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# ECONOMIA AGRO-ALIMENTARE
## *Food Economy*

*(Rivista fondata da Fausto Cantarelli)*

FrancoAngeli

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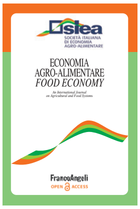

# Special Issue: Innovative Methods and Approaches in Consumer Behaviour Research in the Agri-food Sector Guest Editorial

**Alessandra Castellini**[a], **Domenico Regazzi**[a], **Roberta Spadoni**[a]

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This special issue of *Economia agro-alimentare/Food Economy* is dedicated to the memory of Maurizio Canavari, who served as Editor-in-Chief of the journal during the period 2016-2024. Under his leadership, the journal achieved significant milestones, including its indexing in Scopus and Web of Science (WOS). As an agricultural economist at the Alma Mater Studiorum – University of Bologna, Maurizio Canavari was distinguished by his ability to balance intellectual curiosity with methodological rigor. He firmly believed that, without the exchange and dissemination of knowledge, even the best ideas remain isolated, and that the application of validated methodologies ultimately confers credibility to research. Among the many topics he addressed throughout his career, he devoted particular attention to the study of consumer behaviour and to the development of methodological approaches for its analysis, exploring the broad field of experimental economics. These studies have become increasingly central to the analysis of agri-food systems, which is why the journal has chosen to dedicate this special issue to Maurizio, entitled "Innovative Methods and Approaches in Consumer Behaviour Research in the Agri-food Sector".

Understanding consumer behaviour is essential to addressing the challenges and seizing the opportunities facing the agri-food sector. The current context is marked by rapid changes in consumer values and demands, the emergence of new technologies, and growing attention to sustainability, health, ethics, and information transparency. Consumers, increasingly immersed in a digital environment, are required to choose among products, production systems, and distribution channels that differ not only in terms of price and sensory attributes but also in environmental performance, ethical implications, geographical origin, social meaning, technological content, and health-related attributes (Kleisiari *et al.*, 2026; Bohen *et al.*, 2025; Sequeira *et al.*, 2026; Tellechea *et al.*, 2025). Researchers are, therefore, called upon to adopt innovative methodologies and approaches to investigate consumer attitudes, preferences, and choices in the agricultural and food sector. This requires methods capable of capturing complexity, heterogeneity, and interconnections with the broader socio-economic context. Over time, the literature has highlighted the need for more flexible, data-rich, and interdisciplinary approaches that integrate, for example, behavioural insights and innovative analytical methodologies (Byrne, 2020; Wuepper *et al.*, 2023; Cecchini *et al.*, 2018; Steenkamp, 1997). This perspective is particularly relevant in agri-food economics, where many of the most pressing issues are complex, applied, and inherently interdisciplinary.

This special issue brings together original contributions that propose or apply advanced methods and innovative, interdisciplinary perspectives in the study of consumer behaviour, aiming to stimulate scientific dialogue on emerging tools such as data analytics techniques, neuroscience, behavioural experiments, innovative qualitative methods, digital approaches, and predictive models. These papers demonstrate how methodological innovation can deepen the understanding of agri-food choices and generate results that are more relevant for public policies, businesses, and society.

A first group of contributions expands the methodological frontier in the analysis of preferences, particularly with regard to willingness to pay. The article by Sergio Rivaroli, Mariagrazia Nitri, and Massimiliano Calvia on "Natural Wine: An Evaluation using the Price Sensitivity Meter and Contingent Valuation" provides a particularly interesting example, both for the product considered and for its methodological design. By combining contingent valuation with the Van Westendorp Price Sensitivity Meter (Van Westendorp, 1976), the authors compare two approaches based on different cognitive mechanisms and distinct modes of respondent engagement. The study not only estimates a premium price for natural wine but also investigates whether, and which, consumer attributes influence economic choices in the surveyed market, and how. The comparison is theoretically relevant as it echoes a longstanding concern in consumer behaviour research: stated values are not neutral outcomes but may depend on question framing, price salience, and whether respondents are asked to reason in terms of social value, personal utility, or acceptable price ranges. The article thus contributes not only to the literature on wine consumption but also to the broader debate on methodological triangulation and the interpretation of stated preferences in food markets. Its strategic and managerial relevance is equally evident, as pricing decisions in emerging niche markets often need to rely on multiple sources of evidence rather than a single evaluative metric.

A different but complementary perspective is offered by the study of Chaowana Phetcharat, Jeffrey D. Vitale, Pavalee Chompoorat Tridtitanakiat, Wanlanai Saiprasert, and Weirong Lu, on "Exploring Red Kidney Bean Flour as a Partial Substitute to Rice Flour in Gluten-free Ramen Noodles: Consumers' WTP in Thailand", which adopts an experimental auction design (first-price auction) to elicit non-hypothetical willingness to pay. This contribution links product innovation, nutritional aspects, and market behaviour through a method that involves a real economic commitment, as opposed to traditional survey-based approaches. In the agri-food sector, where hypothetical bias remains a recurring concern, experimental auctions, which serve as non-hypothetical and incentive-compatible choice experiments, continue to represent a benchmark for behavioural validity. In this case, the method is used to investigate consumer acceptance and willingness to pay for alternative gluten-free flour formulations, as well as to identify how specific product characteristics and consumer attributes influence bidding behaviour. The study highlights that methodological innovation does not merely consist of increasing sophistication for its own sake, but rather of selecting a research design that is appropriate to the research question, the product context, and the behavioural mechanism under investigation.

A second area addressed in this special issue concerns the analysis of consumer decisions with multiple attributes using discrete choice experiments. Three papers confirm their role not only as highly versatile and theoretically grounded tools but also demonstrate the richness and flexibility of their applications, made even more interesting by their implementation in substantially different ways. The contribution by Vera Ventura, Achille Amatucci, and Chiara Tomasoni on "Ecosystem Services in Food Labels: the Role of Different Information Layers in Shaping Consumers' Preferences" stands out for moving beyond the generic treatment of sustainability claims as simple binary attributes. Instead, it examines how different levels of information shape preference formation, ranging from broad, relatively abstract references to ecosystem services to more specific and measurable representations. One of the persistent challenges in sustainability communication is that consumers often respond not only to the content of the information, but also to its level of abstraction, complexity, and perceived credibility. By analysing alternative information architectures, the article shows that methodological innovation in consumer research is closely linked to innovation in communication design. Furthermore, by situating labels within a broader informational environment that includes complementary explanations external to the packaging, the contribution acknowledges that labels rarely operate in isolation. These insights are relevant for both policy and practice. From a methodological perspective, the article presents an innovative and integrated approach, linking values and preferences while maintaining interpretability.

The study "Balancing environmental benefits and agricultural technologies – perspectives from German consumers", proposed by Johanna Garnitz, Agnes Emberger-Klein and Andreas Gabriel, extends the discrete choice experiment approach to the analysis of agricultural systems that are complex from both a social and environmental perspective. Rather than focusing on a single food product with a standard set of quality attributes, the article investigates consumer preferences for alternative agricultural scenarios, translating production system attributes into dimensions of consumer-relevant welfare. The paper highlights the difficulty of making production characteristics, often distant from the direct consumption experience, meaningful at the point of choice. It addresses an increasingly important issue, namely how consumers perceive the interaction between ecological outcomes and technological innovation, offering insights that are also relevant for communication strategies and policy support. The analysis shows that consumer responses to technology are not uniform: some consumers value environmental improvements even when associated with less familiar technologies, while others are more cautious or price-sensitive.

The article by Giulia Maesano, Roberta Spadoni, Andrea Baroni, and Katia Laura Sidali on "High-Altitude, High Value? Consumer Preferences and Willingness to Pay for Mountain Wines" provides a further contribution, focusing on geographical labelling, sustainability perceptions, and territorial identity. The study shows that consumers are willing to attribute value to a potential extension to the wine sector of the EU optional quality term "mountain product". The "mountain" designation generates positive utility independently of organic certification, suggesting that the two labels convey distinct meanings rather than redundant information. From a methodological perspective, the article illustrates how discrete choice experiments can be used not only to estimate marginal willingness to pay, but also to test whether different trust-related attributes reinforce each other, overlap, or remain independent in consumers' minds.

The special issue also includes contributions that more directly address consumer heterogeneity through segmentation analysis and multivariate methods. The study proposed by Kristína Predanócyová, Peter Šedík, Cristina Bianca Pocol, Mihaela Mihai, and L'ubica Kubicová, on "Consumer segments and determinants shaping meat consumption in Slovakia", employs principal component analysis and cluster analysis to identify four distinct consumer segments and three broad classes of influencing factors. The study highlights that consumer behaviour is rarely homogeneous and that even within apparently stable markets, there is considerable variability. From a methodological standpoint, the paper also shows how aggregate results often conceal precisely the diversity that is most relevant for designing effective policies and market strategies.

Another theme explored concerns digitalisation and the evolving nature of expertise in agri-food markets. The conceptual contribution on "AI and Consumer Perception of Expertise: A Conceptual Framework for Studying Algorithmic Trust in Wine Recommendations", proposed by Jochen Heussner and Jon H. Hanf, examines how artificial intelligence may influence trust, authority, credibility, and perceived authenticity. The article proposes a conceptual framework integrating information asymmetry, signalling, and source credibility, identifying key constructs such as transparency, explainability, perceived expertise, and cognitive effort. This is a particularly timely topic, as AI systems are increasingly entering the market as intermediaries that aim to reduce uncertainty and information asymmetry by recommending, classifying, personalizing, and, at times, mimicking the judgment of actors.

Taken together, the studies included in this special issue illustrate, albeit not exhaustively, the richness of methodological approaches currently available. They show that innovation does not mean abandoning established methods, but rather refining, combining, and extending them, improving choice designs, modelling heterogeneity more carefully, and exploring new contexts of consumer action. Moreover, they highlight that methodological progress is strongest when it remains connected to real-world issues, thus reflecting one of the core principles of Maurizio Canavari's work. We hope that this special issue will enrich the dialogue among researchers, bringing together different generations of scholars in a multidisciplinary perspective on agri-food consumer analysis, while also highlighting the importance of engaging practitioners and public institutions.

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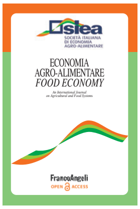


# Natural Wine: An Evaluation using the Price Sensitivity Meter and Contingent Valuation

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## *Abstract*

Natural wines have garnered increasing attention from health-conscious and environmentally aware consumers, thereby carving out a distinct niche within the broader wine market. This study adopts the Contingent Valuation method and the Van Westendorp Price Sensitivity Meter to explore consumer willingness to pay and the acceptable price range for natural wine (hereinafter: NW), verify the convergence of results, and investigate which consumer attributes influence the economic appreciation for this beverage. An online survey was conducted on a sample of 370 Italian wine enthusiasts and experts. The results indicate a reasonable level of consumer awareness of the economic value of the NW, despite their willingness to pay a lower price for this beverage. Age, individuals' income status and product market price have a positive impact on the willingness to pay for NW. Conversely, the effects of the level of education, naturalness attitude, and wine consumption habits are not significant. The results could support the efforts of the wineries to develop adequate pricing strategies for gaining a competitive advantage and expanding their market share.

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## Introduction

Understanding consumer behaviour and preferences is crucial for producers and marketers in the wine industry, especially considering the rapidly evolving segments of Natural Wines (hereinafter: NW) and low- or no-alcohol wines (Alonso González & Parga-Dans, 2020). While the definition of NW remains ambiguous among consumers due to the lack of clear and regulated definitions (Parga-Dans *et al.*, 2023; Vecchio *et al.*, 2023), NW has gained increasing attention from health and environmentally conscious consumers, thereby carving out an interesting niche within the broader wine market (Galati *et al.*, 2019).

Studies indicate heterogeneity in consumer perceptions of wine's naturalness (Vecchio *et al.*, 2023). For example, investigating the social representation of wines produced by various methods, Urdapilleta *et al.* (2021) observed that French consumers perceive NWs as healthier and more eco-friendly because they lack chemicals, whereas New Zealand consumers perceive them as lower-quality products. Italian consumers consider NW products to be environmentally friendly, additive-free, and handcrafted (Vecchio *et al.*, 2021). Swiss and Australian consumers perceive wines as "*more natural*" when produced without added sugar, sulfites, or selected yeasts, and with winemaking practices such as mechanical filtration (Staub *et al.*, 2020). Again, organic and biodynamic winegrowing practices are frequently associated with NW (Delmas & Lessem, 2017; Sogari *et al.*, 2016).

Characterised by minimal intervention in the winemaking process and a strong emphasis on ecological sustainability, NW production requires answering two key questions: How do wineries signal their commitment to customers? What is the consumers' willingness to pay (hereinafter: WTP) for the NW? The first question highlights the need to effectively bridge the gap between wineries and consumers by providing reliable information on the natural qualities of wine, such as those promoted by the NW protocol of the Italian association Vinnatur®. Indeed, Ginon *et al.* (2014) noted that most logos are not able to convey a message of environmental sustainability effectively. The second question sheds light on the economic effectiveness of labelling a wine as "*natural*". According to Bazzani *et al.* (2024), consumers value specific winemaking techniques and ecological certifications more than the general NW claim, underscoring the importance of conveying specific natural features rather than a natural label to enhance consumer perception of naturalness and WTP.

Given the growing appeal of natural products (Galati *et al.*, 2019; Migliore *et al.*, 2020), investigating consumers' WTP for NW and identifying the socio-demographic and attitudinal aspects that might influence it is crucial for uncovering new insights into a key trend in the wine market and to identify suitable price marketing strategies for wineries. Although less precise than direct incentive-compatible methods such as experimental auctions (Steiner & Hendus, 2012), the Contingent Valuation Method (hereinafter: CVM) and the Van Westendorp Price Sensitivity Meter (hereinafter: VW-PSM) (Van Westendorp, 1976) prove to be reliable yet relatively cheaper and simpler methods to assess the price that respondents are willing to pay for a product. Even if the CVM is questioned for hypothetical responses that overestimate WTP (Lusk & Schroeder, 2004), recent literature suggests that biases are less significant for low-priced private goods (Vecchiato *et al.*, 2021). Furthermore, as noted by Steiner and Hendus (2012), the VW-PSM is considered the most widely used method firms employ to measure WTP when establishing pricing strategies, thereby bridging the gap between academic theorisation and the pragmatism of managerial action.

Pricing a new product or service is one of the most crucial decisions a winery must undertake. This need arises during the development of a new product or the introduction of an existing product in a new geographical area or distribution channel. As such, this study employs CVM and VW-PSM to investigate consumer WTP and prices for NW, thereby verifying the convergence of results and examining which consumer attributes influence economic appreciation. From a theoretical perspective, this research broadens the current understanding of consumers' pricing and economic valuation of NW. From a managerial standpoint, the findings provide actionable insights for producers and retailers. The remainder of this article is organised as follows: the hypotheses at the core of this study are presented, along with a review of scholarly literature on consumer attitudes and preferences for NW. Subsequently, the research data and methods are presented, followed by results, discussion, conclusions, and implications for research and business.

## 1. Background and research hypotheses

According to Meiselman (1995), launching a new product is undoubtedly a considerable challenge that necessitates understanding in advance whether it aligns with customers' perceived monetary values, beyond sensorial appreciation. Additionally, consumer prices can be examined by considering how specific socio-demographic and attitudinal factors may influence perceptions of a product's value (Costa & Jongen, 2006). Thus, understanding the socio-demographic and attitudinal drivers of consumer WTP in the niche market of NW seems essential for wineries and marketers aiming to segment and target potential buyers effectively. Considering that every food product's success can also be related to specific pricing strategies targeted for consumer segments, these research questions arise: Are WTP's central estimates and confidence intervals significantly different between CVM and VW-PSM price thresholds? (RQ1) Are customers' socio-demographic aspects and food naturalness attitude relevant to their WTP for NW? Which of them prevails, if any? In which measure? (RQ2).

*Convergence of WTP measurement results*

Among the various approaches to investigating consumers' WTP, the CVM is a stated-preference, survey-based method for determining the value of non-market goods and services. This method involves constructing a hypothetical market in which respondents are asked to state their monetary valuation (Bateman, 2002). It is grounded in welfare economic studies to measure the total economic value of non-market goods, including use and non-use values. Despite its versatility and its use for market goods, the CVM has been subject to critical scrutiny, particularly regarding hypothetical bias that tends to overestimate WTP (Lusk & Schroeder, 2004). On the other hand, focusing on the consumer preferences for tinned chianina meat, Vecchiato *et al.* (2021) recently suggested that these biases are less significant for low-priced private goods. The CVM has gained prominence in the food science literature as a valuable tool for determining consumer preferences and the WTP for various beverages. For example, in their study exploring the factors affecting consumers' WTP for ready-to-drink fruit drinks, Vorasayan *et al.* (2018) concluded that the CVM can effectively capture consumer WTP in the food and beverage industry. Staples (2024) employs the CVM to evaluate consumer preferences for cannabis-infused beverages and the WTP for different beverage categories, providing valuable market insights. Again, Ruggeri *et al.* (2022) adopted the CVM to define Italian wine consumers' preferences and WTP for canned wine.

The VW-PSM, on the other hand, is a heuristic pricing tool widely used to assess consumer price perceptions and WTP. The goal is to evaluate the optimal price range for marketing a specific, usually new, product (Paczkowski, 2019). Despite its widespread corporate use, the VW-PSM has also proven particularly useful in research spanning several contexts, such as the measurement of WTP for on-demand software services (Harmon *et al.*, 2007), 4G in India (Khandker & Joshi, 2019), lion protection fees in several African countries (Moorhouse *et al.*, 2023), on-farm processed skimmed yoghurt (Gellynck & Viaene, 2002), microalgae meat substitutes in Germany (Weinrich & Gassler, 2021), German husbandry labels (Kühl *et al.*, 2024), and fish fed with insects (Arru *et al.*, 2022). A few insightful examples also encompass the evaluation of optimal price ranges for alcoholic and non-alcoholic beverages. Kim *et al.* (2012) employed the VW-PSM method to estimate the impact of observing the process of squeezing fresh oranges on consumers' WTP for a glass of fresh juice. A two-sample t-test essentially highlighted a non-significant effect on the price of a glass of orange juice. Moving to alcoholic beverages, Szakál *et al.* (2023) employed the VW-PSM method to assess the optimal price, in a Van Westendorp sense, of three wine varieties, namely Irsai Olivér, Rosé and Merlot-Shiraz, under three different labels in Hungary. The analysis allowed to assess which label was the most profitable for each kind of wine. Recently, Calvia *et al.* (2025) used the VW-PSM to determine the WTP for the attribute "*precision viticulture*" of the Italian wine "*Falanghina del Sannio*", thus providing a valuable benchmark for its potential market pricing. Despite the studies mentioned above confirming the suitability of the VW-PSM method for generating compelling results at moderate cost, the findings might be biased, leading to an underestimation of the WTP value. Indeed, although both the CVM and VW-PSM methods for determining WTP are affordable, the lower monetary valuations produced by the VW-PSM method seem to stem from differences in cognitive framing and methodological design. The VW-PSM method, in fact, encourages individuals to evaluate price perception directly, thereby activating "*value-for-money thinking*", which refers to the consumer's overall assessment of a product's utility based on perceptions of what is received and what is given (Zeithaml, 1988). The CVM, on the other hand, encourages respondents to consider both personal utility and social/environmental value, thereby capturing a total economic value and eliciting a higher WTP. Thus, considering the points mentioned above, the following hypothesis was tested:

**Hypothesis 1 (H1)**: The price estimated for a 0.75 L bottle of NW using the Van Westendorp Price Sensitivity Meter is significantly lower than the WTP estimated using the Contingent Valuation Method.

