps, their evaluation is still higher than after the label step. These observations suggest that more knowledgeable participants may require additional extrinsic information, represented by the expert step, to complete their evaluation after reviewing the label. The experience of tasting the wine does not significantly influence their estimation of the wine's value. This behavior resembles what is typically observed in the market for search goods, where consumers primarily rely on gathering information prior to making a purchase in order to assess the quality of the product. Based on these findings, it can be inferred that the behavior of informed agents, such as those who attended wine-tasting courses, is likely to differ from that of less informed agents. This suggests the need for further research to investigate and validate these results. However, it is important to exercise caution due to the low number of participants who declared to have attended a wine-tasting course.

[Figure 7 about here.]

In summary, the results of the study confirm that the availability of both intrinsic and extrinsic information has a significant effect on the WTP for wine. However, this effect is also influenced by several factors, including age, gender, drinking habits, and the participants' previous knowledge and experience.

5.3 Some limitations of the study

To estimate the causal effect of information (i.e., treatment with three levels: label, expert and sensorial) on WTP, the usual workflow should include: i) randomly sampling subjects from the population of interest, ii) randomly assigning them to different groups according to the treatment levels, and iii) comparing the average WTP across treatments while providing some measure of uncertainty to evaluate the statistical significance of the differences.
At stage ii), different experimental settings and randomization strategies can be envisioned; two very simple are described next. The simplest approach would be to randomly divide subjects into three groups, with each group experiencing only one of the treatment levels: 'labels', 'expert', or 'sensorial'. The effect of 'expert' and 'sensorial' can be compared against the control group, which receives 'label' only. Another simple design would be to randomly split subjects into two groups, with one group experiencing 'label' followed by 'expert', and the other group experiencing 'label' followed by 'sensorial'. Within each group, the WTP observed at the treatment level (i.e., expert or sensorial) would be compared against the WTP observed at the 'label' control level, and the results would be averaged across subjects (This design would

[24] Credible intervals for the participants who stated that they attended at least a wine-tasting course are wider with respect to those of other participants. This is due to the low number of participants (6) who answered positively.

permit to study to some extent the effect that cumulating the information has on WTP, as both groups are exposed to the minimum amount of information, i.e., the 'label' step). Both options described above involve randomization of the subjects within groups, which offers a systematic way to control for factors that may confound the relationship between cumulative information and WTP.

However, in our scenario, randomization was not possible due to social inclusion reasons. This study was conducted within a public event where visitors could attend various activities, including scientific seminars, art performances, and collective games. Hence, the group participating in the data collection was self-selected. Conducting a randomized controlled experiment would be unpractical and go against the principle of social inclusion, as we had to provide all participants with the same experience, which means that all of them would need to be exposed to the 'label', the 'expert', and the 'sensorial' steps. Additionally, we were constrained by the enrollment of participants who were visiting the event and the limited time frame of approximately two hours to conduct the study, as well as by the budget available for the event.

Given these challenges, we decided against randomization and instead opted for an observational study design where we observed the response (WTP) on all subjects before and after incremental treatments (information). This type of study gave us the opportunity to investigate the relationship between WTP and cumulative information, i.e., the information accumulated by participants across the three stages of the experiment: label, expert and sensorial. Since we were working with observational data from a non-randomly selected sample, we employed mixed models to adjust the effect estimates for both observed confounding variables and unobserved heterogeneity. Although observational studies have limitations in establishing causal associations, the statistical tools we applied allow for an exploratory (i.e., not confirmatory) investigation of the relationship between cumulative information and WTP. In fact, some sources of heterogeneity present in observational data – such as, in our case, correlation within subjects – can easily be accommodated in a mixed model framework through the use of random effects, as described in Section 4.3.

Another limitation worth discussing regards the origin of wines used in the study and the location of the event, both of which were specific to Italy. As mentioned in Section 3, we included both Italian wines with an internationally recognized denominations and Italian wines which have a national or local reputations. It is important to note that potential participants who are not familiar with these specific wines, especially non-Italian citizens, may have different reactions to the extrinsic information provided. Similarly, if the study were conducted in Italy but used wines from outside the country with non-internationally recognized denominations, the results may vary. This lack of generalizability should be taken into account when interpreting the findings. However, despite these limitations, this study still contributes to understanding the relationship between cumulative information and WTP.[25] While an ideal setting would involve randomly selected participants from diverse backgrounds and randomly selected wines, such a design would not align with the inclusive nature of the public event who hosted the data collection.

6 Conclusions

Complex-quality goods, such as wine, pose challenges for consumers in evaluating their quality, making them to rely on intrinsic and extrinsic cues as signals. Previous studies have examined the role of information in the evaluation of complex-quality goods, including wine, mostly focusing on the role of either intrinsic or extrinsic cues. However, few studies have explored the

[25]We would like to express our gratitude to the anonymous referee who brought attention to this limitation, thus paving the way for future research to address and overcome it.

impact of both types of information within the same framework. In this paper, we conducted a study to investigate how the WTP for wine changes based on the amount of information available to participants, subjected at first to extrinsic information and then to intrinsic information. In particular, the goal of the study was to examine the relationship between WTP and cumulative information, i.e., the information accumulated by the consumers across three stages of the data collection process. To establish this link between the cumulative information to the observed WTP, we defined a Bayesian linear mixed model that accounts for some potential sources of bias arising from data heterogeneity.

The study revealed a significant impact of cumulative information on the participants' WTP, with a greater effect of extrinsic information compared to those of intrinsic information, which followed. These results challenge the hypothesis that wine is solely a search good for all participants, as WTP is influenced by both extrinsic and intrinsic cues. However, it is important to note that more experienced consumers may rely primarily on extrinsic information. This preliminary result needs further investigation, since it raises questions about the potential influence of other experiential characteristics of consumers on the evaluation process. This suggests that the classification of a complex-quality good as a search or an experience (or even a credence) good may vary depending on the consumer's accumulated experience. To the best of the authors' knowledge, this specific aspect has not been investigated previously, and additional empirical evidence is required to confirm the initial intuition.