### *Naturalness attitude*

Consistent with the existing literature, information about wine ingredients, such as sulphites, may affect consumers' WTP due to their perception of naturalness. In a study investigating perceptions of sulfites and WTP for non-sulfited wines, Costanigro *et al.* (2014) found that US consumers are willing to pay a premium for non-sulfited wines. In the same vein, D'Amico *et al.* (2016) found that naturalness is an attribute of organic wines positively related to the probability of paying a premium price for wine with no added sulfites. In a study aimed to assess consumers' WTP for wine bearing a sulphite-free label in Italy and Spain, Amato *et al.* (2017) show that consumers who associate the headaches with drinking wines with sulphites are also willing to pay a premium price for no-sulphite wine. More recently, Chikumbi *et al.* (2021), in a study investigating perceptions and preferences for several wine attributes among South African consumers, found that they are willing to pay at least three times more to replace sulphur-based preservatives with a natural alternative. Therefore, in this context, the following hypothesis was examined:

**Hypothesis 2 (H2)**: The perception of a product's naturalness positively influences individuals' WTP for NW.

*Age*

Previous studies have investigated the socio-demographic aspects affecting consumers' wine WTP. Age, among other factors, appears to be a significant driver of attitudes and of individual WTP for wine, including NW. Younger consumers, such as Millennials and Gen Z, tend to exhibit greater openness toward sustainable and unconventional products, including NW (Forbes *et al.*, 2009; Gow *et al.*, 2024; Migliore *et al.*, 2020), probably due to their most pronounced inclination to value authenticity and seek food and beverage products that align with their lifestyles and ideal values. Galati *et al.* (2019), in a study aimed at identifying which consumers are willing to pay for NW, found that the probability of higher WTP for NW increases among young consumers. Thus, the following hypothesis was tested:

**Hypothesis 3 (H3)**: An increase in respondents' age negatively affects WTP for NW.

*Gender*

Furthermore, the existing literature suggests that there are gender differences in wine consumption behaviour. Studies indicate that women may be more sensitive to health-related attributes and environmental concerns when selecting wines, which could positively influence their interest in NW and their WTP (Sogari *et al.*, 2016; Vecchio, 2013). Conversely, men are often perceived as being more brand- and price-aware, which may influence their WTP for NW. Therefore, the following hypothesis was tested:

**Hypothesis 4 (H4)**: Women have higher WTP for NW than men.

*Education Level*

Regarding socio-demographic wine consumption patterns, the existing literature suggests that higher education levels are consistently linked with greater awareness of sustainable food and beverage trends (D'Amico *et al.*, 2016), including NW. Educated consumers are more likely to read labels, understand certifications, and show interest in production processes. They may also be better able to navigate the ambiguity surrounding definitions of "natural," which remains controversial (Mann *et al.*, 2012). Thus, this trait might enhance the likelihood of purchasing NW and increase the WTP for it. The following hypothesis was subsequently tested:

**Hypothesis 5 (H5)**: Educated consumers have higher WTP for NW than less educated consumers.

*Income*

Consistent with the existing literature, higher income levels are positively correlated with both purchase frequency and WTP for wine, particularly for sustainably produced wines (Mauracher *et al.*, 2019; Modica *et al.*, 2025; Polzin *et al.*, 2023; Pomarici *et al.*, 2016; Valenzuela *et al.*, 2022, among others). In analysing the WTP for a sustainable wine, Sellers-Rubio & Nicolau-Gonzalbez (2016) found that higher income is associated with a higher propensity to pay a premium price. Affluent consumers may also be more engaged in exploratory consumption, perceiving NW as a cultural or experiential product rather than a commodity, and therefore willing to pay a premium price for it. In light of this evidence, the following hypothesis was tested:

**Hypothesis 6 (H6)**: Affluent consumers have higher WTP for NW.

*Wine consumption frequency*

Extant research provides slightly contradictory findings regarding the effect of consumption habits on the WTP for sustainable wines, including NW. According to recent investigations, the frequency of wine consumption may positively influence consumers' WTP. Migliore *et al.* (2020), for example, examined which consumer habits affect WTP for a premium-priced bottle of NW in Italy. The findings indicated that drinking frequency is positively associated with a higher WTP. While Vecchio *et al.* (2021)

demonstrate that the frequency of wine consumption affects the consumption of NW, Vecchio *et al.* (2023) added that wine drinking frequency is a relevant driver of the WTP for NW. On the other hand, while Mauracher *et al.* (2019) showed that low wine consumption frequency increases WTP for organic wines, Moscovici *et al.* (2020) discovered that consumers purchasing wine for a special occasion, i.e., not frequently, are more likely to pay higher prices for sustainable wine compared to more regular buyers. Despite these contradictory findings, the following hypothesis was tested:

**Hypothesis 7 (H7)**: Higher wine consumption frequency is associated with higher WTP for NW.

### *Price*

The relevance of the relationship between wine pricing and consumers' WTP for wine has been recognised by scholars in the field. According to Lewis *et al.* (2014), price is a component of customers' perceived utility and is closely related to WTP. In particular, the study, based on a wine-tasting experiment, reveals that consumers' WTP is significantly influenced by the price presented, which potentially acts as a proxy for product quality, especially for consumers with less wine expertise. Similarly, Goldstein *et al.* (2008) pointed out that price is a proxy for the quality of wine that influences the individual's WTP, this result holding in particular for non-expert consumers. In light of this evidence, it was predicted that:

**Hypothesis 8 (H8)**: The proposed price during the contingent valuation experiment positively influences the individuals' WTP for NW.

## 2. Materials and methods

### *Participants*

This study employed a non-probabilistic sampling design, utilising data collected between December 2023 and February 2024. Three hundred seventy participants were recruited through social media network platforms, specifically thematic groups on Facebook for Italian wine enthusiasts and LinkedIn for Italian wine experts, through snowball sampling. Although snowball sampling does not ensure representativeness, it allows researchers to reach targeted populations (i.e., wine enthusiasts) that would otherwise be difficult to survey, thereby offering valuable exploratory insights into the behavioural determinants under examination. The post provided a brief description of the study and included a link to the questionnaire on the Qualtrics® platform.

The target of an even gender distribution was closely achieved, with 52.3% of the respondents being men and 47.3% being women. The respondents' ages ranged from 21 to 75, with a mean of 42.9 and a standard deviation of 12.2. A total of 54.2% (N = 110) of respondents held an academic degree, 78.8% (N = 160) were employed, 7.9% (N = 16) were students, and 5.9% (N = 12) were seeking employment. A total of 7.4% (N = 15) of respondents were retired. 55.2% of respondents live in North-West Italy, 17.5% in North-East Italy, 13.9% in Central Italy, and 12.6% in South Italy or the Italian islands, while 0.8% live abroad. Furthermore, 38.6% of interviewees stated that they have no financial problems at all, and when they feel like buying something, they do so. Despite having enough to get by, 47.1% of respondents rarely allow themselves any luxuries. Meanwhile, 14.3% of individuals pay close attention to their spending and sometimes find their income insufficient for essential purchases.

### *Questionnaire and Measurement Scales*

The questionnaire was divided into five sections. The first part included a preliminary overview of the study's aim and a question regarding consent to participate. If the interviewee agreed to participate, drinking frequency was measured by a single item that asked, "*On the day you drink wine, how many glasses of wine do you typically drink during meals?*", consistent with a similar item that Goldsmith & d'Hauteville's (1998) operationalised as a measure of wine drinking frequency in their study. Responses were recorded on a 5-point scale (1 = Nothing, 2 = one or less than one glass, 3 = two or three glasses, 4 = four or five glasses, 5 = more than five glasses). The survey ended if respondents reported not drinking wine during the meals.

In a second section, attitude for natural food/beverage was assessed using the Preference for Natural Food and the Risk Perception of Addictive subscales adopted in Dickson-Spillmann *et al.*'s (2011) study and two items adapted from the Natural Products subscale proposed by Dantec *et al.* (2025) (Table 1). All items were measured on a 5-point scale (1 = Strongly Disagree and 5 = Strongly Agree), offering the respondents the opportunity to manifest their neutrality and introduce each sentence with the question "*How much do you agree with the following statements concerning the product you eat or drink?*".

In the third section of the questionnaire, respondents' price acceptance and sensitivity were measured using Van Westendorp's Price Sensitivity Meter approach (Van Westendorp, 1976). To identify four price levels, respondents were asked: i. "*At what price would a 0.75 L bottle of natural wine be so expensive that you would not buy it?* (Too expensive); ii. "*At what price* *would a 0.75 L bottle of natural wine be expensive, but you would still buy it?*" (Expensive); iii. "*At what price would a 0.75 L bottle of natural wine be cheap enough to consider it a good bargain?*" (Cheap); iv. "*At what price would a 0.75 L bottle of natural wine be so cheap that you would doubt its quality and therefore decide not to buy it?*" (Too cheap).

*Table 1 - Items and factor statistics for the preference for natural food and beverage (n = 203)*

| Item number | **Median** | **Mean** | **SD** | **α-item** | ***H*-coeff** | ***Factor loading*** |
|---|---|---|---|---|---|---|
| 1. I try to buy foods and beverages without artificial ingredients[(a)] | 5 | 3.87 | 1.06 | 0.87 | 0.56 | 0.76 |
| 2. I avoid foods and beverages containing preservatives[(a)] | 4 | 3.51 | 1.10 | 0.87 | 0.57 | 0.77 |
| 3. I avoid foods and beverages containing additives[(a)] | 4 | 3.63 | 1.06 | 0.86 | 0.61 | 0.81 |
| 4. I avoid consuming foods and beverages that have artificial colours[(b)] | 4 | 3.84 | 1.09 | 0.87 | 0.57 | 0.77 |
| 5. I am worried for hormones, pesticides and chemical residues in foods and beverages[(a)] | 5 | 4.29 | 0.83 | 0.88 | 0.54 | 0.66 |
| 6. I avoid foods produced with OGM[(a)] | 4 | 3.76 | 1.25 | 0.88 | 0.49 | 0.65 |
| 7. I do not eat processed foods, because I do not know what they contain[(a)] | 4 | 3.92 | 1.04 | 0.87 | 0.54 | 0.69 |
| 8. I believe consuming natural foods and beverages is healthier than consuming highly processed foods[(b)] | 4 | 4.08 | 0.98 | 0.89 | 0.44 | 0.61 |

*Notes*: [(a)] Adapted from Dickson-Spillmann *et al.* (2011) [(b)] Adapted from Dantec *et al.* (2025).

The fourth section of the questionnaire, which involved the economic valuation of 0.75 L of NW, was conducted using the CVM via Double-Bounded Dichotomous Choice for its efficiency in WTP estimation (Hanemann *et al.*, 1991). Furthermore, from a behavioural economics perspective, this format reflects how individuals establish their valuations in real-world contexts, i.e., the initial reactions (first bid) are adjusted after reflection or exposure to a slightly modified reference price (second bid). Two consecutive questions (Q1 and Q2) asked whether respondents would buy a 0.75 L bottle of NW at a given selling price. Based on dichotomous "buy" or "do not buy" responses, this method identified the upper and lower bounds of respondents' willingness-to-pay (WTP). During Q1, respondents were initially presented with a randomly selected price ($P_0$). The price was chosen randomly from €10.00 to €30.00 in Q1. The price range was based on the selling prices in Tannico (Tannico S.r.l., 2024), one of Italy's leading online wine shops specialising in Italian and international wines, champagnes, and spirits. By offering a wide selection of both traditional and NW across various price ranges and regions, Tannico acts as a consistent benchmark for assessing market prices in the Italian wine industry. Additionally, using a single, well-established platform ensured data consistency and comparability. Depending on the yes/no response to Q1, a 50% price increase ($P_h$) or a 50% discount ($P_l$) was considered in Q2. Thus, from the combination of responses to Q1 and Q2, four paired outcomes were possible: (1) no-no; (2) no-yes; (3) yes-no; (4) yes-yes. Thus, the respondents' WTP for a 0.75 L bottle of NW will fit into one of four intervals: (-∞; $P_l$), ($P_l$, $P_0$), ($P_0$, $P_h$) and ($P_h$, +∞), and the discrete outcomes of the bidding process (D) are defined as follows:

$$D = \begin{cases} 1 & WTP \leq P_l \quad (No - No\ responses) \\ 2 & P_l \leq WTP \leq P_0 \quad (No - Yes\ responses) \\ 3 & P_0 \leq WTP \leq P_h \quad (Yes - No\ responses) \\ 4 & P_h \leq WTP \quad (Yes - Yes\ responses) \end{cases} \tag{1}$$

Thus, the survey data were classified as left-censored for "no-no" responses, right-censored for "yes-yes" responses, and interval-censored for "no-yes" and "yes-no" responses given by each respondent.

The questionnaire concluded with a section collecting participants' socio-demographic characteristics, including sex, level of education, age, and income status. Current income status-related data was obtained through a checklist, which had three options among which respondents were able to choose only one of the following statements: "*I am very careful about what I spend; sometimes my income is not enough for necessary purchases*", "*I have enough to get by; I rarely allow myself any luxuries*", and "*I have no financial problems; when I feel like buying something I do so*".

### *Empirical model and data analysis*

In this study, it is assumed that each respondent *i* had a WTP for a 0.75 L bottle of NW ($WTP_i^*$), that is to say, the latent variable in equation (2) below:

$$WTP_i^* = \beta X_i + \varepsilon_i \tag{2}$$

where $\beta$ is a vector of coefficients, $X_i$ is a vector of the WTP determinants (i.e., attitudes towards natural products, age, gender, income status and wine drinking frequency) and the error term $\varepsilon_i$ is assumed to have a mean of zero and be normally distributed. Thus, $WTP_i^*$ is unobserved. Still, it remains within the range of the lower bound ($L_i$) to the upper bound ($U_i$), consistent with the right-censored and interval-censored data collected. If a respondent has a "yes-no" response, the probability of the true $WTP \subset [P_0, P_h]$ could be represented by equation 3:

$$Pr(P_0 \leq WTP \leq P_h) \tag{3}$$

whereas if the respondent has a "yes-yes" response, the probability of the true $WTP \subset [P_h, \infty]$ is:

$$Pr(P_h \leq WTP) \tag{4}$$

The same rule could be applied to the two WTP values in interval data referred to as "no-yes" and "no-no" responses. Since the dependent variable WTP is in the interval and involves (right/left) censored data, the information collected through the double-bounded contingent valuation online survey was analysed employing an interval regression model (Cawley, 2008) in STATA 18 (StataCorp LLC, 2024) via the interval regression command "*intreg*". This helped estimate the factors influencing the WTP of Italian respondents for a 0.75 L bottle of NW. The initial bidding price ($P_0$) value was included into the empirical model to detect the bias of the anchoring effect, while the categories "*I am very careful about what I spend; sometimes my income is not enough for necessary purchases*" and "*1 = Nothing*", were respectively adopted as a reference for the variables "*Income status*" and "*Wine consumption frequency*". Data cleaning was previously performed to delete the answers that included missing values.

To assess the interviewees' attitudes towards the natural food/beverage construct, the items' properties were evaluated using the "*validscale*" command in STATA 18 (Perrot *et al.*, 2018). Internal consistency and scalability were evaluated using Cronbach's α and Loevinger's *H* coefficients; the acceptable thresholds were 0.70 for Cronbach's α and 0.30 for Loevinger's *H*. Specifically, Cronbach's α assesses how well items measure the same underlying construct, while Loevinger's H coefficient shows the strength of the hierarchical structure of the items.

Construct validity was tested using confirmatory factor analysis (CFA) and goodness-of-fit indices. The adequacy of the statistical model was assessed using RMSEA and CFI indices. An RMSEA < 0.10 and a CFI > 0.90 are generally considered to indicate a good model fit (Hu & Bentler, 1999). The z-scores resulting from the factor analysis of the items were used in the interval regression analysis, along with the initial bidding price ($P_0$), to test for anchoring. To illustrate the relative importance of the WTP determinants, the Shorrocks-Shapley decomposition of the *R*-squared obtained after conducting ordinary least squares regression using a WTP midpoint value was applied (Shorrocks, 2013). This approach allows us to assign a proportion of variance explained to each explanatory variable, providing a more precise measure of their relative importance than simple regression coefficients. The predicted latent WTP from the interval regression was used to plot the distribution of latent WTP for 0.75 L of NW across the sample and to compare convergence with the VW-PSM price-sensitivity model results visually.

The Van Westendorp Price Sensitivity Meter was used to identify significant price points of interest. The proportions of each response to the four pricing inquiries were plotted: Too Cheap, Cheap, Expensive, and Too Expensive. The intersection of the plotted lines labelled "*Expensive*" and "*Too Cheap*" is defined as the Point of Marginal Cheapness (PMC). Conversely, the Point of Marginal Expensiveness (PME) is defined as the intersection of lines labelled "*Cheap*" and "*Too Expensive*". These two points define the Pricing Options Range (POR), that is, the best range of prices from which the seller should choose the actual price. Indeed, for prices outside this range, customers generally seek a replacement product or service. The Optimal Price Point (OPP), i.e., the crossing of the "*Too Cheap*" and "*Too Expensive*" lines, can be interpreted as the point where purchase resistance is at its lowest, in that it reflects the lowest percentage of consumers that would not buy a certain product because they find it too cheap or too expensive. In other words, the majority of customers would find that price acceptable if not optimal.

On the other hand, the indifference point (IPP), i.e., the intersection of the "*Cheap*" and "*Expensive*" lines, is the point at which a relatively large percentage of consumers would judge the NW as relatively ordinary, i.e., a good bargain, in terms of price. In other words, the PP is the price at which the maximum share of potential buyers can be reached (Arru *et al.*, 2022) and, as such, it can be considered as the normal market price (Harmon *et al.*, 2007). The Stress Factor (SF) is also measured as

$$SF = \frac{(IPP - OPP)}{(PME - PMC)} 100 \tag{5}$$

which can be interpreted as the percentage level of price stress attributable to the spread between OPP and IPP over the Pricing Options Range. In other words, a large discrepancy between the amount consumers consider a good deal (IPP) and the price most respondents would like to pay (OPP) reflects a greater degree of stress, leading to consequent price movements. On the other hand, the more similar the OPP and the IPP, the lower the market price stress for that product, reflecting higher price stability (Paczkowski, 2019).

The points mentioned above and the related ranges identified by the VW-PSM procedure were identified rearranging the original dataset according to a two-steps procedure: first, all the answers to the "*Too expensive*" question with a value larger or equal than €250 have been deleted since they basically represent outliers; second, only the logically as consistent responses were kept, which comply with the logical rule Too cheap Cheap Expensive Too Expensive (Paczkowski, 2019). According to this procedure, the results of the VW-PSM analysis are based on 198 observations.

## 3. Results

*Validation of the preference for natural food subscale*

Internal consistency and scalability were adequate to support the consideration of the unidimensionality of the consumer attitude towards the natural food construct. The loadings of all eight items are equal to or exceed 0.6 (Table 1), indicating that the variables employed can measure the same concept. Cronbach α for the dimension investigated was 0.89, while $\chi^2(20) = 65.45$, $p = 0.000$, RMSEA (0.101), SRMR (0.052), and CFI (0.939) suggest an acceptable fit of this construct.

*WTP estimation model*

The fit of the regression model is relatively moderate, as indicated by the McKelvey & Zavoina *R*-squared test (Table 2), which is widely regarded as one of the most appropriate $R^2$ equivalents for models with limited dependent variables (McKelvey & Zavoina, 1975). This suggests that while socio-demographic and attitudinal variables were included in the model, additional psychological and contextual factors not captured in the dataset likely account for further variation in consumers' WTP for NW.

Analysing the results of the estimates reveals that the anchoring effect variables are significantly linked to the WTP ($p < 0.01$) and explain the majority of the model's *R*-squared (65.46%). This result may be attributed to respondents anchoring their WTP to the first bid presented by interviewers they perceived as trustworthy, rather than to ambiguity or limited familiarity with the valued scenarios, given the recruitment strategy of contacting wine enthusiasts and experts.

The second most significant factor influencing consumers' WTP for NW is the age of the interviewees (% R2 = 8.12; $\beta = -0.21$; $p < 0.05$), indicating that younger consumers are more likely to pay for NW, with no significant difference observed between men's and women's WTP (Figure 1). As expected, higher income status was associated with significantly greater

WTP, despite the model's low *R*-squared (1.45%). Compared with respondents who declared a low income status, those without financial problems were willing to pay an additional 9.62€ ($p < 0.01$). The coefficients for "*Gender*" (% $R^2$ = 6.97%) and "*Education*" (% $R^2$ = 6.02%) were positive, suggesting a potentially positive relationship with WTP. However, the impact of these determinants was not statistically significant ($p > 0.1$). Therefore, this result should be interpreted with caution.

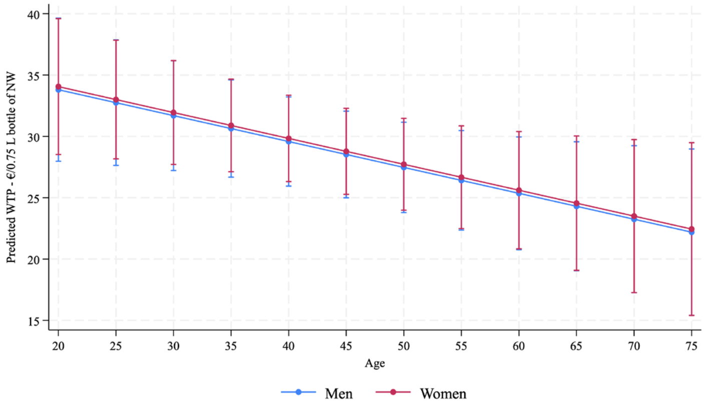
Based on interval regression estimates, the mean predicted WTP was €29.07 (95% CI: €26.54 – €31.61), indicating a good economic appreciation for a 0.75L bottle of NW.

*Table 2 - Determinants of respondents' WTP for natural wine (interval regression outcomes; n = 203)*

| **Variables** | **Hypotheses** | *β* | **(SE)** | ***p*-value** | ***[95% CI]*** | ***%R2*** |
|---|---|---|---|---|---|---|
| **Food naturalness** | $H_2$ | 0.56 | 1.34 | 0.68[b] | –2.13,3.24 | 5.80 |
| **Age** | $H_3$ | –0.21** | 0.10 | 0.03[b] | –0.40,0.02 | 8.12 |
| **Gender** | $H_4$ | | | | | 6.97 |
| – Female[a] | | – | – | – | | |
| – Male | | 2.89 | 2.36 | 0.22 | –7.52,1.73 | |
| **Education** | $H_5$ | | | | | 6.02 |
| – No academic degree[a] | | – | – | – | | |
| – Academic degree | | 1.38 | 2.23 | 0.54 | –3.00,5.75 | |
| **Income status** | $H_6$ | | | | | 1.45 |
| – IS-1[a] | | – | – | – | | |
| – IS-2 | | 1.48 | 3.16 | 0.64 | –4.71,7.68 | |
| – IS-3 | | 9.62*** | 3.52 | 0.01 | 2.72,16.52 | |
| **Wine drinking frequency** | $H_7$ | | | | | 6.12 |
| – 1[a] | | – | – | – | | |
| – 2-3 | | 3.67 | 2.51 | 0.14 | –1.26,8.60 | |
| – 4-5 | | 9.38 | 7.16 | 0.19 | –4.66,23.41 | |
| – >5 | | 12.67 | 11.00 | 0.25 | –8.89,34.24 | |
| ***Anchoring effect ($P_0$)*** | $H_8$ | 0.53** | 0.22 | 0.01 | 0.11,0.96 | 65.46 |
| ***_cons*** | | 22.14*** | 6.70 | 0.01 | 9.00,35.28 | |
| **Sigma** | | 13.58 | 0.89 | | | |
| **McKelvey & Zavoina's $R^2$** | 0.18 | | | | | |

Notes: *** p<.01, ** p<.05, * p<.1; [a] Reference category; [b] Hypothesis rejected; [c] Hypothesis accepted; IS-1="I am very careful about what I spend; sometimes my income is not enough for necessary purchases"; IS-2="I have enough to get by; I rarely allow myself any luxuries"; IS-3="I have no financial problems; when I feel like buying something I do so".

*Figure 1 - Predicted WTP for a 0.75 L bottle of natural wine by age and gender*




*Van Westendorp Price Sensitivity Meter*

As shown in Table 3 and Figure 2, the VW-PSM analysis indicates a meaningful price range of €10.12-€17.00 for 0.75 L of NW. Only a minority of respondents (9.92%) find the price of €10.64 (OPP) too extreme, suggesting that this could be an excellent price to attract a relatively large number of potential customers. On the other hand, a relatively larger number of customers (29.80%) find €15.60 (IPP) an acceptable price for 0.75L of NW. Finally, an SF of 70.09% is measured, indicating a relatively high level of price stress and, consequently, a potential source of price dynamics in the NW market. Figure 3 illustrates a disconnection between perceived and latent price preferences (i.e., VW-PSM vs CVM). The Van Westendorp thresholds (€10.12 – €17.00/0.75L of NW) are completely detached from the density curve peak. Respondents report a lower acceptable price despite their higher economic valuation of NW (i.e., WTP), thereby indicating consumer surplus. Another hypothesis is that interviewees may undervalue the NW when responding to questions about price sensitivity.

*Table 3 - Van Westendorp price points for 0.75L of natural wine (n = 198)*

| **VW's price points** | **Price [€/0.75 L of NW]** | **Respondents [cum. %]** |
|---|---|---|
| Point of marginal cheapness (PMC) | 10.12 | 16.22 |
| Point of marginal expensiveness (PME) | 17.00 | 19.70 |
| Optimal price point (OPP) | 10.64 | 9.92 |
| Indifference price point (IPP) | 15.60 | 29.80 |
| Range of acceptable pricing (ARP) | 10.12-17.00 | – |

*Figure 2 - Van Westendorp price sensitivity plot for natural wine (n = 198)*

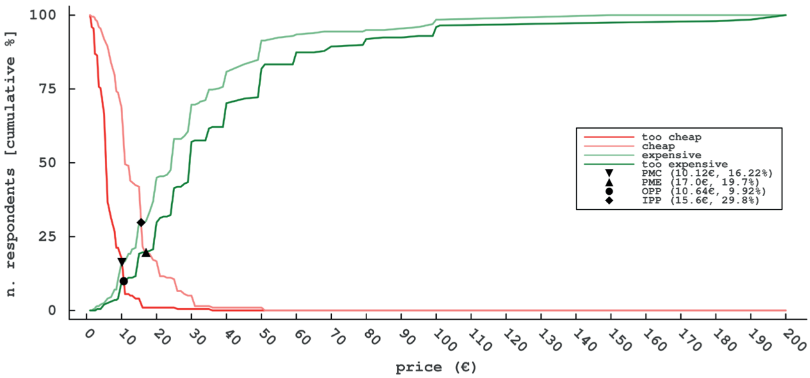
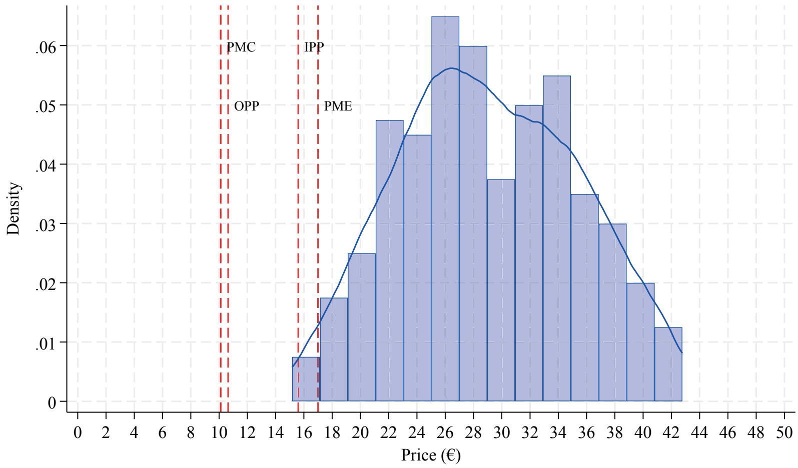



*Figure 3 - Interval Regression vs. Van Westendorp Thresholds for natural wine (H1)*




## 4. Discussions

The study aimed to analyse the convergence of consumers' WTP for a 0.75 L bottle of NW using the CVM, alongside pricing findings from the VW-PSM method. Additionally, we examined which consumer attributes affect the perceived economic value of this beverage. In this context, eight hypotheses were tested. The results make a valuable contribution to the literature on economic appreciation and pricing strategies within the broader wine market niche, particularly those related to NW.

The monetary valuation produced by the VW-PSM method is considerably lower than the WTP calculated by the CVM, prompting us to accept **Hypothesis 1**. This result aligns with the findings of Kim *et al.* (2012) and seems to stem from a lack of incentive compatibility in the VW-PSM method as well. As noted by Mitchell and Carson (2013), in the VW-PSM method, respondents may express low price thresholds without consequences, relying on personal reference prices, social norms, mental shortcuts, or decision rules, rather than on external cues, which tend to undervalue the product. In line with Zeithaml (1988), the VW-PSM method appears to activate the so-called "*value-for-money thinking*" by asking respondents to reflect on acceptable versus unacceptable prices, rather than their maximum WTP, as some customers possess high price awareness (PME) but prefer a lower price (PMC). Conversely, the CVM, as developed by Mitchell & Carson (2013), is intended to measure both use and non-use values, thereby estimating the total economic value for a 0.75L bottle of NW. It elicited a higher WTP due to its incentive-compatible design, which presents interviewees with a hypothetical market transaction through a specific scenario using the question: "*Would you be willing to pay €X for a bottle of 0.75L of natural wine?*". According to Carson and Groves (2007), the use of direct questions and initial reference prices may lead to an overestimation of the WTP. However, in this study, we minimised these potential distortions by providing interviewees with a clear, neutral description of the good being evaluated and by randomising the initial bids. Accordingly, while we acknowledge these limitations, we consider the CVM approach appropriate for capturing the NW's comprehensive economic value. Thus, the findings shed light on the interaction between the economic value of NW and the price consumers are willing to pay for it. Given that the perceived range values exceed the acceptable pricing range established by the VW-PSM method (i.e., the Kernel density curve is to the right of the ARP limits), this can reasonably be attributed to consumer surplus, which could generate and reinforce strong purchasing power motivation. One rationale for this evidence is the hypothesis that consumers may underestimate the direct monetary efforts or minor financial gains associated with the natural winemaking process, despite recognising the product's implicit value. In any case, we intend to explore this assertion further in future research.

Contrary to the hypothesis, the consumer's attitude towards natural food and beverages does not significantly influence interviewees' WTP for a 0.75 L bottle of NW, thereby rejecting **Hypothesis 2**. This outcome could be attributed to multifaceted motivations. One such motivation may arise from the adopted construct, which generally refers to freshness, minimal processing, and the absence of artificial additives and chemical residues. Conversely, NW may involve specific winemaking techniques and the absence of certain chemicals, such as sulphites, gelatin, or added sugar (Staub *et al.*, 2020). These factors require further consideration and exploration to define the referenced construct more accurately. This discrepancy in the conceptualisation of the construct may have hindered the likelihood that a positive attitude towards food naturalness will directly translate into a higher WTP for NW. Furthermore, as noted by Vermeir and Verbeke (2006), positive attitudes towards naturalness alone are insufficient to overcome the economic barriers associated with premium pricing, highlighting an "*attitude-behavioural intention*" gap. Again, according to Vecchio *et al.* (2021) and Gazzola *et al.* (2023), Italian consumers still have limited knowledge and awareness of NW, often confusing it with organic or biodynamic wines. Consequently, the lack of familiarity with NW, combined with the absence of unified certification, may hinder consumers' ability to relate to naturalness when assessing it. This could lead to a weak or non-existent connection between this attitude and their WTP for a premium price for NW, as observed in this study.

As hypothesised (i.e., **Hypothesis 3**), the negative and significant relationship between age and WTP aligns with the findings of Galati *et al.* (2019), which suggests that younger consumers are more likely to exhibit a higher WTP for NW. This result supports the evidence that young consumers are more interested in the sustainability aspects of food products than older consumers (Sogari *et al.*, 2016). Contrary to expectations, there is insufficient evidence to suggest that gender and customers' level of education influence their WTP for NW, thereby rejecting **Hypotheses 4 and 5**. Despite research suggesting that gender and level of education are consistently linked with greater awareness of sustainable food and beverage trends, including NW (Sogari *et al.*, 2016; Vecchio *et al.*, 2021, 2023), in line with the findings of Gow *et al.* (2024), our study reveals that gender and education were not the most significant drivers of WTP. A potential motivation may stem from the observation that personal values, rather than demographic traits, could influence WTP for NW more significantly. In any case, we aim to explore this affirmation in more depth in future research.

Our study reveals that income status significantly impacts customers' WTP for NW; specifically, affluent consumers are more willing to pay for this beverage, thereby confirming our conjecture (i.e., **Hypothesis 6**). This result contrasts with the recent findings of Gow *et al.* (2024), who report that income did not have a positive influence on the WTP for a premium price for sustainably produced wines among Italian consumers. This discrepancy may be due to the target product investigated, considering that our study focuses explicitly on the NW.

Unlike our initial theoretical framework, consumers' wine-drinking habits did not significantly affect their WTP for NW, leading us to reject **Hypothesis 7**. From our perspective, this result may be interpreted in light of the conflicting findings in the literature. In some studies, the frequency of wine consumption is a relevant driver of wine WTP (Migliore *et al.*, 2020; Pomarici *et al.*, 2016, among others), whereas in others, low-frequency drinkers exhibit higher WTP (Mauracher *et al.*, 2019). Considering our findings, these contrasting results support the evidence that frequent wine drinkers are not necessarily more informed or engaged with NW as a category and, consequently, are not willing to pay for it.

In line with the existing literature, this study's results confirm that the CVM inflates the resulting WTP due to anchoring and the adjustment process, even without prior personal information about the product being valued (Ariely *et al.*, 2003). The proposed price during the contingent valuation experiment has a positive influence on individuals' WTP for NW, leading us to accept **Hypothesis 8**. This suggests that market-driven factors may significantly affect customers' WTP for NW, as external cues can serve as reference points (i.e., $P_0$).

The findings from the VW-PSM price sensitivity meter enabled us to identify price points that indicate price sensitivity levels in the niche market of NW. Specifically, the OPP (€10.64), i.e., the price a relative majority of consumers would like to purchase the NW (as opposite to a relative minority of them considering it too extreme), is lower than the IPP (€15.60), i.e., the price at which a relatively large percentage of respondents perceives the product as a bargain (IPP). This translates into a high stress factor (70.09%), which denotes a relatively high probability of downward price dynamics involving the NW. Both OPP and IPP are included in the interval of actual market prices for NW found in Tannico S.r.l. (2024); however, prices larger than €17.00 might realistically discourage consumers from purchasing NW.

In addition, the price at which NW is perceived as too cheap – meaning the price customers consider too low to instil doubt about the product's quality – is lower than the anchor market price range used in this study. This aspect highlights that for NW, low prices do not necessarily lead consumers to question the quality to the extent that it prevents them from making a purchase. One rationale for this evidence is the hypothesis that customers may underestimate the direct monetary efforts or the minor monetary gains associated with the natural winemaking process. Furthermore, this situation may be related to consumers associating NW with product quality (Alonso González & Parga-Dans, 2020; Migliore *et al.*, 2020), even if it is offered at a low price. This evidence can also stem from the high economic value perception identified by the CVM and the lower acceptance price levels defined by the VW-PSM method. In addition, the wider acceptance price ranges for NW may reflect low familiarity with the product among interviewees in terms of market price and/or brand knowledge and, in line with Lewis *et al.*'s (2014) findings, this result corroborates the verified hypothesis that price significantly influences the economic appreciation of the NW.

## Conclusion, limitations and outlook

Given that pricing is a crucial element in the wine market, it seems particularly pertinent in niche markets like those in the NW. Setting the right prices for wineries and retailers is essential to gaining a competitive advantage and expanding market share. In this context, this study integrated NW research streams with consumers' WTP and price-sensitivity measures, offering the following implications.

From a theoretical standpoint, this research expands existing knowledge on consumers' pricing and economic valuation of NW. Previous research has mainly examined consumers' awareness, attitudes, and motivations towards natural or sustainable wines, but has offered limited evidence on how these factors affect economic value. By combining the CVM with the VW-PSM, this study captures both consumers' stated preferences and perceived acceptable prices. This approach advances behavioural economics of credence goods by showing that consumers' focus on cues such as naturalness and sustainability influences their WTP through mechanisms such as anchoring and price-quality inference. The findings deepen understanding of how attention-based evaluations affect economic decisions in niche markets like NW. This study identifies the factors most strongly associated with consumers' WTP for this beverage, thereby supporting the decision-making process and providing a critical lens for examining consumer behaviour towards NW. According to Lewis *et al.* (2014), the expansion of the wine industry was generally achieved by adopting a strategy of buying market share through price, thus offering a wine for which the WTP was initially high at a "*value-for-money*" price. For non-expert wine consumers who struggle to assess a wine's intrinsic quality accurately, a low price may be perceived as an indicator of low quality. Thus, this situation can induce a systematic and progressive decline in customers' WTP, leading wine industries to fall into what D'Aveni (2010) defines as the "*commoditisation trap*" to maintain their market share. From this perspective, the combined use of CVM and VW-PSM methods provides a dual lens that yields valuable insights for more effectively defining a product's collocation in its economic life cycle, assisting wineries and retailers in developing efficient market pricing strategies without falling into the commoditisation trap.

From a managerial perspective, the results offer actionable insights for producers and retailers, highlighting a reasonable level of consumer awareness of the economic value of NW (i.e., the mean predicted WTP is

€29.07 for a 0.75L bottle of NW) and an optimal price point of €10.64 (OPP). Hence, wineries should use the OPP price as a reference average starting point for a 0.75L bottle of NW. Products with intrinsic and extrinsic attributes that make them above average should be priced higher, and vice versa. In this light, the POR values (€10.12-€17.00) for a 0.75L bottle of NW could serve as a guide. Furthermore, since the Kernel density curve of the WTP for a 0.75L bottle of NW lies to the right of the ARP limits, this might suggest that the consumer sample undervalues the product. This could be due to the lack of familiarity with NW, the absence of a unified certification, and the possible anchoring effect that ties consumers to their personal reference prices. The study's findings suggest that external cues can significantly serve as reference points for customers. This situation might enable the use of a strategy with higher reference prices in communications. This could include introducing specific premium cues (e.g., storytelling, packaging, awards) to shift consumer reference price points upward, along with a gradually increasing pricing strategy. Furthermore, employing a market segmentation approach based on the evidence from this study allows for adopting an entry price slightly above the IPP or PME for value-seeking consumers, or offering a premium version of the product near the peak of the CV density.

From a methodological perspective, because WTP measures may be influenced by overestimation bias arising from the CVM, it would be beneficial to calculate them using non-hypothetical, incentive-compatible evaluative methods. This would provide a more accurate overview of the extent to which price and WTP ranges overlap, allowing for better identification of the product's stage in its economic life cycle and potential pricing strategies.

The study suffers from obvious limitations. The inability to generalise the results due to the convenience sample, which used the snowball sampling method, forces us to replicate the study on a larger, carefully defined population, including other factors that might affect price sensitivity and consumers' WTP. Moreover, future studies may focus on exploring factors that can widen the range of acceptable pricing and reduce the stress associated with it. Furthermore, extending the questionnaire to other countries would be interesting to explore cultural differences in terms of NW price sensitivity and economic appreciation.

## Ethics statement

Before beginning data collection, participants were informed of the purpose and the subsequent statistical analysis. Participation in the study was completely voluntary and anonymous, and individuals could withdraw from the survey at any time and for any reason. Respondents were required to sign a privacy and consent policy form in advance, which outlined how their data would be collected and processed, in accordance with the Italian Data Protection Law (Legislative Decree 101/2018) and the European Commission's General Data Protection Regulation (679/2016). The investigation was conducted in line with the principles outlined in the 1975 Declaration of Helsinki (World Medical Association, 2013). As this research did not involve any invasive procedures or laboratory assessments and did not induce any lifestyle changes, ethical review and approval were waived.

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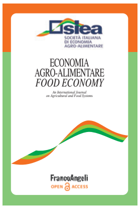


# Exploring Red Kidney Bean Flour as Partial Substitute to Rice Flour in Gluten-free Ramen Noodles: Consumers' WTP in Thailand

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## *Abstract*

This study aims to elicit consumers' willingness to pay (WTP) for gluten-free ramen noodles, exploring the alternative flour formulation of red kidney bean (RKB) to substitute for rice flour. Using the experimental method, first-price auction, with adult consumers as participants, truncated regression was applied to identify the WTP bids for three types of gluten-free ramen noodles. The findings reveal that the WTP bids for rice kernel and 30% RKB flour-based ramen noodles are not significantly different, whereas consumers would pay 12.56 baht/150 g less for the 40% RKB flour item compared to the rice kernel item. The results also suggest that participants in the experiments would pay 15.452 baht/150 g less for the 40% RKB flour item compared to the 30% RKB flour item. These results underscore the 30% RKB flour is the optimal formulation for producing gluten-free ramen noodles to substitute for rice flour. This study also highlights the distinct preferences across individual characteristics and nutritional concerns, which underscores the potential for developing ramen noodles to satisfy consumer preferences beyond celiac concerns – providing food nutrition and improving well-being of consumers through dietary choices.