The results have important implications for both theoretical understanding and practical applications. From a theoretical perspective, this study contributes by proposing a model that allows us to identify the nature of the good (search or experience) based on the accumulation of information. This framework can be extended and applied to other complex goods, such as food and artworks, where consumers heavily rely on quality-related information. From an empirical standpoint, the findings provide a valuable tool for testing and validating this model in the context of complex goods. Researchers can further explore the relationship between cumulative information and consumer preferences to gain deeper insights into consumer decision-making processes, making use of the Bayesian setting we suggest, useful to take into account heterogeneity in the data.

Concerning practitioners, particularly managers in the wine industry, they can leverage the findings to develop effective marketing strategies. In fact, by considering consumers' characteristics, such as their information accumulation patterns, managers can segment the market and tailor their offerings to specific consumer segments. This targeted approach can enhance customer satisfaction and loyalty. Additionally, for small businesses, the results suggest that the type of information to be shared with consumers should be tailored to the level of consumer knowledgeability. While certain consumer characteristics, such as age and gender, are easily observable and can provide some insights, there are other factors that may influence purchase choices, requiring careful consideration.

Furthermore, the results may be taken as a basis to suggest potential policy actions that can address adverse selection problems and mitigate the effects of asymmetric information. Policymakers could focus on providing accurate and reliable information about the quality of complex goods, while also offering training programs to educate consumers on how to effectively utilize this information, so they can make more informed decisions.

Declarations of interest

None

Funding source

The study was part of one of the events of the Rimini Campus of the University of Bologna 'European Researchers' Night', the funding for that event come from University of Bologna's Rimini Campus funds. The funding source had no role in the design of the study, in the collection, analysis, and interpretation of data, in the writing of the report, and in the decision to submit the article for publication.

Ethical statement

The participants to the study had to book it (for free) on a website, knowing that they would have been part of a data collection process and to a wine tasting event, with an expert speaking. During the event, they got to know that their data will be used for a statistical analysis. They were able to leave the event whenever they wanted.

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A A conceptual framework

Let q_j be the perceived quality of wine j, which is characterized by uncertainty and varies from subject to subject, and $E(q_j)$ be the expected quality of wine j, which is a population quantity that can be estimated from empirical data. We assume that the expected quality at time t depends on the level assumed by variables $\theta_{j,t}$ and $\eta_{j,t}$ representing, respectively, intrinsic and extrinsic clues at time t. Our goal is to investigate changes in the (unobservable) expected quality for different information settings, i.e. different levels of θ and η, by assuming that the WTP is a function of perceived quality $WTP_{j,t} = f(q_{j,t}|\theta_{j,t}, \eta_{j,t})$, or a proxy of it. When either the intrinsic or the extrinsic information changes, the expected quality (and hence the WTP) could change as a result of a change in the perceived quality by the consumers. With this in mind and by an observational study, we have collected data on the WTP of a sample of subjects for different wines to look for changes in the expected WTP, $E(WTP_j)$, as a way to investigate whether significant changes occur in $E(q_j)$. Other factors characterizing the consumer may impact the expected quality (and hence the WTP). Various characteristics of the consumers could potentially modify both the level of their WTP and the way this can be changed by the received information. We can check for these effects by specifying the interaction between the received information and the individual consumers' characteristics in the statistical model performed in Section 4.

By using our data, this conceptual framework allows us to investigate a series of hypotheses. First, in the case of a search good, tasting or consuming it should not modify consumers' evaluation, since they know everything they need to know to rightly evaluate its quality without the need of experiencing the good. In other words, the expected quality of a search good would be unchanged in subjects exposed to more and more intrinsic information about that good. Formally, we have

$$E(q_{j,t-1}|\theta_{j,t-1}, \eta_{j,t-1}) = E(q_{j,t}|\theta_{j,t}, \eta_{j,t-1}) \tag{6}$$

with $\theta_{j,t}$ and $\theta_{j,t-1}$ referring to intrinsic information at different time steps (e.g., tasting/no tasting), and $\eta_{j,t-1} > 0$ referring to all the extrinsic information available (e.g., those coming from the label and the expert). Clearly, $\theta_{j,t-1} \geq 0$, and $\theta_{j,t} > \theta_{j,t-1}$. Note that hypotheses in (6) can be evaluated empirically by comparing the average WTP at time steps t and $t-1$. Other hypotheses can be represented within this framework. For example, an experience good would require that experiencing the good will change the evaluation of the quality (indeed, it would require that the evaluation could not be done precisely unless the good is experienced). In this case the equality (6) would not hold.

Second, this framework allows us to identify how information is cumulated in this study, helping to grasp the interpretation of the coefficients we will estimate in the empirical analysis. We assume three time steps where the information is cumulated: the label step, the expert step, and the sensorial step such that the information set at each step contains the information available at previous steps. Let's $t = 0$ be the time before the label step, $t = 1$ the time after the label step, $t = 2$ the time after the expert step, and $t = 3$ the one after the sensorial step. After participants have been exposed to the label information ($t = 1$), the expected evaluation of wine j shifts from $E(q_j|\theta_{j,0}, \eta_{j,0})$ to $E(q_j|\theta_{j,0}, \eta_{j,1})$, and we can identify the (average) effect due to increasing extrinsic information from $\eta_{j,0}$ to $\eta_{j,1}$,

$$\tilde{\beta}_1 = E(q_j|\theta_{j,0}, \eta_{j,1}) - E(q_j|\theta_{j,0}, \eta_{j,0}) \tag{7}$$

which is unbounded, namely $\tilde{\beta}_1 \lesseqqgtr 0$. Here, $\eta_{j,1} \geq \eta_{j,0}$, which is strict also in the case the participant already had some (but not all) of the extrinsic information present in the label before being exposed to it.
At time $t = 2$, participants have been further exposed to extrinsic information, coming from the expert speech. Its impact can be written as

$$\tilde{\beta}_2 = E(q_j|\theta_{j,0}, \eta_{j,2}) - E(q_j|\theta_{j,0}, \eta_{j,1}) \tag{8}$$