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## 1. Introduction

A notable recent global trend toward finding substitutes for basic food ingredients has been driven by several compelling factors (Wang & Jian, 2022). One significant catalyst for this shift is food security, which has garnered increasing concern among consumers, with gluten being a particularly crucial aspect. In recent years, there has been an increase in the number of people suffering from celiac disease due to gluten-related disorders, which may lead to inflammation and complications (Lebwohl *et al.*, 2018). This results in patients with celiac disease having new needs, such as reducing the risk of noncommunicable diseases (NCDs) and improving their health and the economic aspects of nutrition. Gluten-free food products, which are in increasing demand, are becoming a prospective market segment. Based on the average growth rate of 12.3% from 2009 to 2014 across various countries in Europe, America, and Asia, the gluten-free food market was forecasted to increase annually by 11% by 2020 (Lobanov *et al.*, 2018). And, the market of gluten-free products is estimated to grow from USD 6.3 billion to USD 12.4 billion by 2035, with baked goods, infant formula, ready meals, and pasta being important such products in the market (Future Market Insights, 2025). Corresponding shifts in number of diagnosed coeliac patients suggest that gluten-free products potentially appeal to the individuals owing to their perceived health benefits. However, Bathrellou *et al.* (2025), Gorgitano and Sodano (2019), Guennouni *et al.* (2019), Hassan *et al.* (2024), and Jamieson *et al.* (2018) identified consumption constraints limiting access to gluten-free products, with individuals with gluten sensitivity or celiac disease often facing challenges regarding the unavailability, quality, and affordability of gluten-free products. Gorgitano and Sodano (2019) found that only 44% of the 212 stores in their sample offered these specialized products. Gorgitano and Sodano's (2019) study in Italy revealed that the average price of gluten-free pasta is 2.5 times higher (USD 0.427/100 g) than that of regular pasta, with the price premium ranging from 7.92% ($0.018/100 g) to a significant 31.4% (USD 0.710/100 g).

Despite these price differentials, the demand for gluten-free products, accounting for 14% of pasta consumption, appeared to far surpass dietary safety needs, since less than 1% (0.34%) of the Italian population is genuinely gluten-intolerant. Globally, there is a growing emphasis on healthier and more secure lifestyles, which has resulted in an increasing demand for innovative functional foods, such as nutrient-rich and non-allergenic food products. Alsubhi *et al.* (2022) provided a comprehensive summary of the research findings from numerous studies investigating consumers' willingness to pay (WTP) for healthier products. Of the 26 experiments reviewed in their study, 88.5% revealed a price premium for healthier foods encompassing attributes such as lower fat, sodium, sugar, and cholesterol, and their various combinations. The observed WTP premiums ranged from 5.6% to 91.5%, with an average of 30.7%. Nganje *et al.* (2008) found the highest WTP premium to be for reduced-fat bread (USD 2.27/100 g) in USA. Jurado and Gracia (2017) found the lowest WTP to be on reduced saturated fat breakfast cereal (USD 0.42/100 g)[1] in Spain. De-Magistris and Lopéz-Galán (2016) found that Spanish consumers were willing to pay an additional 7.2% (USD 0.175/100 g) for cheese labeled as having lower fat content than traditional cheese. Similarly, Di Vita *et al.* (2016) estimated a WTP premium of 21.36% (USD 0.052/100 g) for reduced-salt bread compared to conventional bread.

A promising alternative to wheat is red kidney bean (*Phaseolus vulgaris* L.) (RKB), a gluten-free pulse that enhanced nutritional benefits, including being an excellent source of fiber, protein, and other micronutrients (Chompoorat *et al.*, 2018a; Hangen and Bennink, 2002). The red kidney bean flour is a high potent pseudo-cereal for improving protein and fiber levels in gluten-free products. Food nutritionists emphasize the nutritional value of legumes, characterizing them as wholesome, nutrient-dense, and high-protein food choices, capable of reducing the risk of heart disease and stroke (Margier *et al.*, 2018; Tharanathan & Mahadevamma, 2003). The use of non-meat-based proteins, such as beans and pulses, is an affordable means of improving nutrition among households in developing countries. Simultaneously, there is a heightened awareness of sustainability issues throughout the entire supply chain, extending from farm to fork. An illustrative example of this is the multitude of benefits that legumes offer across diverse domains. Replacing meat and dairy products with legumes provides an opportunity to alleviate the strain on agricultural resources and mitigate greenhouse gas emissions associated with livestock management (Day, 2013; Davis *et al.*, 2010; Jones & Ejeta, 2016; Röös *et al.*, 2017). Legumes can serve as viable meat and gluten alternatives, addressing consumer preferences and health benefit of dietary allergenic proteins, in addition to their environmental benefits (Bellarby *et al.*, 2013; Gao *et al.*, 2018). This transition to functional foods, such as gluten-free products and non-meat based proteins, aligns with the broader push for sustainability in the food industry, promoting food security and more environmentally responsible food system. Embracing these changes proactively allows the industry to meet evolving demands and contribute to sustainable and resilient food systems on a global scale.

1. EUR 1 approximately equals to USD 1.133 in May 2025 (European Central Bank, 2025).

### 1.1. *Focus of the study*

Ramen noodles are popular food products, especially in Asia, because they are quick, convenient, and easy to cook, with a long shelf life. Based on recent statistics, 121.2 billion servings of ramen noodles were consumed worldwide, totaling USD 21 million in 2022 (Global Industry Analysts, 2023; World Instant Noodles Association, 2023). Ramen noodles are manufactured using wheat flour that contains gluten as their main ingredient. Although there is an increasing demand for food products using substitutes of traditional wheat flour, manufacturers' search for profitable substitute ratios has been difficult because of properties of wheat such as viscoelasticity, which provide baking benefits, including a desirable texture, taste, and other qualities not found in other grains and legumes (Capriles *et al.*, 2014; Chompoorat *et al.*, 2018b). Nonetheless, several studies have demonstrated the potential feasibility of substituting wheat with other processed flours. For example, Ouazib *et al.* (2016) observed that processed rather than raw chickpeas were an improved substitute for wheat in bread when mixed at a 10% substitution rate. Awolu (2017) suggested that the composite flour with 85% pearl millet flour in addition to kidney beans and tigernut flours could be used as an alternative flour to the 100% wheat flour in bread. In addition, Chompoorat *et al.* (2020) reported that the combination of RKB flour with rice flour forms a different dough structure owing to the higher protein content and presence of amylose and amylopectin. However, the pursuit of such attributes – flavor and texture profiles – may entail additional processing steps (Gao *et al.*, 2018), resulting in elevated production costs.

On the consumer front, the purchase decision depends not only on the price of goods and income but also on sociodemographic factors such as age, gender, and education (Croson and Gneezy, 2009; Perrin *et al.*, 2019; Sgroi *et al.*, 2024). Sgroi *et al.* (2024) reported that the frequency of consumption of functional foods is influenced by sociodemographic factors such as age, gender, and income. Furthermore, extensive literature indicates that consumers' preferences and expectations regarding foods are often associated with their nutritional value and sensory aspects, particularly taste, texture, and smell (Alencar *et al.*, 2021; Diep *et al.*, 2014; Fu, 2008; Hatcher *et al.*, 2014; Liu *et al.*, 2019; Miskelly & Moss, 1985; Smewing, 2016). Hence, the use of substituting ingredients can address these challenges, meet consumer preferences, and offer potential benefits to the food industry.

In rice-producing countries, such as Thailand, rice flour is used as a substitute for wheat flour in ramen noodles, but only in small markets. To the best of our knowledge, no study has directly examined consumer WTP for gluten-free ramen noodles in Thailand and Asia. This study aims to (1) investigate associations between consumers' WTP values, demographic factors, and consumers' nutritional concerns, and (2) verify WTP estimate differences between three flour-based formulations of gluten-free ramen noodles. An experimental method (auction) was employed to elicit consumers' WTP bids. This study presents initial evidence of Thai consumers' WTP for different types of ramen noodles. The experimental auctions provide non-hypothetical preference data, enabling insights into consumer acceptance of the flour formulations. The findings aim to inform businesses in designing and developing innovative products that support healthier diets and improve consumers' nutritional well-being.

To familiarize the reader with experimental auctions and WTP studies, the following subsection (Section 2) describes the development of such approaches based on a review of recent methodological developments and the experimental method. The experimental designs and regression model are presented and discussed in Section 3. Section 4 reports the results of the experimental auctions and discusses the findings and compares them with previous studies. Conclusions and suggestions for further research are presented in the final section.

## 2. Background on experimental auction

Experimental auctions have been applied in food valuation literature to determine consumers' willingness-to-pay value for market and non-market goods – which are a non-hypothetical and incentive-compatible choice experiments – in which individuals exchange real money for real goods. Unlike the state-preferences surveys which elicits consumers' WTP from hypothetical choices, the auction mechanism incentivize participants to place bids to reveal their true preferences (Canavari *et al.*, 2018; Fox *et al.*, 1998; Lusk *et al.*, 2001). This experimental method can be applied to examine biding behavior of the consumers and understand the factors influencing consumers' WTP bid for a good (e.g., Alemu & Olsen, 2020; Bernard *et al.*, 2006; Huffman *et al.*, 2003; Lee *et al.*, 2011; Lusk *et al.*, 2001; Rousu *et al.*, 2004).

Various auction mechanisms have been used to elicit valuations, including first-price, second-price, (random) *n*th-price auctions, and the Becker-DeGroot-Marschak (BDM) mechanism. Selecting an appropriate auction format is an important methodological consideration because each mechanism possesses distinct properties that needs to be considered (Canavari *et al.*, 2018; Lusk *et al.*, 2001; Lusk and Shogren, 2007). Canavari *et al.* (2018) found that the second-price auction is the most frequently used format, followed by the BDM and (random) *n*th-price auction mechanisms. A Vickrey second-price auction encourages participants to bid their true maximum WTP; however, it may not fully capture the preferences of participants whose bids fall outside the market-clearing price range. In contrast, a randomness in the *n*th-price auction absorbs off-margin bids and motivates participants to reveal their private bids closer to market clearing price (Canavari *et al.*, 2018; Huffman *et al.*, 2003; Lusk *et al.*, 2001; Shogren *et al.*, 2001).

Despite this advantage, the *n*th-price format can be costly, as the number of units sold increases with the value of *n*. The BDM mechanism is often preferred by researchers who wish to avoid the logistical challenges of bringing participants together at the same time and place (Canavari *et al.*, 2018). However, concerns regarding potential biases persist, as valuation outcomes may depend on the underlying distribution of the randomly generated comparison prices (Vassilopoulos *et al.*, 2018, as cited in Canavari *et al.*, 2018).

When the objective is to elicit valuations for products that are new or not yet available in the market – and when only a single trial can be conducted – the first-price auction may provide a suitable approximation of consumers' WTP (Lusk *et al.*, 2001). In this mechanism, the winning bidder purchases the product at their bid price using real money, which motivates participants to bid cautiously and sincerely. Although first-price and second-price bids may converge under assumptions of risk neutrality and independent private valuations, the second-price auction often requires repeated trials, which may lead to confusion among participants unfamiliar with auction procedures (Lusk *et al.*, 2001).

In this research, ramen noodles made from red kidney bean (RKB) flour are a new product that is unfamiliar to consumers and not yet commercially available, while rice kernel–based products are found only in a limited number of health food stores. A single-trial auction was used to examine consumers' WTP for each type of gluten-free ramen noodles with participants who had little prior experience with auction mechanisms. Therefore, the first-price seal bid auction is an essential component of this study. In order to observe the effect of consumer demographics and concerns on nutritional profiles on participants' behavior in the experiment, demographic variables and scale-based measures of participants' nutritional concerns were incorporated as predictors of WTP. This indirect method provides a causal interpretation of the effects of individual characteristics on consumer preferences and enhances the precision of WTP estimates (Canavari *et al.*, 2018; Lusk *et al.*, 2001).

## 3. Material and methods

Primary data were collected using a laboratory experimental auctions. This approach allows researchers to elicit consumers' WTP for gluten-free ramen noodles by controlling for key constituents of the market. Auctions were conducted mainly at Chiang Mai University, Thailand, from June to July, 2019. Participants were recruited using several methods, including word-of-mouth, phone, social media posts, and flyers placed at the entrances of common areas in the office buildings of Chiang Mai University. The study questionnaire was piloted in March and April 2019, and the adjusted version was submitted to the Chiang Mai University Research Ethics Committee for ethical review and approval[2]. During the recruitment process, participants were told they would be paid 200 baht cash, of which 100 baht was given for their time as a gift, and another 100 baht was provided for them to use to make a purchase of a product[3]. Participants were also informed that they would learn about the auction mechanism through a practice round to ensure their understanding of the experimental procedure.

### 3.1. *Study's experimental design and sample size*

In the experiment, three types of gluten-free ramen noodles were conducted to access the mean difference in consumers' WTP for flour-based formulations. Six experimental sessions were conducted with two sessions for each ramen flour-based formulation. The sample size per flour treatment was calculated using the optimum sample arrangement – Sixteen S-squared over D-squared – proposed by previous studies (Canavari *et al.*, 2018; Drichoutis *et al.*, 2015; Lehr, 1992; List *et al.*, 2011; Noordzij *et al.*, 2010). This standard approach was applied to our study by using a Type I error level (alpha) of 0.01, a statistical power of (1 – *beta*) 0.90, and a 10-unit standard deviation change in the mean bids between flour-based items. The minimum sample size per treatment was therefore 30 (see Appendix, Table 1 for the sample size calculation). While the experiment was designed to have 30 participants in each flour-based treatment; some recruited participants might not show up in a given session. Hence, 15-18 individuals were recruited on average for each auction session to account for possible no-

2. This research was approved by the Chiang Mai University Research Ethics committee in CMUREC No. 62/049.

3. 1 THB (baht) approximately equals to 0.033 USD in November 2025 (Bank of Thailand, 2025).

shows. A total of 105 individuals aged 18-70 years participated in the study, with 35 participants per treatment. This recruited number was also aligned with the sample size calculated based on power and alpha values of 0.95 and 0.01, respectively.

The recruited participants were randomly assigned into experimental sessions without being given any information about the product details. Prior to the experiment, the participants were told that they could participate in only one experimental session. The experiment followed a between-subject design, in which participants evaluated only one type of product treatment (Charness *et al.*, 2012). This is similar to what would occur in a real market setting for new and/or healthy products, such as in bistros and restaurants, where not many gluten-free food options are available. The randomization procedure of the study is also supported by the Neyman-Rubin model of causal inference, which notes that a within-subject design does not provide a causal interpretation of the treatment effect due to confounding responses from the same individual under both control and treatment conditions. Conversely, the between-subject design with the proper randomization is considered an unbiased estimate of the causal effect that the research wants to isolate (Rubin, 1974, as cited in Briz *et al.*, 2017; Canavari *et al.*, 2018).

We acknowledge of the study's limitations related to the efficient estimation and inference of the results for the broader population based on a small group of samples. However, an equal number of participants per treatment and a larger sample size than the number of model predictors would provide sufficient power to estimate the treatment effect on the outcome of this pilot study. In addition, the observations collected for this study met the minimum requirements, ensuring an acceptable level of statistical power and detectable effect size (Drichoutis *et al.*, 2015, as cited in Briz *et al.*, 2017).

### 3.2. *Experimental trial and flour-based treatments*

In the auction, three types of gluten-free ramen noodles were prepared for the experimental trials: pure rice kernel flour and two blended alternatives with different proportions of RKB flour (30% and 40% RKB flour-based formulations). The cooked gluten-free ramen noodles were placed in disposable plastic bowls and served to the participants along with a manufactured non-gluten free item. The manufacturing of non-gluten-free ramen noodles primarily uses wheat flour; these noodles have long been available in the market and are commonly consumed in Asia. A conventional non-gluten-free item was used as a benchmark product to help consumers compare the characteristic differences between gluten- and non-gluten-free products. The manufactured non-gluten-free item was presented to subjects with its label removed to avoid the effect of brand reputation on consumers' WTP, whereas the gluten-free item was labeled with its weight and product flour composition. Information about the average market price per package of 150 g of manufactured non-gluten-free ramen noodles (42 baht) was provided to the participants.

For each session, participants were informed that Ramen A was a non-gluten-free product made from wheat flour and contained gluten, whereas Ramen B/C/D did not contain gluten and was made from pure rice kernel, 30% RKB or 40% RKB flour-based formulations, respectively. The participants received information about gluten: that it is a protein found in wheat, barley, and rye (Lebwohl *et al.*, 2017). Gluten can pose health risks to patients with celiac disease, who are sensitive to gluten. To verify WTP differences among three types of gluten-free ramen noodles, participants in the experimental trial were asked to submit only their bids for the gluten-free item (Ramen B/C/D) beginning at zero. The experimental auction involved several steps, which are explained in the next subsection.

### 3.3. *Participant activities in the auction session*

After the participants arrived and registered for the experiment, the auction was conducted in the following five steps:

*Step 1*: Each participant was given an ID number to maintain anonymity and assigned a seat. The seats were placed far apart to ensure that the participants were unable to communicate with one another.

*Step 2*: The study monitors welcomed the participants and provided details of the research project and experimental auction procedure. Once the participants signed a consent form, the study monitor asked them to complete the first part of the questionnaire, which consisted of questions on their demographics and concerns regarding food nutritional profiles.

*Step 3*: After the participants completed the pre-auction questionnaire, a warm-up round auction of a napkin was conducted. Participants were asked to examine the napkin and provide the WTP bid for the product that they would purchase using the given 100 baht. Once the participants provided a written WTP bid, the study monitors collected a sealed bid from all the participants and announced the highest bid. The bids were written on a whiteboard. The winner of the auction paid the highest bid, that is, their own bid, in exchange for the napkin. At this stage, the participants were encouraged to clarify the auction methods before proceeding to the real auction round.

*Step 4*: Following the warm-up round, the first-price auction for specific flour formulations of gluten-free ramen noodles was conducted: (1) rice kernel flour, (2) 30% RKB-blended flour, and (3) 40% RKB-blended flour. In this session, cooked ramen noodles were served along with the manufactured items. After experiencing the products, the participants were asked to submit their bids for the gluten-free item in that experimental trial.

*Step 5*: Session monitors collected and ordered the bids from highest to lowest. The highest and second highest bids in that session were announced. Those who gave the highest bid were the winners of the trial and paid their bid in exchange for a 150 g pack of gluten-free ramen noodles.

### 3.4. *Econometric model*

In the survey, demographic variables and scale-differential questions regarding participants' concerns regarding nutritional profiles were used to quantify the WTP values. Participants' concerns regarding protein content, saturated fat content, and gluten-related ingredients were elicited using a scale between 1 and 10. A value of 1 indicates the participant is not concerned about these nutritional values at all, whereas a score of 10 is given if the participant is extremely concerned. Initially, the study included other variables, such as participants' average years of schooling, income, concern regarding carbohydrate and sodium contents, and interaction variables between demographics and nutritional concern, as the components of an explanatory variable, but only the five variables stated above were included in the model. Model selection was based on the Schwarz criterion – Bayesian Information criterion (data available upon request from the authors). In accordance with the study's sample size, the Schwarz criterion penalizes the loss of degrees of freedom resulting from the addition of variables to the model (Greene, 2008; Schwarz, 1978). The study also used the Variance Inflation Factor and White's tests to detect multicollinearity problems and heteroskedasticity. The test results revealed no collinearity between the independent variables and failed to reject the null hypothesis of homoskedasticity.

In the regression model, participants' WTP bids were set as dependent variables, and two demographic variables (age and gender) and three questions on participants' concerns regarding food nutritional profiles (protein content, saturated fat content, and gluten-related ingredients) were included in the $x$ vector. During the experiments, none of the participants placed negative or zero bids, and the bids for all flour treatments were consequently truncated above zero, in which the Ordinary Least Squares estimator was not an appropriate approach (Amore & Murtinu, 2019; Green, 2008; Wilson & Tisdell, 2002). Therefore, a truncated regression was applied to identify the WTP bids, which was formulated as:

$$WTP_{i,j} = \alpha_0 + \sum_{k=1} \beta_k X_{k,i} + \sum_{n=1} \delta_n Z_{n,i} + \sum_{j=1} \psi_j TR_j + e_{i,j} \quad (1)$$

where the existing variables $WTP_{i,j}$ represents the bidding price of participant $i$ for ramen noodles that made from flour-based formulation $j \in$ {rice kernel, 30% RKB blend, and 40% RKB blend}; $X_{k,i}$ is the $k$th explanatory variable for participant demographics ($k$ = 1, 2 for age and male gender, respectively); $Z_{n,i}$ indicates participants' concern regarding nutritional profile $n$ ($n$ = 1, 2, 3 for protein content, saturated fat content, and gluten, respectively); $TR_j$ is a dummy variable for flour-based treatments; $\alpha_0$ denotes the intercept representing a reference category of the rice kernel flour item; $\beta_k$ and $\delta_n$ are parameters to be estimated for the effects of participant demographics and concern, respectively; $\psi_i$ is the parameter capturing how flour-based formulation influences WTP values; and $e_{i,j}$ is the corresponding error term for flour formulation $j$.

As stated earlier, the study objective was to investigate the associations between consumers' WTP values, demographics, and participants' nutritional concerns. The hypotheses regarding the demographics and concern factors – $H_0$: $\beta_1 = 0$, $\beta_2 = 0$ and $H_0$: $\delta_1 = 0$, $\delta_2 = 0$, $\delta_3 = 0$ – were tested. It was hypothesized that participants' age, and gender would affect the WTP bid, with male and younger participants placing higher bids for all the gluten-free flour items. It was hypothesized that participants who have a higher level of concern for protein and saturated fat content, as well as gluten-related ingredients, would have increased the participants' bidding amount. The dummy variable for flour-based formulations were tested ($H_0$: $\psi_1 = 0$, $\psi_2 = 0$), which was expected to be significantly different from zero. Additionally, the second objective of this research was to identify WTP differences among three types of gluten-free ramen noodles. The study conducted the tests for mean equality on consumers' WTP from different flour formulations. The WTPs from 30% RKB and 40% RKB flour-based formulations are expected to be equal to that for the rice kernel flour item ($H_0$: $\alpha_0 = \psi_1$, $\alpha_0 = \psi_2$). Moreover, the bidding values for 30% RKB flour and 40% RKB flour-based items were expected to be equal, that is the null hypothesis ($H_0$: $\psi_1 = \psi_2$) cannot be rejected.

## 4. Results and discussion

### 4.1. *Demographic characteristics of the sample*

The variable definitions and descriptive statistics for the 105 participants are presented in Table 1. Of the 105 participants, 77% were women. The average age of the participants was 36.71 years; there were 13 participants aged > 60 years. The mean number of years of schooling for all participants was 18.85 years (at a bachelor's degree), with only 3.8% not having completed high school. More than 22% had a college degree, and 60% were studying in college. The participants had an average monthly income of 26,930 baht. Nearly 80% of the participants had a monthly income of less than or equal to 30,000 baht, whereas only 2.85% had an income greater than 100,000 baht. Most participants had similar education levels and incomes, which may have led to similar opinions toward gluten-free products, given their demographic background.

For the scale-differential question, the participants indicated their high concern for protein and saturated fat content (mean score at 7.26 and 7.38, respectively), whereas the concern for gluten-related ingredients was moderate (mean score at 4.58).

*Table 1 - Summary statistics of the sample*

| Variable | Definition | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Age | Years | 36.71 | 15.12 | 18 | 70 |
| Male | 1 = male; 0 = female | 0.23 | 0.42 | 0 | 1 |
| Edu | Highest education level (year of schooling) | 18.85 | 2.51 | 9 | 26 |
| Income | Baht per month | 26,930 | 28,862 | 4,000 | 150,000 |
| Protein content | 1 = not at all concerned; 10 = extremely concerned | 7.26 | 2.09 | 1 | 10 |
| Saturated fat content | 1 = not at all concerned; 10 = extremely concerned | 7.38 | 2.09 | 1 | 10 |
| Gluten-related ingredient | 1 = not at all concerned; 10 = extremely concerned | 4.58 | 2.93 | 1 | 10 |

Table 2 shows the mean bids for gluten-free ramen noodles by flour formulation. Among the three flour-based products, participants were willing to pay less for the product made from 40% RKB flour-based formulation than for those made from rice kernel- and 30% RKB flour-based. The bidding price for the 40% RKB flour item was only 31.06 baht/150 g, below the bids for the other two items by 11 baht/150 g.

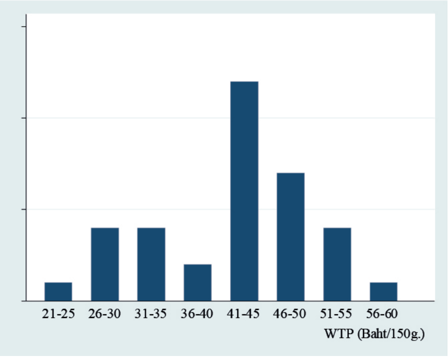
Meanwhile, the mean bid for the 30% RKB flour-based ramen noodles was only one baht lower than that for the item made from rice kernel flour. Additionally, none of the participants placed the bid below 10 baht for all the products; therefore, the consumers' WTP was left-truncated at 10.

*Table 2 - Average consumer WTP for ramen noodles, by flour formulation*

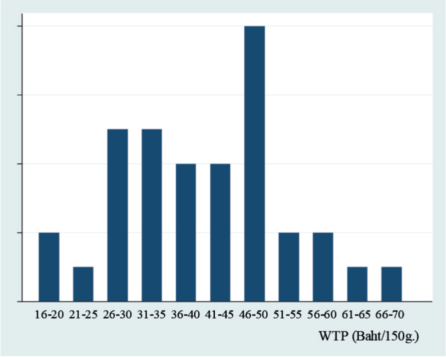
| Flour formulation | Mean (baht/150g) | Std. Dev. | Min | Max |
|---|---|---|---|---|
| Rice kernel | 43.17 | 8.55 | 25 | 60 |
| 30% RKB | 42.26 | 12.12 | 20 | 69 |
| 40% RKB | 31.06 | 14.71 | 10 | 60 |

The histograms presented in Figure 1 (a-c) shows the distribution of the bid prices for gluten-free ramen noodles by flour formulation. The majority of participants gave a higher bid of 41-50 baht for rice kernel- and 30% RKB flour-based formulations. The minimum bids for these two products were 25 and 20 baht, respectively. Conversely, most participants in the 40% RKB experimental trial gave lower bids that fell within a wider range below 41 baht (i.e., 10-40 baht). This result indicates a difference in consumers' WTP between the ramen noodles made from rice kernel- and 40% RKB flour formulations.

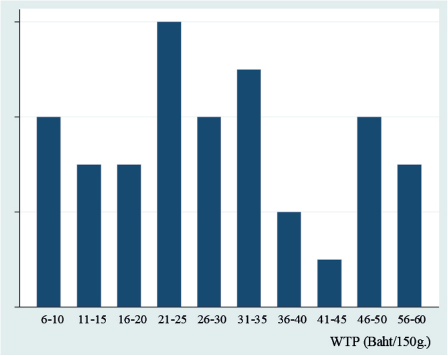
*Figure 1(a-c) - The bid distribution for ramen noodles, by flour formulation*




**(a) Rice kernel flour**




**(b) 30% RKB flour**




**(c) 40% RKB flour**

## 4.2. *Willingness to pay for gluten-free ramen noodles and influencing factors*

The truncated regression results from fitting Equation (1) with the effects of flour treatments are presented in Table 3. The models were estimated using the maximum-likelihood procedure in the TRUNCREG procedure in STATA, version 17. The Wald chi-squared test for all coefficients was zero and was rejected at the 1% level, indicating that the model was statistically significant. The results revealed significant correlations between consumer demographics and concerns on food nutritional profiles, flour formulations, and consumers' WTP values, with clear implications for determining the preferable flour formulation for producing gluten-free ramen noodles.

*Table 3 - Truncated regression results*

| Variable | Coefficient | Standard Error |
|---|---|---|
| Constant | 46.011*** | 5.319 |
| Age | –0.239** | 0.100 |
| Gender (male) | –6.264** | 3.107 |
| Protein_Concern | 2.013** | 0.795 |
| Saturated fat_Concern | –0.822 | 0.751 |
| Gluten_Concern | –0.598 | 0.470 |
| 30% RKB flour | 2.896 | 3.423 |
| 40% RKB flour | –12.556*** | 3.289 |
| Sigma | 11.563 | 0.890 |
| Log likelihood | –400.667 | |

*Note*: (***) significant at 1% level, and (**) significant at 5% level.

The beta coefficients for age and (male) gender were significantly different from zero and negatively correlated with the WTP bid for gluten-free ramen noodles (–0.239 and –6.264 respectively, significant at 5% level). A one-year increase in participants' age leads to a 0.239 baht decrease in the bidding amount. Male participants give lower bids than female ones, as a great magnitude at –6.264 baht/150 g. These results align with prior research highlighting the role of sociodemographic factors (e.g., age, gender, and education) in consumers' decisions to purchase goods and services, including dietary choices (Bärebring *et al.*, 2020; Christoph *et al.*, 2018; Croson & Gneezy, 2009; Sgroi *et al.*, 2024). The negative relationship between age, gender, and WTP bids indicates that older male consumers have limited perception of a healthy diet and less acceptance of a new food product, which is consistent with prior studies on food awareness, such as those by Bärebring *et al.* (2020) and Perrin *et al.* (2019), who reported differences in the perceptions of food nutrition and safety between male and female consumers.

Concern variables for food nutritional profiles further shaped consumers' WTP bid. The positive and significant coefficient of participants' concern for protein content is specifically observed (2.013, significant at 5%), suggesting that an individual who has one higher level of concern above the average for protein content is significantly willing to pay more for the gluten-free ramen noodles (2.013 baht/150 g). This result aligns with the findings of Di Vita *et al.* (2016) and Luga *et al.* (2020), who observed that the sensory score/ WTP value of food products tends to be higher when the foods incorporate healthy nutrients, such as high protein and low sodium. Conversely, concerns regarding gluten had no significant effect on the bidding amount. These findings imply that consumers who have no food intolerance may be reluctant to consume gluten-free products, and that their dietary preference for healthy foods – providing a balance of protein, fat, and fiber – plays a critical role in their consumption choices. Regarding consumers' concerns about saturated fat content, the coefficient shows an unexpected insignificant result.

While the dummy coefficient for the 30% RKB flour-based formulation was not significantly different from zero, The 40% RKB flour formulation was negatively correlated with the WTP amount (–12.556, significant at 1%). This indicates that consumers would pay 12.56 baht/150 g less for the item that made with 40% RKB flour-based formulation compared to the rice kernel item. The insignificant coefficient for the 30% RKB flour-based formulation suggested that the amount consumers would pay for the 30% RKB flour ramen noodles did not differ from the WTP for the rice kernel item ($\rho$ = 0.39). Furthermore, the mean equality test on WTP differences highlights the alternative flour formulation to substitute for rice kernel flour. The hypothesis that the average bids of 30% RKB- and 40% RKB flour items would be equal ($H_0$: $\psi_1 = \psi_2$) was rejected – i.e., $\rho$ = 0.00. The result shows that consumers would pay less for the 40% RKB flour-based ramen noodles compared to the 30% RKB flour item (–15.452, significant at 5%). The results illuminate the 40% RKB flour-based formulation decreases the consumers' preferences for ramen noodles, whereas the 30% RKB flour is the optimal formulation for producing gluten-free ramen noodles in comparison to the rice kernel flour.

Based on the statistical significance and sign of the estimated parameters in Equation (1), the WTP amount for gluten-free ramen noodles across flour-based formulations can be predicted. For instance, if the consumer offers a positive bid, an increase in the substitution rate of rice flour to a 40% RKB formulation will reduce the bids for ramen noodles. The WTP bids for the 40% RKB flour item were only 29.05 baht/150 g when the bidder was male aged 36.71 years and indicating a concern of level 7 for protein content. The same consumer would pay up to 41.61 and 44.50 baht/150 g for rice kernel- and 30% RKB flour-based items, respectively (Table 4). This finding reveals that the extra attributes of gluten-free flour beyond using the 30% RKB flour composition appeared to significantly decrease consumer WTP bids. This is consistent with the findings of Chompoorat *et al.* (2020), who reported that the overall quality score of the flavor – taste, texture, and smell – of RKB cupcakes increased when a higher percentage of rice kernel flour was added to the RKB flour.

Overall, two flour formulations – (1) rice kernel and (2) 30% RKB flour composition – demonstrate higher consumer preferences than a 40% RKB flour formulation. The older male consumers have limited perception of a healthy diet and less acceptance of a new food item than female. An individual concern for protein content increased the bidders' amount for the ramen noodles. These findings highlight the distinct preferences across individual characteristics, which may guide policy intervention to support food industries in developing innovative products to meet consumer demand, bolster food security, and improve well-being for all people.

*Table 4 - Expected mean of WTP for gluten-free ramen noodles, by flour formulation*

| **Flour formulation** | **Mean WTP* (baht/150g)** | **Standard Error** | ***p*-value** |
|---|---|---|---|
| Rice kernel | 41.61 | 2.269 | 0 |
| 30% RKB flour | 44.50 | 2.200 | 0 |
| 40% RKB flour | 29.05 | 2.284 | 0 |

*Note*: The mean of WTP bids were calculated from 105 observations.

## Conclusions

A first-price auction was conducted to quantify consumers' WTP values for ramen noodles with three alternative flour formulations. We found that all participants offered positive bids for all types of gluten-free ramen noodles. The WTP bids did not differ between rice kernel- and 30% RKB flour-based items. Only the average bid level for ramen noodles made from 40% RKB flour was significantly lower than those for the rice kernel and 30% RKB flour items. The scale-differential questions on the participants' concerns about nutritional profiles showed that the individual concern for protein content increased the bidders' amount for the ramen noodles. However, concerns about gluten and saturated fat content did not affect the WTP bid for all types of ramen noodles.

The findings underscore the potential of developing gluten-free ramen noodles to satisfy consumer preferences beyond celiac concerns, driven by health-conscious consumers seeking to improve their well-being through dietary choices. In situations where wheat (non-gluten-free) ramen noodles are available in the market, rice kernel and 30% RKB-flour ramen noodles could become an alternative product for consumers who are gluten-intolerant and/or seeking a healthier diet. Our study reports the results of experimental auctions in which consumers bid on ramen noodles. The method provides non-hypothetical data on consumer preference for the flour formulation of gluten-free ramen noodles, which is the first step in identifying consumer perceptions in the development of commercial products. Although our experiment was conducted only in Thailand, this is the first experimental study to determine the effects of RKB flour, consumer demographics, and concerns regarding food nutritional profiles on the WTP amount for ramen noodles, which is a popular food in Asia. A larger sample size from a wider geographical region and recent year should be considered in future studies. The experimental analysis should be further extended to include more auction formats to improve the accuracy of the current findings. Potential failures in randomization across treatments, due to unobserved heterogeneity arising from the auction practice round, may lead to biased estimates and should therefore be carefully addressed in future experimental auctions[4]. Furthermore, the manufacturing cost for alternative products that made from RKB flour is an essential factor that should be considered to obtain a better estimate of whether this change actually benefits consumers as well as the food processing industry.

## Data availability statement

The data supporting the findings of this study are available from the first author on reasonable request.

## Conflict of interest disclosure

There is no conflict of interest.

## Ethics approval statement

Authors confirmed that this research was approved by the Chiang Mai University Research Ethics Committee in CMUREC No. 62/049.

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- Chiang Mai University, Thailand.

4. For further discussion of the failure of randomization to treatment, see Briz *et al.* (2017).

## Authors' contributions

Chaowana Phetcharat: conceptualization, data collection, perform the statistical analysis, and writing original draft for methodology, result, and conclusion; Jeffrey D. Vitale: conceptualization, writing final draft, and supervision; Pavalee Chompoorat Tridtitanakiat and Wanlanai Saiprasert: conceptualization and data collection, as well as writing original draft for the introduction; Weirong Lu: prepared data and writing second draft for introduction and literature review.

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## Competing interest

Authors have no relevant financial and non-financial competing interests that could affect the work reported in this paper.

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## Appendix - *Sample size calculations*

To determine the optimum number of sample size per flour-based treatment, the study employed the approach proposed by Canavari *et al.* (2018); Drichoutis *et al.* (2015); Lehr (1992); and List *et al.* (2011). This approach calculates the sample size based on three key elements, which are: (1) a level of Type I error $\alpha$, (2) the power of the statistical test $1-\beta$, and (3) the minimum detectable size of the treatment effect ($\mu_1 - \mu_2$). This sample size calculation is commonly known as a Sixteen S-squared over D-squared (Lehr, 1992), which is defined as:

$$n = \frac{2\left[Z_{1-\alpha/2} + Z_{1-\beta}\right]^2 \sigma^2}{[\mu_1 - \mu_2]^2} \tag{1}$$

where, $n$ is the number of samples per group, $\sigma$ is a pool variance estimate, $\alpha$ is a Type I error level, $\beta$ is Type II error, and $\mu_0 - \mu_1$ is the difference to be detected between the mean response of treatments.

By given a specific values of two-tailed $\alpha$ 0.05 and power $(1-\beta)$ 0.80, the values of $Z_{1-\beta}$ and $Z_{1-\alpha/2}$ are equal to 0.84 and 1.96, respectively. Then, the numerator, $2[Z_{1-\alpha/2} + Z_{1-\beta}]$, is approximately equal to 16. The equation (1) becomes:

$$n = \frac{16\sigma^2}{[\mu_1 - \mu_2]^2} \tag{2}$$

This crude sample size estimate can only apply when the values of alpha and power are 0.05 and 0.80, respectively. In our study, the alpha and power values were set at 0.01 and 0.90, with an expected detectable effect size of 10 and a pool variance estimate of 100. The given coefficient '30' proposed by Lehr (1992) was applied into the equation (2) to substitute for '16' – i.e., the values of $\sigma$ and $\mu$ are 1.28 and 2.58, respectively.. The sample size per treatment of our study was 30. Table 1 presents the sample size for different values of alpha and statistical power, with the detectable effect size and pool variance of the study.

*Table A1 - The sample size for different values of alpha ($\alpha$) and power ($1-\beta$)*

| **Power of the statistical test ($1-\beta$)** | **The sample size at** | | |
|---|---|---|---|
| | **$\alpha$ = 0.01** | **$\alpha$ = 0.05** | **$\alpha$ = 0.10** |
| 0.80 | 23.5 | 16 | 12.5 |
| 0.90 | 30 | 21 | 17.5 |
| 0.95 | 36 | 26 | 22 |

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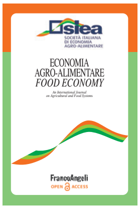


# Ecosystem Services in Food Labels: The Role of Different Information Layers in Shaping Consumers Preferences

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## *Abstract*

Information on the provision of ecosystem services has the potential to contribute to an integrative food labelling framework. This study examines that potential by explicitly communicating ecosystem services provided by agricultural producers. The research analyzes how different label formats-ranging from generic references to ecosystem services to specific indicators-influence consumer preferences. An on field Discrete Choice Experiment was conducted with 552 Italian consumers of extra virgin olive oil. A Latent Class Model identified consumer heterogeneity, and to address the endogeneity of environmental attitudes in class allocation, a two-stage Control Function approach was applied. Two consumer segments emerged. The first, showed a consistently higher and statistically significant willingness to pay for sustainability attributes. Their willingness to pay increased with the level of informational detail. However, a negative halo effect was observed when ecosystem services labels appeared alongside organic certification, suggesting a perception of redundancy. The second segment was more price-sensitive and resistant to additional information. From a policy perspective, the results indicate how ecosystem service labeling strategies, particularly when linked to measurable environmental outcomes, can stimulate market-based incentives.