$\tilde{\beta}_2 \lesseqqgtr 0$. Here, $\eta_{j,2} \geq \eta_{j,1}$, with the equality sign holding if participants already knew the information shared by the expert, for example by inferring it from the label given their possible developed experience.
Finally, after the sensorial step ($t = 3$), participants have now been exposed to intrinsic information too, so we can write the impact of the experience on participants i's evaluation as

$$\tilde{\beta}_3 = E(q_j|\theta_{j,3}, \eta_{j,2}) - E(q_j|\theta_{j,0}, \eta_{j,2}) \tag{9}$$

with $\tilde{\beta}_3 \lesseqqgtr 0$ and $\theta_{j,3} \geq \theta_{j,0}$ with the strict sign holding whenever the tasting experience adds new information to the participants set, which can be the case also if participants have already drunk the wine in the past, since they could possibly have now additional extrinsic information at their disposal, from the two previous steps.
Given this framework, we can study the impact of information on the valuation of quality wines. Essentially, we can do this by comparing the levels of the estimate β_1, β_2, and β_3 (the credible intervals of the coefficients in the model presented in section 4) which carry direct information regarding the quantity of interest $\tilde{\beta}_1$, $\tilde{\beta}_2$, and $\tilde{\beta}_3$ in the framework above, but averaging over the various wines used in the study. In particular, to verify if equation (6) holds in our sample, we can contrast the estimated β_2 and β_3.

B Information not revealed to the participants

Table 5 reports restaurant prices, quality levels, distance in km between the production location and Rimini (road distance and in a straight line), and the number of bottles produced by the wineries for each of the six wines.

[Table 5 about here.]

C Questionnaire

Since the data collection was held during an event aimed at spreading awareness about the research of Italian researchers, it was conducted in Italian. The questionnaire, translated into English, follows. Notice that questions 1 to 3 are repeated in each round (i.e., for each wine). Question 1 is administrated after the participants were exposed to the label of the bottle, question 2 after the expert made his speech about the wine, and question 3 after the participants tasted the wine. When all the participants answered the additional questions, the lottery for the reward was carried through. Supplementary materials contain the original version of the questionnaire (in Italian), as well as the forward-backward translation (from Italian to English to Italian).

Question 1, Wine 1
What is the maximum price (in EUR) you would be willing to pay for the bottle you just saw?
Question 2, Wine 1
After having listened to the expert description of the wine, what is the maximum price (in EUR) you would be willing to pay for a bottle of this wine?
Question 3, Wine 1
After having tasted the wine, what is the maximum price (in EUR) you would be willing to pay for a bottle of this wine you tasted?
Question 1, Wine 2
What is the maximum price (in EUR) you would be willing to pay for the bottle you just saw?
Question 2, Wine 2
After having listened to the expert description of the wine, what is the maximum price (in EUR) you would be willing to pay for a bottle of this wine?
Question 3, Wine 2
After having tasted the wine, what is the maximum price (in EUR) you would be willing to pay for a bottle of this wine you tasted?
Question 1, Wine 3
What is the maximum price (in EUR) you would be willing to pay for the bottle you just saw?
Question 2, Wine 3
After having listened to the expert description of the wine, what is the maximum price (in EUR) you would be willing to pay for a bottle of this wine?
Question 3, Wine 3
After having tasted the wine, what is the maximum price (in EUR) you would be willing to pay for a bottle of this wine you tasted?
Question 1, Wine 4
What is the maximum price (in EUR) you would be willing to pay for the bottle you just saw?
Question 2, Wine 4
After having listened to the expert description of the wine, what is the maximum price (in EUR) you would be willing to pay for a bottle of this wine?
Question 3, Wine 4
After having tasted the wine, what is the maximum price (in EUR) you would be willing to pay for a bottle of this wine you tasted?
Question 1, Wine 5
What is the maximum price (in EUR) you would be willing to pay for the bottle you just saw?
Question 2, Wine 5
After having listened to the expert description of the wine, what is the maximum price (in EUR) you would be willing to pay for a bottle of this wine?
Question 3, Wine 5
After having tasted the wine, what is the maximum price (in EUR) you would be willing to pay for a bottle of this wine you tasted?
Question 1, Wine 6
What is the maximum price (in EUR) you would be willing to pay for the bottle you just saw?
Question 2, Wine 6
After having listened to the expert description of the wine, what is the maximum price (in

EUR) you would be willing to pay for a bottle of this wine?
Question 3, Wine 6
After having tasted the wine, what is the maximum price (in EUR) you would be willing to pay for a bottle of this wine you tasted?
Additional questions:
Please indicate:
1. Your age:
2. Your gender:
3. Your last recent education title:
4. Your job:
5. How many times do you consume wine in a week?

- Once or less than once per week
- From two to four times per week
- More than four times per week

6. Do you usually drink together with other people?

- Yes
- No

7. Have you ever bought a bottle of wine from a winery?

- Yes
- No

8. Have you ever bought a bottle of wine from a wine shop?

- Yes
- No

9. Have you ever bought a bottle of wine in a restaurant?

- Yes
- No

10. When you buy a bottle of wine, do you usually take into account possible pairing with food?

- Yes
- No

11. Do you usually read wine guides and specialized magazine on wine (such as Bibenda, Wine Spectator, etc.)?

- Yes
- No

12. Do you use or refer to smartphone apps for the evaluation of wines (such as Vivino)?

- Yes
- No

13. Have you ever taken part to a wine tasting course?

- Yes
- No

D Additional figures

This Appendix contains additional figures recalled in the paper.