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## Introduction

Today's global food system has a significant impact on both the environment and climate. It accounts for approximately 29.7% of total greenhouse gas emissions (FAO, 2024) and is a major driver of biodiversity loss and ecosystem degradation (O'Brien *et al.*, 2024). At the same time, food systems play a central role in achieving key social goals, including reducing hunger and poverty (Searchinger *et al.*, 2019). Due to this dual role – both contributing to and being affected by environmental and social challenges – there is a pressing need to transition toward more sustainable and resilient models (Schulze *et al.*, 2024).

Policymakers have a wide range of interventions and tools at their disposal. From the producers' perspective, strategies to internalize the negative externalities of food production have primarily focused on conditional subsidy payments, as exemplified by the European Union's Common Agricultural Policy (CAP) (Pe'er *et al.*, 2019). On the consumer side, policy efforts have largely aimed at influencing purchasing choices (Just & Byrne, 2019). Understanding public attitudes toward various policy options is essential for designing effective interventions (De-loyde *et al.*, 2025; Reisch & Sunstein, 2016). Governments have access to a wide range of tools to achieve consumer-focused food policy goals, including information campaigns, behavioral nudges, financial incentives (such as taxes or subsidies), and regulatory approaches. In general, consumers are more likely to support less intrusive measures – such as informational tools and nudges – than stricter options like taxes or bans, despite the latter often proving more effective (Ammann *et al.*, 2025).

Among the less intrusive measures, front-of-pack (FOP) labels are increasingly used to help consumers make healthier and more environmentally responsible food choices (Hallström *et al.*, 2015; Canavari *et al.*, 2002). These labels aim to bridge the information gap between producers and consumers by highlighting product characteristics that are difficult to observe (Canavari & Coderoni, 2020), even after purchase – specifically, credence attributes such as environmental impact and sustainability performance (Lin & Nayga Jr, 2022). By enhancing awareness, reducing search costs, and encouraging more sustainable consumption, FOP labels also have the potential to incentivize environmentally responsible production (Carlsson *et al.*, 2022). Gorton *et al.* (2021) examined the use of eco-labels – especially organic certifications in the EU – and found that they play a key role in transforming unobservable product attributes into actionable market signals.

However, many existing labels focus on broad standards, such as organic production, and fail to communicate specific environmental contributions –

for instance, efforts by agricultural producers to conserve pollinator habitats or sequester carbon in soils, which more generally can be described as agriculture's contribution to the provision of ecosystem services (ES). These services, defined as the benefits people obtain from nature, are receiving increasing attention in both EU policy and academic research (Bouwma *et al.*, 2018; Costanza, 2020; Nes & Ciaian, 2022). Yet despite their growing significance, ES remain absent from current food labeling and consumer communication frameworks.

This study contributes to the literature on ES labelling along three complementary dimensions. First, it moves beyond treating ES labelling as a homogeneous attribute by explicitly focusing on the design of ES-related information. The analysis compares alternative communication strategies, ranging from a generic reference to ES to a specific and measurable representation of a single service, articulated across different levels of informational detail. Second, the study situates ES labelling within a broader information environment by jointly analyzing on-pack labels and complementary off-pack communication aimed at explaining the meaning and relevance of ES. Third, integrating multiple attitudinal scales into a latent class framework while explicitly addressing the associated endogeneity concerns, the study provides a parsimonious and empirically robust alternative to hybrid choice models, enabling attitudes to inform preference heterogeneity and yielding stable and interpretable welfare measure estimates.

Helping consumers understand the environmental role of agriculture – particularly through the lens of ES – may encourage more sustainable consumption patterns. Labels that clearly convey these contributions could motivate consumers to reward producers for their efforts, enhancing the effectiveness of sustainability policies (Laksmawati *et al.*, 2024). If consumers value these practices, targeted financial incentives could be more impactful, especially in encouraging change among less sustainable producers (Just & Byrne, 2019).

## 1. Background

Emerging research has started to examine novel food labeling schemes that incorporate ES. Schulze *et al.* (2024) explored how information on ES provision could inform future labeling practices in the EU's Farm to Fork Strategy, identifying three potential label types: producer-driven, consumer-oriented, and EU-wide sustainability labels, based on expert input from multiple countries. Their work highlights the importance of integrating diverse stakeholder perspectives in label design. The study by Voglhuber-Slavinsky *et al.* (2023) explores private valorization options for biodiversity and ES in the agri-food value chain and confirm that labeling has the potential to complement or even substitute public policy instruments by operating beyond the production stage and actively shaping consumer demand. Altmann and Berger Filho (2020) examined the potential of certification and labeling as economic instruments to promote biodiversity conservation and ES in the Pampa Biome, using grassland beef certified under the "Alianza del Pastizal" scheme as a case study, demonstrating that such mechanisms can create market incentives through premium pricing, though their effectiveness depends on system design and consumer responsiveness.

Other studies have investigated how ES certification can influence market dynamics through direct consumer surveys. Jaung *et al.* (2019), through a DCE on bottled water with ES claims in Indonesia, found that certification improved brand equity but struggled to outperform established competitors, emphasizing the role of branding and market positioning. Borrello *et al.* (2022) demonstrated that cultural ES from traditional agricultural landscapes could be valued through labeling: consumers expressed willingness to pay (WTP) for products certified as linked to terraced olive groves, particularly when combined with organic and protected designation of origin (PDO) certifications.

Nevertheless, the literature has not yet explored the optimal communication strategy for ES labels-specifically, how consumers perceive, interpret, and value them, both in terms of visual design and informational content.

Individuals differ in how they interpret and use labels: some rely on general food knowledge, while others depend on label familiarity (Sørensen *et al.*, 2012; Silva *et al.*, 2018), making effective label design a complex challenge (Boncinelli *et al.*, 2023; Duckworth *et al.*, 2022). Van Loo *et al.* (2015) outline the importance of label salience and consumer education, noting that visibility and clarity are essential to converting credence attributes into meaningful decisions. Informational framing is equally important: clear explanations, and eco-metrics help reduce information asymmetries and build consumer trust (Canavari *et al.*, 2016; Aprile & Punzo, 2022). However, the complexity and multidimensional nature of ES increase the risk of information overload, which may impede consumers' ability to effectively process and act on label information (Grunert & Wills, 2007). This is further supported by a recent study on extra virgin olive oil (EVOO) across Italy, Greece, and Israel, which highlights that the abundance of certifications (e.g., PDO, organic, carbon footprint) can cause consumer confusion, ultimately diminishing the communicative effectiveness of labels (Paffarini *et al.*, 2025). These elements are particularly relevant in the context of ES labeling, as ES are, by definition, a diverse set of benefits provided by nature. In the case of agriculture, these services can include provisioning services such as food, fiber, and biomass production; regulating services such as carbon sequestration, pollination, water purification, erosion control, and climate regulation; supporting services including soil fertility and nutrient cycling; and cultural services such as landscape aesthetics, cultural heritage, and recreational value (United Nations *et al.*, 2021). Given the variety of services involved, communication through labeling can take two different approaches: a generic label that certifies the overall provision of ES, or a targeted label that highlights a specific ES delivered by the farm. For example, a farm could adopt a targeted labeling strategy to communicate its contribution to pollination services. In this case, a possible indicator could be Net Pollination Index, which quantifies the contribution of on-farm practices such as the maintenance of wildflower strips, hedgerows, or pollinator habitats to pollinator activity and crop yield (Martínez-López *et al.*, 2019). Together, this body of evidence suggests that effective ES labels should balance visual clarity, meaningful content, and credible certification to foster informed choices and reward environmentally responsible production – especially considering that these new labels may appear alongside existing environmental (e.g., organic) or quality certifications (e.g., PDO) on the product.

## 2. Materials and method

### 2.1. *Data and Survey Design*

Survey was conducted from May to August 2024, through a face-to-face field experiment approach at a supermarket chain store in Brescia, Italy. The focus of the survey was a DCE on EVOO for consumption at home. In Italy, EVOO is a widely consumed product and plays a key role in the Mediterranean diet, being therefore often chosen for reasons related to health, culture, and product quality (Del Giudice *et al.*, 2015; Perito *et al.*, 2019).

The sample consisted of 552 people, aged eighteen years and older, regular consumers of EVOO (at least 2 times a week) and main responsible for their household's food expenditure. Subjects were recruited at the entrance of the supermarket store. We promoted a brief collaboration with a store belonging to a national supermarket chain present in Brescia, Italy, in a middle- to high-income neighborhood. In Mompiano, the median household annual income was estimated at €31.835, with residents accounting for 3.84% of total taxpayers in the municipality (Dipartimento delle Finanze, 2022). The reference population of the study is therefore defined as adult, frequent consumers of extra virgin olive oil who are primarily responsible for household food purchases and who shop in large-scale retail outlets.

Given the single-store setting and the socio-economic characteristics of the neighbourhood, the sample reflects a specific segment of Italian consumers and should not be interpreted as statistically representative of the national population.

A preliminary pilot study of 52 students was conducted to test the clarity of the experiment, the quality of the responses and to optimize the experimental design.

The survey was conducted in a standardized face-to-face setting using a tablet, with interviewers following a fixed script and simultaneously presenting and reading aloud all information shown on the screen. The questionnaire was structured into four main sections. The first investigated awareness and attitudes related to sustainability of food supply chains. The second section contained the DCE. To ensure data quality, before presenting the set of choice tasks, we asked respondents whether they had "devoted their full attention to the questions up to that point" and whether, in their honest opinion, they felt we should have used their answers for the study (Meade & Craig, 2012). We strategically placed this question immediately before more important ones, such as choice tasks (Asioli *et al.*, 2022). Prior to the DCE tasks respondents were also instructed on how to complete the DCE and given a cheap talk script to mitigate hypothetical bias (Cummings and Taylor, 2009). For transparency and replicability, the full text of the cheap talk script provided to respondents is reported in the Supplementary material (S1).

The third section of the questionnaire investigated respondents' knowledge and usage habits related to food labels and ES. Prior knowledge was measured through self-reported familiarity. Specifically, respondents were asked whether they had previously seen selected food labels (Organic, Eco-label, PDO/PGI, Carbon Footprint) and whether they had ever heard of ecosystem services, using dichotomous response options (Yes/No/Don't know). Objective knowledge was assessed using performance-based measures. For food labels, respondents answered multiple-choice questions asking them to identify the correct meaning of each label, with one correct option among several alternatives (Grunert *et al.*, 2014). For ES, objective knowledge was measured through a set of true/false statements covering core ES concepts (e.g. the role of biodiversity, human dependence on ES, and the possibility of quantifying ES). Objective knowledge scores were constructed as the number of correct answers provided by each respondent. In addition, self-reported label use was measured through Likert-scale questions asking how frequently different types of information typically available on food packages are considered during purchase decisions, using a 7-point scale ranging from 1 ("Never") to 7 ("Always"). The last section, with socio-demographic questions, concluded the questionnaire.

### 2.2. *Experimental Design*

Different labeling strategies have been investigated using DCEs, which allows the estimation of a welfare measure in terms of citizens' marginal willingness to pay (mWTP) for different labeled information options (Bazzani *et al*., 2025; Lusk *et al*., 2018; Thiene *et al*., 2018; Van Loo *et al*., 2014). Some of the most relevant studies evaluating how environmental impact information drives consumer choices have implemented this approach (Lin & Nayga Jr, 2022; Mameno *et al*., 2023). Hypothetical DCE was also used to elicit preferences for different qualities of EVOO (Panico *et al*., 2014; Scarpa & Del Giudice, 2004). DCEs allow to decompose the good into different attributes, estimating preferences for each of them and representing the decision-making mechanisms that individuals enact in a context such as the supermarket (Canavari *et al*., 2023; Caputo *et al*., 2023; Cerroni *et al*., 2019; Grebitus *et al*., 2013; Muller *et al*., 2019).

The first step in designing the experiment was to define the product, which is an EVOO in a one-liter bottle. EVOO was selected as case study because in Italy EVOO production represents one of the main permanent tree productions, occupying about 8 percent of the national utilised agricultural area (ISTAT, 2021). Second, areas designated for EVOO production generally represent an ecosystem with important potential for the conservation and maintenance of biodiversity (Salazar-Ordóñez *et al*., 2021). Moreover, in Italy, EVOO production has been abandoned in some areas in the last 5 years (Mediobanca - Area Studi, 2024), representing the potential case study of the effective capacity of a labeling strategy on the provision of ES as an incentive for a premium price to make production economically viable.

Second phase involved the selection of attributes and related levels to describe the EVOO bottle proposed in the experiment (Table 1).

*Table 1 - Attributes and relative levels used in the choice experiment*

| **Attributes** | **Levels considered** | **Logo** |
|---|---|---|
| Ecosystem Services | • None<br>• ES logo | |
| Organic | • None<br>• EU Organic logo | |

| | |
|---|---|
| ES Maintenance of Biodiversity (preservation of pollinator species) | • None<br>• Farming for Biodiversity<br>• Farming for Biodiversity + Bees<br>• Farming for Biodiversity + Bees + Net pollination index |
| Designation of origin | • None<br>• PGI<br>• PDO |
| Price | • 9,1 €<br>• 10,6 €<br>• 12,1 €<br>• 13,6 €<br>• 15,1 € |

Given the intention to also investigate the effect of co-occurrence with the most common labeling types associated with EVOO, labels for organic certification and designation of origin were selected (Čehić *et al.*, 2021). For the former, levels indicating the presence or absence of the logo were included. For the latter, levels corresponding to absence, Protected Geographical Indication (PGI), and PDO were selected.

Regarding the provision of ES two hypothetical attributes were employed. The attributes were selected based on the Common International Classification of Ecosystem Services (CICES) (Haines-Young and Potschin-

Young, 2018). In particular, the generic ES logo does not correspond to a specific CICES service but represents an aggregate and hypothetical signal of ES-oriented agricultural management. By contrast, the 'ES maintenance of biodiversity' attribute refers to regulating ES related to habitat provision, with a specific focus on farming practices supporting pollinators (CICES v5 code 2.2.2.1). For this specific attribute, levels of increasing informational detail were selected: an absence level, an initial informational level labeled "Farming for Biodiversity", an enhanced level "Farming for Biodiversity + Bee", which includes the image of a bee to represent the service being provided, and a further detailed level, "Farming for Biodiversity + Bee + Net Pollination Index", which introduces a value scale based on the Net Pollination Index (Martinez-Lopez *et al.*, 2019). The idea that communicating to consumers the efforts and services that producers can potentially offer to the community may provide producers with new opportunities for product differentiation motivated the selection of these attributes. Finally, based on data from the Italian bottled EVOO market and current literature, the price attribute for one liter bottle of EVOO was constructed with five levels (9.1€, 10.6€, 12.1€, 13.6€ and 15.1€) selected on the basis of price monitoring in the supermarket where the survey was conducted and the results of the pilot study.

In designing the DCE, we initially developed an optimal orthogonal in differences design. This design was employed in a pilot study involving a sample of 52 students, following the design principles outlined by Street *et al.* (2001, 2005). Subsequently, the parameter estimates obtained from the pilot study were used to generate a Bayesian D-efficient design aimed at minimizing the average D-error. Design simulations were conducted using 500 Halton draws, resulting in a design comprising 36 choice tasks (Bliemer *et al.*, 2008; Ferrini & Scarpa, 2007; Rose & Bliemer, 2013; Scarpa & Rose, 2008). The 36 choice sets were orthogonally divided into four blocks, each consisting of nine tasks. This means that each respondent was randomly assigned to one block and asked to evaluate nine purchase scenarios. Each scenario presented two product alternatives and a third opt-out alternative (no purchase).

### *2.3. Choice Tasks and Treatment Design*

As an introduction to the DCE, respondents were instructed on the mechanism of the experiment. They were asked to imagine themselves in a real-life choice situation within the supermarket and that they would have to select one liter bottle of EVOO for home consumption under nine different scenarios. Respondents were asked to indicate their preferred option based on the label information provided or to opt-out if none of the alternatives were considered acceptable.

In addition, respondents were randomly assigned to one of two treatment groups that differed in the presence of an additional informational component external to the product label. In detail, in the control treatment (Info = 0), participants were presented with choice tasks preceded by a brief and generic introduction to ES. In contrast, in the information treatment (Info = 1), respondents were provided with an explanation prior to the choice tasks detailing how ES are measured, and what the information on the hypothetical labels really represents. For example, the Net Pollination Index was explained, as an index that ranges from –1 to +1 and measures how well an ecosystem supports crop pollination. Habitats such as forest edges and flowering hedgerows help pollinating insects. An olive grove that preserves these habitats and reduces pesticide use will have a positive index (0 to +1). Conversely, a field that does not preserve these habitats and reduces the availability of shelter and protection for pollinator species will have a negative index (0 to –1) (Martínez-López *et al.*, 2019). This information covered both the general informational levels of the labels and the more detailed information levels, elaborating on the methods used for measuring and representing the ES. This approach was intended to simulate a potential external informational campaign – distinct from product labeling – as a form of nudging, assessing the effect of additional off-label information and information asymmetry gap filling on consumer preferences.

## *2.4. Econometric Approach*

### 2.4.1. Latent Class Model

From DCEs data, estimates of discrete choice models (DCMs) can be obtained. DCMs are consistent with random utility theory (McFadden, 1974), which states that the utility that individual *n* gets from alternative *j* in the set of choices *t* can be decomposed into an observed, deterministic part ($V_{njt}$) and an unobserved, random part ($\varepsilon_{njt}$):

$$U_{njt} = V_{njt} + \varepsilon_{njt} = ASC_j + x'_{njt}\beta + \varepsilon_{njt} \tag{1}$$

where $x'_{njt}$ is a vector containing attributes of the asset to be evaluated, $\beta$ is the vector of corresponding parameters, $ASC_j$ are the alternative specific constants. This structure of utility is consistent with Lancaster's (1966) theory, which assumes total utility resulting from the choice of a product as a decomposition of additive utilities arising from the attributes of the product itself.

The literature on consumer behavior in relation to food labels shows that consumers have heterogeneous preferences (Lusk *et al*., 2003). Heterogeneity of preferences (e.g., taste variation) in sustainability claims must also be considered for correlation between utilities and between taste parameters (Van Loo *et al*., 2014). Heterogeneity can be assumed to be continuous or discrete, and recent literature has shown that taste variation has asymmetric and multimodal distributions (Caputo *et al*., 2018; Scarpa *et al*., 2021).

An initial approach on the continuous and discrete nature of heterogeneity was conducted using Mixed Logit models in WTP space (Scarpa *et al*., 2008; Train & Weeks, 2005). The results showed a multimodality of preferences distributed in subgroups that supports our latent class model (LCM) approach (Yagi *et al*., 2025).

LCM consists of a structural equation for the choice model (Equation 1) and a class allocation function (Greene & Hensher, 2003). In LCMs, individuals are indirectly allocated into $q$ classes, and the researcher is unable to know which class an individual belongs to. The probability that an individual $n$ will choose an alternative $i$ is the logit probability conditional on membership in class $q$. The probability of sequence of choices of individual $n$ is then represented as:

$$P_n(i|q) = \prod_{t=1}^{T} P_{nit}\,(i|q) = \prod_{t=1}^{T} \left(\frac{\exp\left(ASC_i + x'_{nit}\beta_q\right)}{\sum_{j=1}^{J} \exp\,(ASC_i + x'_{nit}\beta_q)}\right) \tag{2}$$

The probability $\Psi_{nq}$ that individual $n$ belongs to class $q$ is modeled as a logit probability:

$$\Psi_{nq} = \frac{\exp\,(\gamma_{0q} + z'_n\gamma_{1q})}{\sum_{q=1}^{Q} \exp\,(\gamma_{0q} + z'_n\gamma_{1q})} \tag{3}$$

where $z'_n$ are observable exogenous characteristics (e.g., sociodemographic), $\gamma_{1q}$ is the corresponding parameter vector, and $\gamma_{0q}$ are constant terms.

The unconditional probability that individual $n$ will make the set of choices will be given by the sum of the conditional probabilities on the $q$ classes (Equation 2), weighted by the probability of membership in each class (Equation 3) (Mariel *et al*., 2025). It is not possible to estimate the number of classes a priori, but it is necessary to orient based on informative criteria about the model fit, as well as the researcher's judgment (Scarpa & Thiene, 2005).

### 2.4.2. Endogeneity in the allocation function of an LCM and the two-step Control Function approach

A growing body of literature describes the influence of individual attitudes toward an environmental good or service on environmental valuation (Hess *et al.*, 2013). Heterogeneity of preferences, particularly in an LCM, shows its best representation with the inclusion of such attitudes. While generally the problem related to endogeneity concerns the structural equation (Equation 1) (Guevara, 2018), it can also occur in the allocation function of an LCM (Equation 3). As described in Mariel and Arata (2022) this function can be seen as the propensity to belong to a specific class $q$, and can be described as:

$$F_{nq} = \gamma_{0q} + z_n'\gamma_{1q} + \gamma_{2q}s_n + \xi_{nq} \quad (4)$$

where $z_n$ is a vector of observable exogenous characteristics (e.g., sociodemographic), $s_n$ is a vector of individual attitudes (e.g., attitudinal scale) and $\gamma_{0q}$, $\gamma_{1q}$ and $\gamma_{2q}$ are the corresponding parameters.

Assuming that $s_n$ is defined as:

$$s_n = \alpha_0 + c_n'\alpha_1 + \eta_n \quad (5)$$

where $c_n$ is a vector of exogenous variables independent of error terms $\xi_{nq}$ (Eq. 4) and $\eta_n$, and $\alpha_0$ and $\alpha_1$ are unknown parameters. The vector $c_n$ may contain all or some of the observable exogenous variables $z_n$ (Eq. 4).

Therefore, assuming the influence of individual attitudes related to the environmental good or service ($\gamma_{2q} \neq 0$), we could have endogeneity in Equation (4) due to the omission of the relevant variable ($s_n$); due to the measurement error of the attitude itself (under appropriate assumptions); or in the case where the error terms $\xi_{nq}$ in Equation (4) is correlated to the error term $\eta_n$ in the Equation (5). In the latter case, $s_n$ in Equation (4) is endogenous by definition (Alcorta & Mariel, 2025).

Our case study evaluates the inclusion of an endogenous indicator ($s_n$) representing individuals' attitudes toward the sustainability of the agribusiness supply chain. This is the case where, as the classes defined by equation (4) are representative of preferences for label information regarding the environmental sustainability of EVOO production, the error terms $\xi_{nq}$ and $\eta_n$ are correlated.

To address this potential endogeneity problem, we apply the two-stage Control Function (CF) approach (Guevara & Polanco, 2016). In the first stage, the attitudinal indicator is regressed on the exogenous variables $z_n$, on an instrumental variable ($\mathrm{Instr}_{1n}$) for which typical instrument assumptions apply (Guevara, 2018), and on two additional instruments formed by seven additional statements on sustainability of agrifood supply chain collected and used to define the two main factors from an exploratory factor analysis ($Fact_{1n}$, $Fact_{2n}$):

$$s_n = \alpha_0 + z_n'\alpha_1 + \alpha_2 Instr_{1n} + \alpha_3 Fact_{1n} + \alpha_4 Fact_{2n} + \eta_n \tag{6}$$

where $\eta_n$ is assumed to be i.i.d. normally distributed. Equation (6) is estimated by ordinary least squares regression to obtain the residuals $\hat{\eta}_n$. The second step of the CF approach is to include in equation (4):

$$F_{nq}^{CF} = \gamma_{0q} + z_n'\gamma_{1q} + \gamma_{2q}s_n + \gamma_{3q}\hat{\eta}_n + \xi_{nq} \tag{7}$$

where $\hat{\eta}_n$ residuals collect the part of $s_n$ that generates correlation with the error term in equation (4).

The entire DCM was estimated using Equation 7 in the LCM allocation function.

To verify the necessary condition that the instruments used in Equation (6) are exogenous, the test of refutability of instrument exogeneity was used (Guevara, 2018). The test is based on the condition of overidentification and first estimates the LCM using Equation (7) in the allocation function, then recalculates the model with a modified allocation function that includes Equation (7) with all instruments except one. The test statistic is defined as:

$$S_{ref} = -2\,(LL^{CF} - LL^{CFinstr}) \sim \chi^2_{df} \tag{8}$$

where *df* are the degrees of freedom equal to the number of instruments minus the number of endogenous variables. The null hypothesis of the test is that the instruments are exogenous, while the alternative hypothesis is that one or both instruments are endogenous, and it is repeated for all possible combinations of instruments.

## 2.5. *Empirical Model*

The random utility discrete choice model (Eq. 1) is specified as:

$$\begin{aligned} U_{nit|q} = {} & ASC_q[1 + 1(Inf)_n] + \alpha p_{nit} + \tilde{\beta}_q' x_{nit} + \delta_q[x_{nit} \times 1(Inf)_n] \\ & + \gamma_q\left[x_{nit}^{ES} \times Organic\right] + \vartheta_q\left[x_{nit}^{ES} \times PDO\right] + \varepsilon_{nit|q} \end{aligned} \tag{9}$$

where $ASC$ denotes the alternative-specific constant for the opt-out alternative, it takes the value 1 when respondents choose not to purchase any of the proposed products. The model also includes interaction effects between $ASC$ and an external information variable, which equals 1 if the respondent received additional information processing. The variable $p_{nit}$ is a continuous measure representing the five price levels used in the experiment. The vector $x_{nit}$ comprises non-price attributes, including:

1. Organic production certification, treated as dummy variable (1 if the logo is present, 0 otherwise).
2. Indicator for generic ES provision, treated as dummy variable (1 if the logo is present, 0 otherwise).
3. A variable for the specific ES attribute concerning the maintenance of biodiversity preserving pollinator species, modeled as dummies across three experimental levels reflecting increasing information content (the absence of a label serves as the reference level with a value of 0).
4. The designation of origin attribute, also represented by dummy variables for each experimental level and associated logo presence (PGI and PDO).

The parameter $\alpha$ denotes the marginal utility of income (i.e., the price coefficient). The vector $\tilde{\beta}_q$ includes coefficients for non-price attributes specific to class $q$, which are assumed to vary randomly and continuously among respondents in that class according to a normal distribution. The vector $\delta_q$ captures class-dependent, within-class fixed parameters reflecting the effects of information on the quality attributes represented by the treatment dummy variable *Inf*. The vector $\gamma_q$ comprises class-specific fixed parameters describing the interaction effects between ES-related logos ($x_{nit}^{ES}$) and the "Organic" dummy. Similarly, $\vartheta_q$ represents the interaction effects between ES-related logos ($x_{nit}^{ES}$) and the PDO dummy. The parameters $\gamma_q$ and $\vartheta_q$ describe the potential halo effect of well-recognized and widely adopted certifications (Organic and PDO) on the perception of ES-related information.

The class allocation function corresponding to Equation 4 is defined as:

$$\begin{aligned} F_{nq} = \gamma_{0q} + \gamma_{1q} Female_n + \gamma_{2q} Age_n + \gamma_{3q} Education_n + \gamma_{4q} Income_n \\ + \gamma_{5q} Full\ time_n + \gamma_{6q} Household_n + \gamma_{7q} Children_n \\ + \gamma_{8q} Environmental\ damage_n + \xi_{nq} \end{aligned} \tag{10}$$

where the attitudinal statement *Environmental damage* is added to the sociodemographic variables to assess the potential role that attitudes toward the relationship between food production and the environment may have on individual class allocation. We applied the CF approach to consistently estimate the model defined above being this additional explanatory variable endogenous by definition (Mariel and Arata, 2022).

Finally, the negative ratio between the estimated average value of the coefficient associated with the quality attribute of the EVOO and the price coefficient was used to estimate the marginal WTP.

## 3. Results

### 3.1. *Descriptive analysis*

Data were collected on a sample of 750 respondents from the adult population who frequented the supermarket in question in the Mompiano neighborhood in the city of Brescia. Final sample consisted of 552 correct responses, representing 4968 observations.

Table 2 reports the summary statistics of the sociodemographic variables.

*Table 2 - Sociodemographic variables*

| **Category** | **Variable** | **Mean[a] Control** | **Mean[a] Treatment** | **No diff. in proportion** ***p-value*** | **No diff. in distribution** ***p-value*** |
|---|---|---|---|---|---|
| *Gender* | | | | | |
| | Male | 48.1% | 42.2% | 0.187 | 0.107 |
| | Female | 51.1% | 57.8% | 0.135 | |
| | Prefer not to answer | 0.8% | 0.0% | // | |
| *Age class* | | | | | |
| | 18-24 | 12.2% | 12.1% | 0.953 | 0.812 |
| | 25-34 | 18.5% | 15.6% | 0.425 | |
| | 35-44 | 10.7% | 13.8% | 0.330 | |
| | 45-54 | 20.0% | 20.9% | 0.871 | |
| | 55-64 | 27.4% | 24.8% | 0.553 | |
| | 65+ | 11.1% | 12.8% | 0.641 | |
| *Education* | | | | | |
| | High School | 46.7% | 48.2% | 0.778 | 0.597 |
| | Graduate | 42.2% | 42.6% | 0.937 | |
| | Post Graduate | 11.1% | 9.2% | 0.552 | |
| *Employment* | | | | | |
| | Unemployed | 14.4% | 12.1% | 0.483 | 0.522 |
| | Retired | 9.3% | 12.8% | 0.239 | |
| | Part-time Employed | 14.4% | 12.1% | 0.483 | |
| | Full-time Employed | 61.9% | 63.1% | 0.826 | |

| | | | | | |
|---|---|---|---|---|---|
| *Household Gross Income* | | | | | |
| | ≤15,000€ | 10.7% | 6.4% | **0.091** | 0.281 |
| | 15,001-29,000€ | 27.8% | 29.1% | 0.807 | |
| | 29,001-55,000€ | 38.9% | 39.7% | 0.912 | |
| | 55,001-100,000€ | 16.7% | 18.4% | 0.664 | |
| | >100,000€ | 5.9% | 6.4% | 0.965 | |
| *Household Composition* | | | | | |
| | Household Size | 2.211 (1.340) | 2.131 (1.266) | // | 0.382 |
| | Children Under 15 | 0.267 (0.646) | 0.309 (0.705) | // | 0.428 |
| *Environmental association membership* | | 15.2% | 11.7% | 0.282 | |
| *Sample Size* | N. of respondents | 270 | 282 | | |

*Note*: [a] Refers to proportions for dummy variables; for all other variables, values represent means, with standard errors reported in parentheses.

A total of 270 people were assigned to the Inf = 0 group and 282 to the Inf = 1 group. We conducted equilibrium checks to assess whether the two treatment groups differed systematically in their sociodemographic characteristics. Chi-squared tests and Nonparametric Mann-Whitney U-tests were applied to test for significant differences between the distributions in the two subsamples with and without information, as well as *p*-values for the test of no difference between the proportions was reported. Overall, the sample appears well balanced. Gender differences are not statistically significant, although the Inf = 1 group includes a slightly higher proportion of female respondents (57.8%) than Inf = 0 (51.1%). The age distribution is similar, with the largest shares concentrated in the 45-64 age group. There are no significant differences in education or employment status. Household income levels are also comparable, although the Inf = 0 group includes a marginally higher proportion of low-income respondents (≤ 15,000 euros, p = 0.091), which falls short of conventional levels.

Table 3 shows the relative frequency of scores given by respondents to attitudinal questions regarding concern about the sustainability of food production (adapted from Grunert *et al.*, 2014).

*Table 3 - Attitudinal questions and relative frequency (%) (1 = only slightly concerned; 7 = extremely concerned)*

| | **Label** | **1** | **2** | **3** | **4** | **5** | **6** | **7** |
|---|---|---|---|---|---|---|---|---|
| Environmental damage caused by human use of land and water in food production | env_damage | 6.9% | 10.0% | 15.9% | 11.1% | 15.6% | 17.6% | 23.0% |
| The use of pesticides used in food production | pest | 6.0% | 9.1% | 15.4% | 10.0% | 12.5% | 17.4% | 29.7% |
| Poor treatment of animals in food production | animals | 8.9% | 10.7% | 15.8% | 10.1% | 14.3% | 9.2% | 31.0% |
| The process of deforestation related to food production | deforestation | 4.7% | 6.5% | 16.3% | 7.6% | 13.4% | 19.0% | 32.4% |
| Using too much of the world's natural resources for food production | resources | 6.3% | 8.5% | 15.2% | 9.8% | 13.2% | 19.0% | 27.9% |
| The amount of non-recyclable packaging | packages | 4.5% | 6.9% | 15.4% | 10.3% | 12.5% | 19.9% | 30.4% |
| The amount of $CO_2$ emissions during the transportation of food products | transport | 7.1% | 9.2% | 15.2% | 11.1% | 18.1% | 18.7% | 20.7% |
| The amount of energy used when cooking food products | energy | 16.1% | 14.5% | 13.9% | 15.0% | 17.6% | 13.6% | 9.2% |

The respondents were asked to rate their level of concern for various issues on a 7-point Likert scale, where 1 indicates very low concern and 7 indicates very high concern. The results reveal distinct patterns in public perception across different environmental dimensions.

Overall, respondents express relatively high levels of concern for several issues. The highest levels of concern are observed for deforestation (32.4% selecting 7), poor animal treatment (31.0%), and non-recyclable packaging (30.4%). These issues are also characterized by low percentages at the lower end of the scale (4.5-8.9% selecting 1), suggesting broad consensus around their perceived severity. Similarly, pesticide use (29.7% scoring 7) and excessive use of natural resources (27.9%) are considered pressing problems by a substantial share of respondents.

In contrast, concern about energy consumption during cooking shows a markedly different pattern. This is the only item for which the most frequent response is at the lower end of the scale (16.1% selecting 1, compared to only 9.2% selecting 7), indicating that respondents perceive this issue as less environmentally relevant. $CO_2$ emissions from food transport also rank lower in relative concern, with 20.7% selecting 7, and more evenly distributed responses across the scale.

Responses regarding environmental damage from land and water use and resource overuse are relatively moderate, with around one-quarter of respondents selecting the highest concern level (23.0% and 27.9%, respectively), and notable proportions scoring in the mid-range (categories 4 and 5).

Table 4 reports respondents' levels of both prior and objective knowledge regarding four food-related labels – Organic, Eco-label, PDO, and Carbon Footprint – as well as their knowledge of ES. The table displays mean values across the two treatment groups, with minimal differences observed between the groups.

*Table 4 - Prior and objective knowledge regarding four food-related labels and ES*

| Variable | Mean[a] Control | Mean[a] Treatment | Labels |
|---|---|---|---|
| *Labels prior knowledge declaration* | | | |
| Organic label prior knowledge | 78.1% | 75.9% | |
| Eco-label prior knowledge | 33.3% | 28.7% | |
| PDO label prior knowledge | 64.1% | 62.4% | |
| Carbon foot-print label prior knowledge | 17.0% | 16.3% | |
| *Labels objective knowledge* | | | |
| Organic label objective knowledge | 42.6% | 35.1% | |
| Eco-label objective knowledge | 40.0% | 41.1% | |
| PDO label objective knowledge | 77.0% | 77.0% | |

| | | | |
|---|---|---|---|
| Carbon foot-print label objective knowledge | 60.4% | 56.4% | |
| Labels knowledge score (0-4) | 2.200<br>(1.091) | 2.096<br>(1.086) | |
| *Ecosystem Services knowledge* | | | |
| ES prior knowledge declaration | 37.0% | 33.7% | |
| ES knowledge score (0-5) | 4.056<br>(1.145) | 4.018<br>(1.156) | |

*Note*: [a] Refers to proportions for dummy variables; for all other variables, values represent means, with standard errors reported in parentheses.

Overall, self-reported prior knowledge ("*Have you ever seen this label?*") is highest for the Organic label, with 78.1% of respondents in the control group and 75.9% in the Information treatment group reporting recognition. PDO follows, with roughly 64% of respondents indicating familiarity. In contrast, the Eco-label and Carbon Footprint label show considerably lower recognition levels, with fewer than 35% of respondents reporting prior exposure (Hartikainen *et al*., 2014). These results suggest that while organic and origin-related certifications are widely recognized, environmental indicators such as eco- and carbon-labels remain less familiar to the public (Gorton *et al*., 2021).

Objective knowledge presents a different picture. While recognition of the PDO label is high, only 77% correctly identified its meaning, indicating some consistency between familiarity and understanding. In contrast, only 35.1% (Treatment) to 42.6% (Control) correctly answered questions about the Organic label, revealing a potential gap between perceived and actual understanding. Carbon Footprint label knowledge is moderate (around 58%) (Rondoni & Grasso, 2021), while Eco-label understanding remains low, with only 40–41% correct answers. The composite label knowledge score averages just above 2 out of 4 in both groups, suggesting moderate overall comprehension.

Regarding ES, 37.0% of the control group and 33.7% of the treatment group reported prior knowledge. However, the objective ES knowledge scores are relatively high, averaging around 4 out of 5 in both groups, suggesting that even among those unfamiliar with the term, conceptual understanding is strong when prompted with specific content. This is also due to the basic information received from the whole sample at the beginning of the DCE.

In summary, while prior exposure to food and environmental labels varies widely, objective knowledge tends to be lower, particularly for eco- and organic labels, highlighting potential gaps in consumer understanding.

### 3.2. *Estimation results*

This section reports the estimates of an LCM incorporating the potentially endogenous variable *Environmental damage* within the allocation function. To address endogeneity, suitable instruments were required for the auxiliary equation specified in Equation (6) the results of which are reported in the supplementary material (S4). These instruments must be correlated with the endogenous variable but uncorrelated with the error term in the allocation function.

Based on this theoretical framework, the primary instrument selected is a dummy variable indicating whether the respondent is a member of an environmental association. To strengthen the identification strategy, two additional instruments – *Factor1* and *Factor2* – were derived from an exploratory factor analysis conducted on the remaining seven attitudinal statements. The key results of this analysis are presented in Table 5.

*Table 5 - Exploratory factor analysis*

| Eigenvalues and variability | | | | Factor loadings | | |
|---|---|---|---|---|---|---|
| **Factor** | **Eigenvalue** | **Variance** | **Cumulative** | **Item** | **Factor1** | **Factor2** |
| Factor1 | 5.116 | 88.1% | 88.1% | pest | 0.835 | 0.229 |
| Factor2 | 0.343 | 5.9% | 94.0% | animals | 0.813 | 0.320 |
| Factor3 | 0.209 | 3.6% | 97.6% | deforestation | 0.910 | 0.123 |
| Factor4 | 0.109 | 1.9% | 99.5% | resources | 0.907 | 0.036 |
| Factor5 | 0.025 | 0.4% | 100.0% | packages | 0.829 | –0.257 |
| Factor6 | 0.003 | 0.1% | 100.0% | transport | 0.891 | –0.267 |
| Factor7 | 0.000 | 0.0% | 100.0% | energy | 0.792 | –0.184 |

Factor loadings indicate that Factor 1 captures the largest portion of shared variance across all statements, with high positive loadings for issues such as deforestation (0.910), resource use (0.907), and transport emissions (0.891). These high loadings suggest that Factor 1 reflects a general dimension of concern about the environmental impact of food production. Factor 2, while accounting for a smaller proportion of the variance, shows relatively stronger loadings for the statements related to animal treatment (0.320) and pesticide use (0.229), suggesting a secondary dimension possibly linked to ethical concerns in food production. However, the overall strength of loadings for Factor 2 is weaker, indicating that it plays a more marginal role. The validity of the results is conditioned by the assumption that the instruments used in the estimation are exogenous. The null hypothesis of the refutability test is that all instruments included in Equation (6) are exogenous. The p-values of the refutability test in all cases are greater than 0.92, which leads to the non-reject of the null hypothesis.

Table 6 reports the estimation of the two classes LCM with indicator. While more complex specifications (e.g., three-class models with additional interaction terms) achieve better fit according to the AIC, both the Bayesian Information Criterion (BIC) and the Consistent Akaike Information Criterion (CAIC), which impose stronger penalties for over-parameterization, consistently favor more parsimonious two-class specifications. Furthermore, the three-class model generated some classes with behavioral overlap. A summary table reporting the number of estimated parameters, log-likelihood values, and model selection criteria (AIC, BIC, CAIC) has been added to supplementary materials (S2). Therefore, the allocation function is composed of two additional variables to the observable exogenous variables (sociodemographic). The first is the *Environmental damage* indicator, and the second contains the residuals of the auxiliary regression defined in equation (6).