[Figure 8 about here.]

[Figure 9 about here.]

E Bayesian computation using INLA

All the models in this paper are estimated using the R package INLA (Rue et al., 2017) which performs approximate Bayesian inference following the approach by Rue et al. (2009). There are several advantages to using INLA. First, it returns as output the marginal posterior for all model parameters, i.e., both the fixed and the random effects, and is typically faster than simulation-based methods such as Markov Chain Monte Carlo algorithms. Second, it enables a wide range of structured random effects (e.g., spatially/temporally correlated, splines) with relatively weak effort in coding, and provides computation of several information criteria which is useful for model assessment purposes. As another important feature, INLA gives the user great flexibility in building new structured random effects specifically designed for the application at hand (a feature that we used in our application to build the two types of spatial random effects illustrated in Figure 1). As a final remark, uncertainty about model parameters needs to be specified, at prior, through a probability distribution (the so-called *prior distribution*); thus, for instance, σ^2_δ and σ^2_γ in Eq. (3) will require the user to define a prior. Setting priors for variance parameters is typically a critical issue in Bayesian inference; choice of priors is dealt with in a very practical way in INLA by using Penalized Complexity (PC) priors (Simpson et al., 2017) which are very easy to define by the user. More details on recent developments of INLA can be found in Rue et al. (2017). Our analysis is fully reproducible and the R code is available upon request.

List of Figures

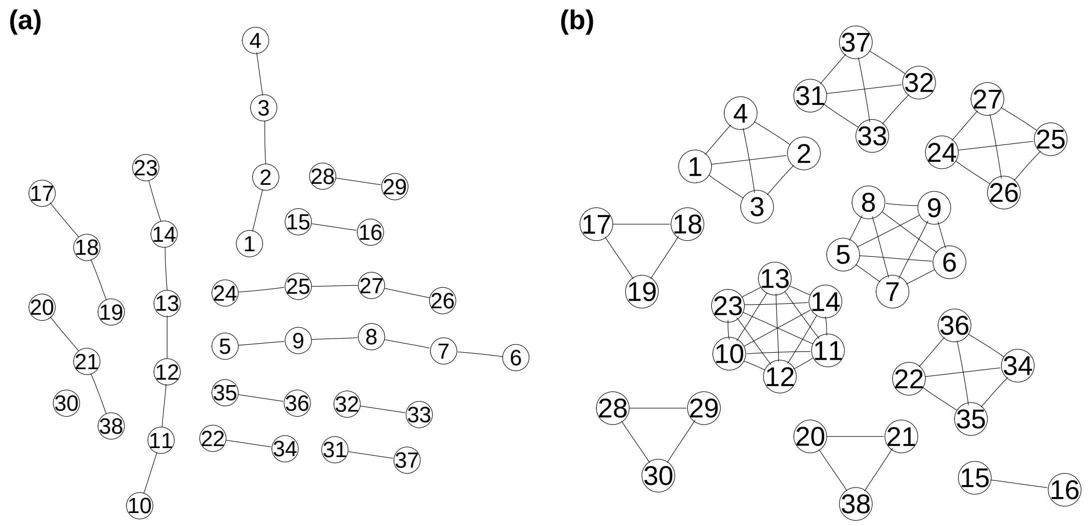

Figure 1: Graph representation of the possible neighbouring relationships between participants. On the panel (a), the graph assumes correlation only between subjects sitting next to each other in the line (note that the graph is made of several disconnected sub-graphs because the event was not fully booked, thus not all seats were occupied). On the panel (b), the graph assumes correlation only between participants sitting in the same line (10 lines in total).

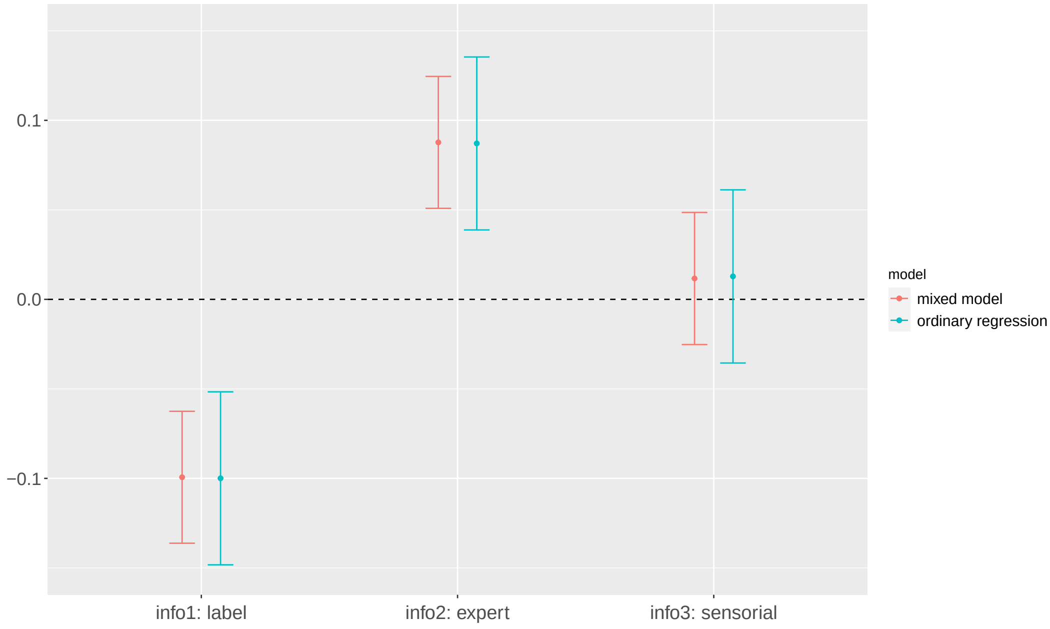

Figure 2: The effect of cumulative information on (log) *WTP*.

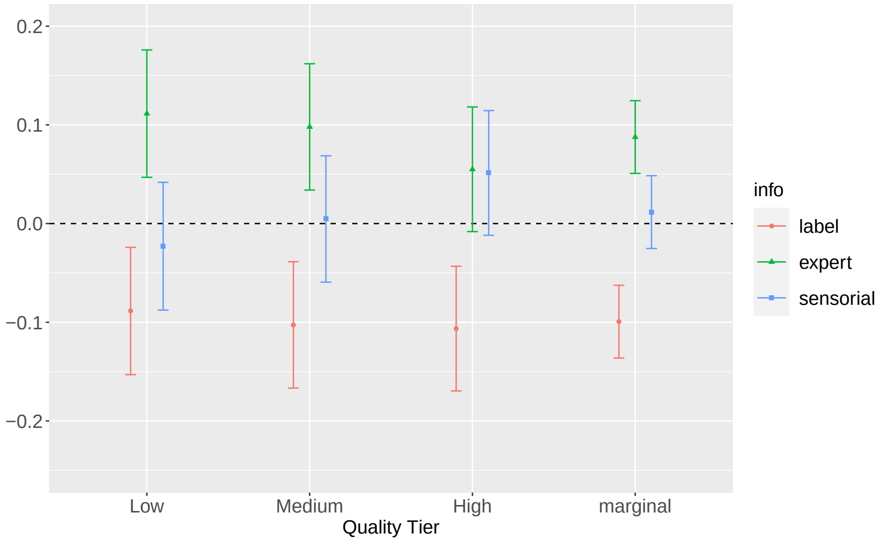

Figure 3: The effect of cumulative information on (log) WTP for each quality tier.

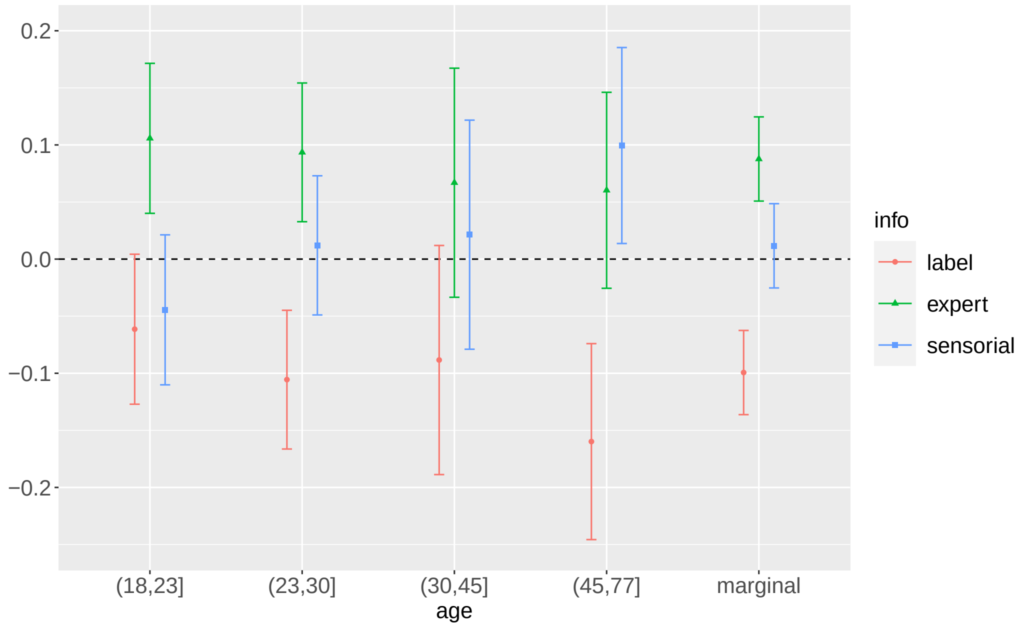

Figure 4: Interaction between cumulative information and age. The plot shows the credible intervals of the estimated β_1, β_2, and β_3 for each separate age class and overall age (marginal).

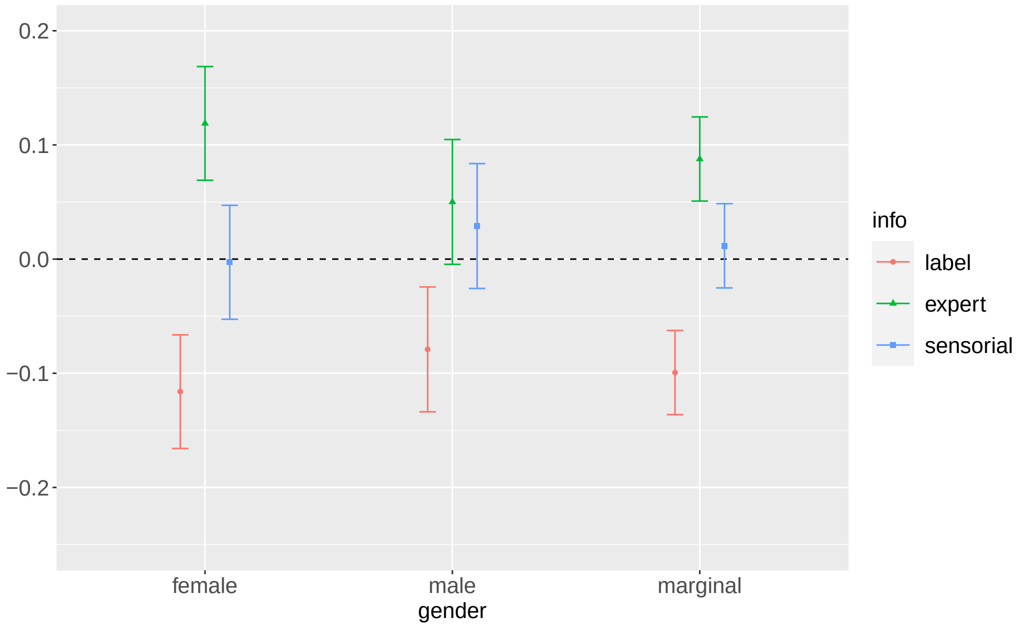

Figure 5: Interaction between cumulative information and gender. The plot shows the credible intervals of the estimated β_1, β_2, and β_3 for females and males separately, and marginally over gender (marginal).

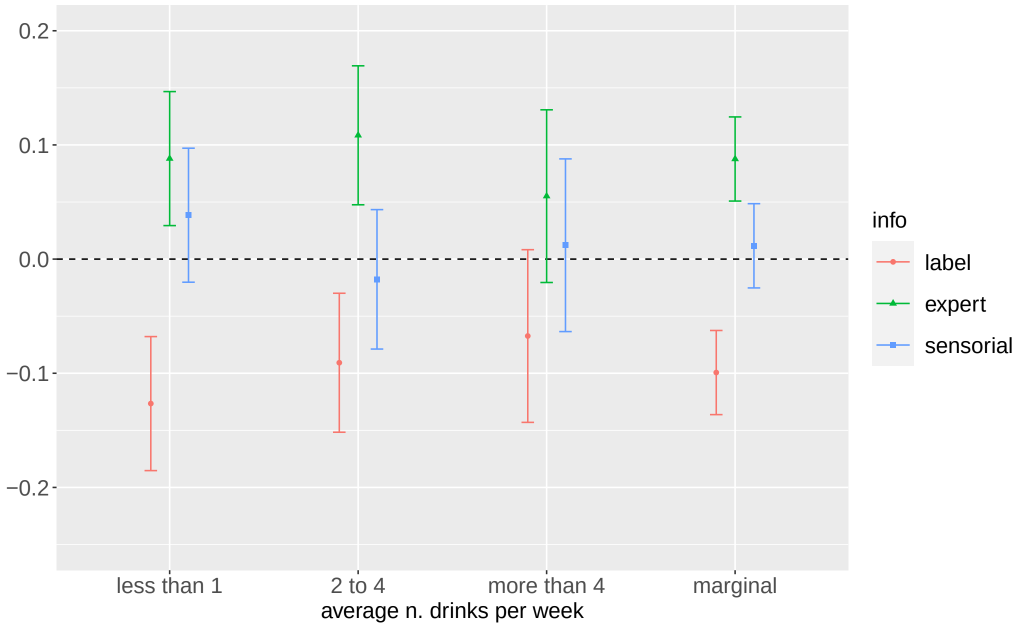

Figure 6: Interaction between cumulative information and drinking habits. The plot shows the credible intervals of the estimated β_1, β_2, and β_3, both separately for each class and overall (marginal).

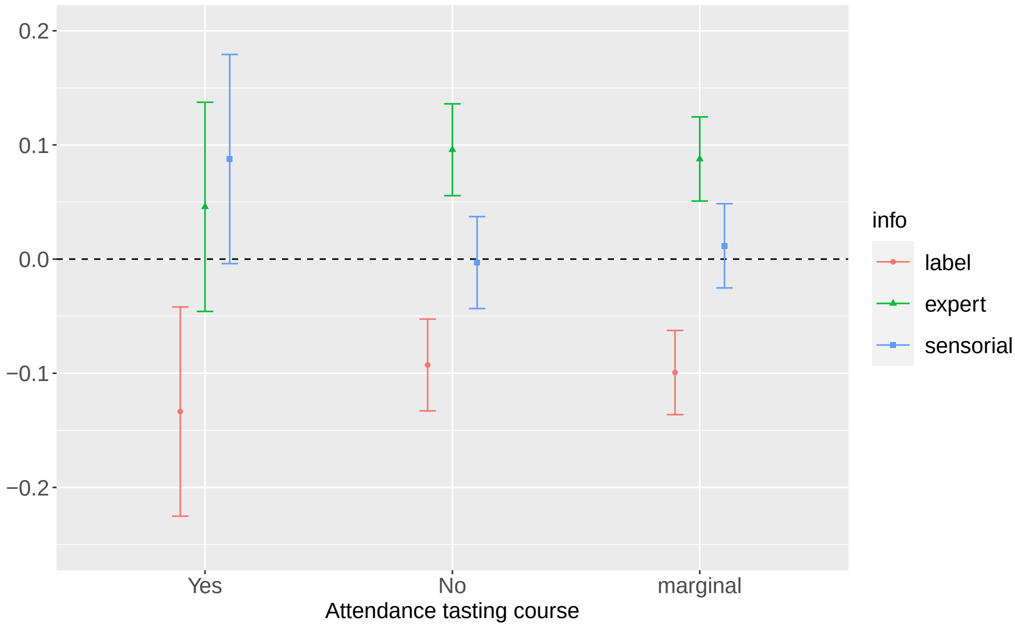

Figure 7: Interaction between cumulative information and attendance to wine-tasting courses. The plot shows the credible intervals of the estimated β_1, β_2, and β_3, both separately for each class and overall (marginal).

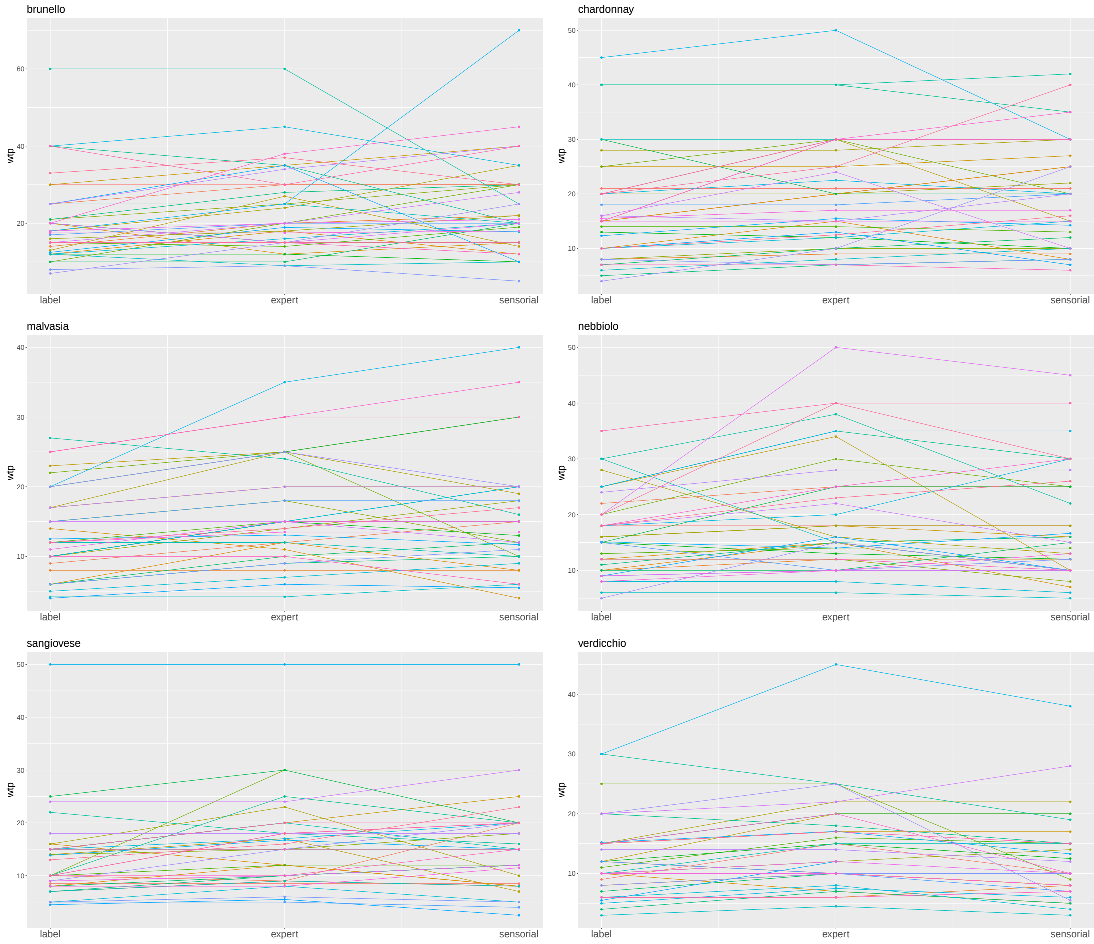

Figure 8: Willingness to pay (WTP) for each participant and wine. Each panel refers to one of the 6 wines considered in the study; in each panel, a line refers to a given participant and depicts observations of the WTP at each level of the factor cumulative information: label, expert, and sensorial.

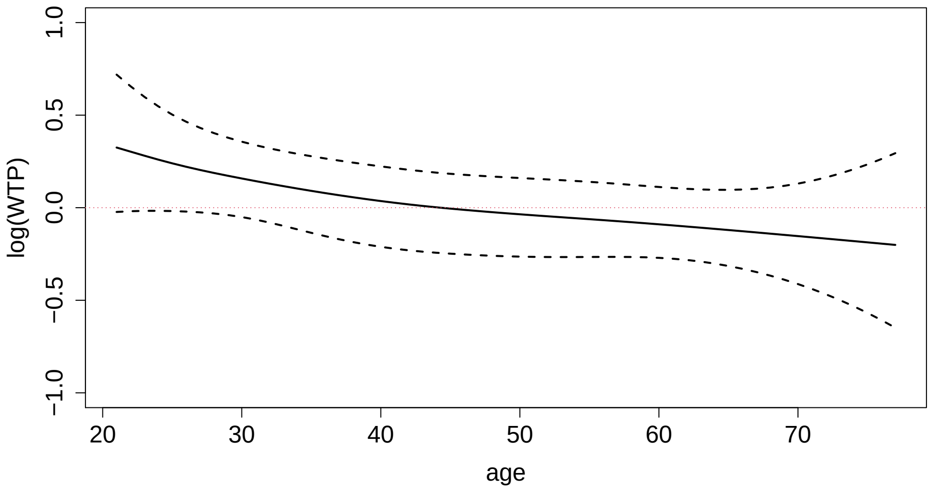

Figure 9: The fitted (log) WTP as a smooth function of age.

List of Tables

Author(s)	Wine(s)	Venue(s)	Participants	Rounds	Sessions	Info treat.	Method(s)	Model(s)
Lange et al. (2002)	5 Brut non-vintage Champagnes (white wines)	Lab and sensory room	57 (66)	–	–	3	Vickrey auc. & hedonic reg.	OLS
Lecocq et al. (2005)	2 Bordeaux and 2 Burgundy (red wines)	Conference	32	–	–	3	Vickrey auc. & bid reg.	OLS
Bazoche et al. (2008)	4 Bordeaux AOC (red wines)	Sensory room	139	–	–	3	Vickrey auc. & BDM	Tobit and Probit
Schmit et al. (2013)	4 Riesling (semi-dry white wines)	Lab	169	–	–	4	Exp. auc. & sensory models	OLS
Vecchio (2013)	3 Rosso Sicilia IGT (sustainable red wines)	Lab	80	5	–	1	Vickrey auc.	Tobit
Gustafson et al. (2016)	7 Cabernet Sauvignon (California red wines)	Sensory lab	236	7	–	5	BDM	Random effects
Boncinelli et al. (2016)	3 Chianti Classico DOCG (red wines)	Computer lab	56	3	–	3	Exp. auc. & blind tasting	Test for the differences
Ay et al. (2017)	2 Burgundy and 2 Rhone Valley (red wines)	Lab	111	–	10	5	BDM	Iteratively Reweighted Least-Squares
Pomarici et al. (2018)	3 Ischia Bianco DOC (white wines)	Computer Lab	200	5	–	1	Vickrey auc.	Random effects and Tobit
Klink-Lehmann et al. (2019)	4 Riesling (white wines)	Lab	87	3	10	4	BDM	Double hurdle model
Eustice et al. (2019)	4 Marquette (dry red wines)	Winery	47	2	–	4	BDM	4 tests (for WTP differences between
Gassler et al. (2019)	8 German, Italian and Spanish wines (4 red and 4 white)	Wine shop	110	2	–	1	Exp. auc. & blind tasting	OLS & serial mediation an.
Vecchio et al. (2019a)	12 Sangiovese of 3 denominations (Tuscan red wines)	Lab	150	2	–	2	Vickrey auc. & BDM	Par. & non-par. tests and cluster an.
Vecchio et al. (2019b)	2 Champenois and 2 Charmat method (white wines)	Lab	100	3	–	3	Exp. auc. & hedonic ratings	Parametric & non-par. tests
Ferreira et al. (2021)	1 Douro, 1 Alentejo, 1 Dao (Portuguese red wines)	Universities or business centre	168	–	9	2	BDM	OLS

Table 1: The table contains the main empirical studies on wine auctions.

Label used in the paper	Denomination	Year	ABV	Estate-bottled	Suggested serving temperature	Winery
Verdicchio	Verdicchio dei Castelli di Jesi DOC	2018	13	Y	10-12 °C	Tenuta dell'Ugolino
Malvasia	Friuli Isonzo Malvasia DOC	2017	14	Y	-	Vie di Romans
Chardonnay	Valle d'Aosta Chardonnay DOP	2016	13.5	Y	-	Les Cretes
Sangiovese	Romagna Sangiovese Superiore DOC	2016	14.5	Y	18 °C	Villa Otto Lune
Nebbiolo	Langhe Nebbiolo DOC	2016	13.5	Y	-	Vietti
Brunello	Brunello di Montalcino DOCG	2016	14.5	Y	18-20 °C	Capanna

Label used in the paper	Logos and other info	Extra text
Verdicchio	Pregnancy warning; Hand-harvested	-
Malvasia	-	-
Chardonnay	Independent Winemakers ("Vignaioli indipendenti")	-
Sangiovese	Pregnancy warning	Description of terroir and vinification technique
Nebbiolo	Pregnancy warning; Vegan	Text on the importance of handcraft and tradition in the winery
Brunello	Numbered bottle; Total number of produced bottles	Description of vinification technique and suggested food pairing

Table 2: The table contains the information reported on the labels of the wine bottles. ABV stands for alcohol by volume. Extra texts were in Italian for Sangiovese and Brunello, and in Italian and English for Nebbiolo.

Table 3: Descriptive statistics of the categorical variables observed for all 38 participants.

Variable	**Levels**	**n**	**%**
Gender	F	21	55.3
	M	17	44.7
	all	38	100.0
Do you have a job?	N	25	65.8
	Y	13	34.2
	all	38	100.0
Age	$(18, 23]$	6	15.8
	$(23, 30]$	18	47.4
	$(30, 45]$	5	13.2
	$(45, 77]$	9	23.7
	all	38	100.0
Wine glasses per week (on average)	1 or less	15	39.5
	2-4	14	36.8
	5 or more	9	23.7
	all	38	100.0
Drink usually with other people	N	2	5.3
	Y	36	94.7
	all	38	100.0
Ever bought a bottle of wine in a winery	N	14	36.8
	Y	24	63.2
	all	38	100.0
Ever bought a bottle of wine in a wine shop	N	7	18.4
	Y	31	81.6
	all	38	100.0
Ever bought a bottle of wine in a restaurant	N	3	7.9
	Y	35	92.1
	all	38	100.0
Thinking at food pairing when buying	N	5	13.2
	Y	33	86.8
	all	38	100.0
Read wine magazines	N	36	94.7
	Y	2	5.3
	all	38	100.0
Use smartphone apps about wine	N	27	71.0
	Y	11	28.9
	all	38	100.0
Ever took a wine tasting course	N	32	84.2
	Y	6	15.8
	all	38	100.0

Table 4: Model assessment results. All models include the following covariates: cumulative information (the inferential target), gender, occupation, drinking behavior, and age.

		Random effects			Performance criteria	
`model`	`interac`	`wine`	`subject`	`graph`	`DIC`	`CPO`
1	no	-	-	-	849.86	424.16
2	no	iid	iid	-	**512.79**	**257.49**
3	no	iid	bym	a	512.75	257.56
4	no	iid	besag	a	512.72	257.58
5	no	iid	bym	b	512.82	257.55
6	no	iid	besag	b	512.89	257.61
7	info:gender	iid	iid	-	513.26	257.83
8	info:age	iid	iid	-	517.25	259.73
9	info:drink	iid	iid	-	517.78	260.11

Label used in the paper	Round	Price	Quality	Distance	Distance SL	Bottles
Verdicchio	1	15.00	L	124	76	11,000
Malvasia	2	28.00	M	378	219	8,000
Chardonnay	3	45.00	H	518	457	18,000
Sangiovese	5	18.00	L	10	7	8,000
Nebbiolo	4	25.00	M	430	370	38,000
Brunello	6	58.00	H	230	141	40,000

Table 5: The table reports the round in which each wine was proposed, the prices in Euros of a bottle of the wine as found in a restaurant wine list, the quality information as determined by price hierarchy, in the ordinal scale L=Low, M=Medium, H=High, and the road distance and the distance in a straight line (SL) in km between the production location of each of the wines and Rimini, where the data collection took place. The last column reports the number of bottles produced by the winery. This information was not shared with the participants.