*Table 6 - Estimation of the LCM with indicator*

| **Variable** | **Class 1** | **Class 2** |
|---|---|---|
| *Main Effects* | | |
| ASC | –2.800***<br>(0.271) | 0.764<br>(0.637) |
| Ecosystem Services | 1.285***<br>(0.227) | 0.615*<br>(0.343) |
| Organic | 1.535***<br>(0.249) | 0.910**<br>(0.452) |
| Farming for Biodiversity | 0.459***<br>(0.155) | –0.066<br>(0.447) |
| Farming for Biodiversity + Bee | 1.090***<br>(0.152) | –0.322<br>(0.489) |
| Farming for Biodiversity + Bee + Net Pollination Index | 1.265***<br>(0.163) | 0.418<br>(0.432) |
| PGI | 0.437***<br>(0.081) | 0.572*<br>(0.296) |

| | | |
|---|---|---|
| PDO | 0.575***<br>(0.172) | –0.306<br>(0.451) |
| Price | –0.190***<br>(0.012) | –0.176***<br>(0.037) |
| *Interaction Effects Organic* | | |
| Ecosystem Services × Organic | –1.220***<br>(0.410) | –0.099<br>(0.348) |
| Farming for Biodiversity × Organic | –0.365*<br>(0.192) | 0.518<br>(0.461) |
| Farming for Biodiversity + Bee × Organic | –0.526***<br>(0.191) | 0.286<br>(0.455) |
| Farming for Biodiversity + Bee + Net Pollination Index × Organic | –1.144***<br>(0.209) | 0.071<br>(0.447) |
| *Interaction Effects PDO* | | |
| Ecosystem Services × PDO | –0.054<br>(0.161) | 0.292<br>(0.338) |
| Farming for Biodiversity × PDO | 0.570***<br>(0.182) | 0.382<br>(0.487) |
| Farming for Biodiversity + Bee × PDO | –0.199<br>(0.206) | 1.082**<br>(0.502) |
| Net Pollination Index × PDO | –0.307<br>(0.236) | 0.858*<br>(0.512) |
| *Treatment Effects* | | |
| ASC × Information | –0.769**<br>(0.301) | –1.721***<br>(0.541) |
| Ecosystem Services × Information | –0.158**<br>(0.075) | –0.947***<br>(0.284) |
| Organic × Information | 0.055<br>(0.080) | –0.257<br>(0.340) |
| Farming for Biodiversity × Information | 0.026<br>(0.124) | –0.605<br>(0.407) |
| Farming for Biodiversity + Bee × Information | 0.025 (<br>0.128) | 0.003<br>(0.449) |
| Farming for Biodiversity + Bee + Net Pollination Index × Information | 0.222*<br>(0.124) | –0.646*<br>(0.389) |
| PGI × Information | –0.079<br>(0.109) | –0.370<br>(0.356) |
| PDO × Information | –0.091<br>(0.107) | –0.807**<br>(0.385) |

| *Parameter of the Class 2 Allocation Function* | |
|---|---|
| Constant | –2.159***<br>(0.759) |
| Female | 0.268<br>(0.258) |
| Age | 0.355***<br>(0.093) |
| Education | 0.030<br>(0.208) |
| Income | 0.167<br>(0.130) |
| Full-Time Employment | 0.030<br>(0.273) |
| Household Size | –0.295***<br>(0.104) |
| Children in Household | 1.098***<br>(0.315) |
| Environmental damage | –0.251***<br>(0.075) |
| Residuals | 0.258*<br>(0.142) |

*, **, *** indicate 10%, 5%, 1% significance level, respectively.
Standard errors of the estimated parameters are shown in parentheses.

First, it's interesting to note that the coefficient associated with the residuals in the allocation function is significant, showing that the *Environmental damage* indicator is endogenous. Second, the coefficient of the indicator is negative and significant (–0.251; $p$-value < 0.000). This points to the fact that individuals' attitudes of concern toward the role of the agribusiness supply chain in damaging the environment through overuse of land and water have significance in distinguishing groups (Hess *et al.*, 2013; Mariel & Arata, 2022). A lower score for this indicator increases the likelihood of belonging to class 2. This is in line with the result that WTP values for the adoption of ES-related labels are lower in class 2 (Table 7) (Califano *et al.*, 2025). Class 2 is thus characterized by less interest in the proposed labeling and less concern about whether food production has a negative impact on the environment.

The model distinguishes two distinct behavioral profiles. Class 1, in which there is a higher probability of belonging accounting for about 82.5 percent of the sample, displays a clear preference for the purchase alternatives presented in the experiment. This is reflected in the negative and significant ASC, suggesting that these respondents value the attributes of the alternatives and actively engage in trade-offs. The probability of belonging to this class increases as age decreases, if no children are present in the household, and if the attitude of concern about the environmental impact of food production supply-chain increase. Class 2 represents a smaller segment that prefers generic information labels, is price sensitive, and is not interested in additional information.

For a detailed comparison we report the WTP values (Table 7) recognizing the marginal utility of the two groups with respect to the specific information levels, the interaction between logos and the information treatment outside the labels.

*Table 7 - Mean WTP values*

| **Variable** | **Class 1** | **Class 2** |
|---|---|---|
| *Main Effects* | | |
| ASC | –14.748***<br>[–17.197, –12.299] | 4.342<br>[–3.903, 12.587] |
| Ecosystem Services | 6.767***<br>[4.281, 9.253] | 3.495*<br>[–0.520, 7.510] |
| Organic | 8.084***<br>[5.442, 10.725] | 5.171*<br>[–0.204, 10.546] |
| Farming for Biodiversity | 2.417***<br>[0.829, 4.006] | –0.375<br>[–5.348, 4.598] |
| Farming for Biodiversity + Bee | 5.741***<br>[4.165, 7.316] | –1.829<br>[–7.311, 3.653] |
| Farming for Biodiversity + Bee + Net Pollination Index | 6.662***<br>[4.933, 8.390] | 2.376<br>[–2.436, 7.189] |
| PGI | 2.300***<br>[1.427, 3.173] | 3.252*<br>[–0.272, 6.776] |
| PDO | 3.030***<br>[1.232, 4.827] | –1.737<br>[–6.906, 3.432] |
| *Interaction Effects Organic* | | |
| Ecosystem Services × Organic | –6.423***<br>[–10.728, –2.118] | –0.562<br>[–4.461, 3.338] |
| Farming for Biodiversity × Organic | –1.924*<br>[–3.899, 0.051] | 2.947<br>[–2.168, 8.062] |

| | | |
|---|---|---|
| Farming for Biodiversity + Bee × Organic | –2.770***<br>[–4.702, –0.838] | 1.628<br>[–3.452, 6.709] |
| Farming for Biodiversity + Bee + Net Pollination Index × Organic | –6.022***<br>[–8.102, –3.943] | 0.406<br>[–4.584, 5.395] |
| *Interaction Effects PDO* | | |
| Ecosystem Services × PDO | –0.285<br>[–1.957, 1.386] | 1.659<br>[–2.164, 5.482] |
| Farming for Biodiversity × PDO | 3.000***<br>[1.086, 4.915] | 2.174<br>[–3.415, 7.762] |
| Farming for Biodiversity + Bee × PDO | –1.046<br>[–3.159, 1.068] | 6.148*<br>[–0.328, 12.625] |
| Farming for Biodiversity + Bee + Net Pollination Index × PDO | –1.619<br>[–4.055, 0.817] | 4.874<br>[–1.427, 11.175] |
| *Treatment Effects* | | |
| ASC × Information | –4.050**<br>[–7.237, –0.862] | –9.781***<br>[–16.336, –3.227] |
| Ecosystem Services × Information | –0.834**<br>[–1.620, –0.048] | –5.383***<br>[–8.958, –1.808] |
| Organic × Information | 0.288<br>[–0.535, 1.111] | –1.461<br>[–5.235, 2.313] |
| Farming for Biodiversity × Information | 0.138<br>[–1.143, 1.419] | –3.436<br>[–8.094, 1.222] |
| Farming for Biodiversity + Bee × Information | 0.131<br>[–1.188, 1.451] | 0.020<br>[–4.977, 5.016] |
| Farming for Biodiversity + Bee + Net Pollination Index × Information | 1.168*<br>[–0.115, 2.450] | –3.674<br>[–8.110, 0.762] |
| PGI × Information | –0.417<br>[–1.542, 0.707] | –2.104<br>[–6.097, 1.888] |
| PDO × Information | –0.480<br>[–1.583, 0.623] | –4.588**<br>[–9.064, –0.111] |

*, **, *** indicate 10%, 5%, 1% significance level, respectively.

Lower and upper limits of the 95% confidence intervals are given in square brackets.

Class 1 demonstrates consistently higher and statistically significant WTP values across most sustainability attributes, while Class 2 shows lower and often statistically not significant valuations, consistent with a more price-sensitive and information-averse profile.

Class 1 exhibits robust positive preferences for Organic production (8.084, $p < 0.000$) and the generic ES provision logo (6.767, $p < 0.000$). For the specific ES the first information level Farming for biodiversity presents a WTP of 2.417 ($p < 0.000$), while the addition of increased information levels further increases WTP, with Farming for Biodiversity + Bee (5.741, $p < 0.000$) and Farming for Biodiversity + Bee + Net Pollination Index (6.662, $p < 0.000$) both yielding highly significant effects. Geographical Indications (PGI: 2.300, $p < 0.000$; PDO: 3.030, $p < 0.000$) are also positively valued.

In contrast, Class 2 values are lower and more varied. In relation to main effects, this group shows that they exclusively prefer the generic level of ES provision (3.495, $p < 0.1$) and Organic certification (5.171, $p < 0.1$), but their confidence intervals include zero, suggesting weaker statistical reliability.

Interaction effects with Organic reveal important halo effects in Class 1. Ecosystem Services × Organic (–6.423, $p < 0.000$), Farming for Biodiversity × Organic (–1.924, $p < 0.1$), Farming for Biodiversity + Bee × Organic (–2.770, $p < 0.000$) and Farming for Biodiversity + Bee + Net Pollination Index × Organic (–6.022, $p < 0.000$), are all significantly negative. These interactions suggest that when the Organic logo is present, the additional value of ES labels diminishes, possibly due to consumer perception that organic production already subsumes these environmental benefits (Jean *et al.*, 2025). In Class 2, none of the Organic-based interactions are significant, implying the absence of such a halo effect in this group.

PDO interactions provide mixed results. In Class 1, Farming for Biodiversity × PDO is positive and highly significant (3.000, $p < 0.000$), supporting the idea that biodiversity attributes gain credibility when paired with PDO. Other PDO interactions are not insignificant.

Treatment effects from information provision show divergent impacts across classes. In Class 1, Ecosystem Services × Information is negative (–0.834, $p < 0.05$), while Farming for Biodiversity + Bee + Net Pollination Index × Information is positive (1.168, $p < 0.1$). This suggests that in this group, the external information layer, which introduces a specificity of service measurement information, increases WTP only in the case of the introduction of the Net Pollination index, while decreasing the marginal utility for the generic ES supply logo. For Class 2, the effect of Ecosystem Services × Information is highly negative (–5.383, $p < 0.000$). These consumers respond poorly to additional information, reflecting skepticism or confusion towards detailed environmental claims. The PDO × Information interaction is also negative and significant (–4.588, $p < 0.05$), suggesting that even established quality cues may lose value when overloaded with information.

## Discussion and conclusion

This study explored the potential of ES-related labels to influence consumer preferences in the food system, using EVOO as a case study. The analysis contributes to the growing literature on sustainable food labeling by assessing how varying label designs and levels of informational detail shape consumer choices. In addition, the moderating role of an external informational treatment – designed to simulate a public awareness campaign – was examined to evaluate whether providing contextual information enhances consumer valuation of ES.

The LCM estimates identified two distinct consumer segments with significantly different preferences. First group showed consistently strong preferences for sustainability attributes. These consumers demonstrated a WTP for a range of ES-related labels, with higher values associated with increasing levels of specificity – from general references to biodiversity, to a visual indicator (bee image), and ultimately to a quantified scientific metric (Net Pollination Index). This group exhibited high engagement with sustainability themes and responded positively to detailed, transparent information (Borrello *et al.*, 2021; Johnson & Geisendorf, 2022). In contrast, a minority segment, displayed lower WTP values and limited responsiveness to detailed ES labels, regardless of the external informational treatment. This group tended to be older, more likely to have children at home, and less concerned about the environmental impacts of food production. Their choices suggest greater price sensitivity and a preference for generic information level, indicating a degree of disengagement or skepticism towards detailed environmental labeling.

The inclusion of the external informational treatment produced differentiated effects across segments. While self-reported and objective knowledge levels did not vary substantially between treated and untreated respondents, preferences modeling indicated that the additional information enhanced WTP in the most involved segment. For this group, the treatment acted as a reinforcing mechanism, validating the relevance of ES-related claims and amplifying consumer trust and valuation. This finding suggests that supplementary communication tools – such as in-store educational materials, QR codes linking to explanatory content, or public campaigns – may increase the effectiveness of ES related labels, particularly when targeted at already receptive consumers (Marchi *et al.*, 2024).

However, the treatment had no observable effect on the more skeptic group (Casati *et al.*, 2023). This is consistent with findings in the behavioral economics and psychology literature, which highlight that information-based interventions may fail when not aligned with individuals' values, motivations, or perceived relevance (Grunert *et al.*, 2014; Reisch & Sunstein, 2016). For this segment, information alone is insufficient to modify behavior, pointing to the potential need for alternative strategies, such as more intrusive policy tools related to prices.

One of the key findings is the importance of label specificity in driving consumer preferences. The highest WTP was recorded for the most detailed labeling option ("Farming for Biodiversity + Bee + Net Pollination Index"), indicating that consumers value clarity, credibility, and precision in sustainability communication. The inclusion of visual and quantified elements improved perceived product quality and producer trustworthiness (Aprile & Punzo, 2022). These results suggest that vague or generic sustainability claims may be less effective, whereas detailed, verifiable, and visually engaging labels are more likely to influence consumer behavior.

Nonetheless, attention must be paid to potential information overload or attribute redundancy. The observed negative interaction between organic certification and ES labels among Class 1 respondents suggests a possible halo effect, whereby the presence of multiple overlapping sustainability claims may dilute the perceived incremental value of additional labels (Janßen & Langen, 2017). This underscores the importance of coherent and complementary label design, where different claims are clearly differentiated in terms of meaning and function (Fresacher & Johnson, 2023).

While these results indicate that metric-based information on ES can affect consumer preferences, the use of a quantitative indicator such as the Net Pollination Index also raises important questions regarding certifiability and verification. While the index provides a scientifically grounded measure of pollination services, its use in a labelling context would require clearly defined protocols for data collection, independent verification, and auditing. In practice, measurement could be carried out by accredited third-party bodies or research institutions, potentially building on existing agri-environmental monitoring schemes. However, such processes would entail non-negligible costs and may pose challenges for smaller producers. Moreover, without standardized verification procedures, the risk of strategic use or greenwashing cannot be excluded. For these reasons, in this study the Net Pollination Index should be interpreted as a proof-of-concept illustrating how metric-based information on ES may be perceived by consumers, rather than as a fully developed certification proposal. Future research should explicitly assess the institutional feasibility and cost-effectiveness of certifying ES indicators at farm level.

From a policy perspective, the results point to the potential of ES labeling strategies – particularly those linked to measurable environmental outcomes – to stimulate market-based incentives for biodiversity conservation and other ES. As agricultural systems play a dual role in contributing to and mitigating environmental degradation, enhancing the visibility of their environmental contributions through credible labels could serve as a promising lever for sustainable consumption.

The heterogeneity in consumer responses also suggests the need for differentiated policy approaches. For highly engaged consumers, information-based nudges and detailed labeling schemes may be sufficient to drive behavioral change. For more disengaged segments, however, regulatory tools, price mechanisms, or default options may be necessary to shift preferences. Policymakers should therefore consider hybrid frameworks that combine voluntary and mandatory elements, tailored to different levels of consumer engagement (Huang *et al*., 2024).

Several limitations of the study should be noted. First, while the DCE included measures to mitigate hypothetical bias and the econometric approach is based on managing respondents' latent attitudes (Czajkowski *et al*., 2017), external validity remains low. In addition, data were collected in a single supermarket located in a middle-to-high income urban area, and participation was voluntary, which may have resulted in self-selection of consumers more interested in food quality or sustainability-related issues. Future research should validate these findings using incentivized experiments or observational data conducted in different retail and socio-economic contexts. Second, the analysis focused on EVOO, a culturally salient product in the Italian context; generalizability to other products or countries may be limited. Third, although the price levels were grounded in observed retail prices, the use of non-rounded decimal values, derived from constant percentage increments, may appear less representative of actual shelf prices, potentially affecting perceived realism; future studies could test alternative price framings to assess their influence on choice behaviour. Fourth, all respondents received a brief, generic introduction to ES to ensure a minimum level of understanding, as pilot testing showed that participants with no prior information produced inconsistent or erratic responses. While this may reduce the contrast between treatment and control, it was necessary to maintain comprehension and the reliability of WTP estimates. Finally, the study did not examine interactions between ES labels and other marketing elements such as branding or packaging, which may influence consumer interpretation and valuation.

In conclusion, the results demonstrate that ES-related food labeling can influence consumer preferences, particularly when labels are specific, visual, and supported by credible information. While most consumers are willing to reward sustainability efforts with price premiums, a notable minority remains unresponsive to information-based strategies. To enhance the market uptake of ES-related labels and their contribution to sustainability goals, future interventions should account for the diversity of consumer motivations, the design of complementary communication strategies, and the broader policy environment in which labeling initiatives are embedded.

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There is no financial support nor conflicts of interest to disclose.

## Declaration of Generative AI Use

During the preparation of this article, the author(s) used ChatGpt to improve writing and grammatical structure. After using this tool, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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# Balancing environmental benefits and agricultural technologies – perspectives from German consumers

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## *Abstract*

Societal and political voices call for stronger environmental protection, biodiversity conservation, and reduced pesticide use. Integrating digital technologies into farming systems like strip intercropping offers promising pathways toward more sustainable and efficient food production. The successful adoption of these innovations depends on acceptance by both farmers and consumers. To explore these intersections of technology, sustainability, and market dynamics from a consumer perspective, a discrete choice experiment (DCE) followed by consumer segmentation was conducted in Germany in September and October 2023 (n = 2,022). The study examines preferences for different farming systems, focusing on autonomous machinery, landscape structure, food prices and environmental factors. Socio-demographic variables, along with value and attitude-based factors, were used to differentiate consumer segments. The study highlights social preferences for welfare-enhancing agricultural systems, such as strip intercropping, and demonstrates a societal demand for more sustainable agroecosystem outcomes, in terms of biodiversity, soil erosion prevention and reduced use of chemical pesticides. Results show that the balance between environmental benefits and agricultural technology differs markedly across four consumer segments, underscoring the need to integrate ecological and technological dimensions in communication and policy to enhance consumer acceptance and to support sustainable transitions in agriculture.

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## Introduction

Germany's Sustainable Development Strategy underscores that achieving climate neutrality, resource efficiency, and longterm competitiveness requires a profound transformation of the economy and society, including agriculture and industry. To meet these goals, the strategy stresses the need for accelerated digitalization and automation, as efficient and sustainable digital infrastructures and technologies are seen as key enablers for innovative, low-carbon and resource-saving production and services (Die Bundesregierung, 2025). In this context, the 'twin transition' describes the simultaneous and interconnected shift towards an environmentally sustainable and more digital economy and society (Myshko *et al.*, 2024). It emphasizes that digitalization and sustainability should not be pursued in isolation but aligned so that digital technologies actively support environmental and social goals (for example climate neutrality, resource efficiency, and biodiversity protection). In agriculture, the twin transition means using digital tools to make farming more climate-friendly, resilient and resource-efficient (such as precision agriculture, IoT sensors, and AI-driven analytics, which enable optimized inputs like water, fertilizers, and pesticides), supporting environmental goals outlined in the European Green Deal while at the same time ensuring that digitalization itself follows principles of sustainable, fair and inclusive development (Myshko *et al.*, 2024; Brunori, 2022). Put differently, digital innovation is seen as an enabler of new forms of environmental, social and economic sustainability. One concrete example are small-scale diversified cropping systems as exemplified by (strip) intercropping (Vandermeer, 1989), which have been shown to deliver multiple environmental benefits. The main advantages of strip intercropping lie in increasing economic and ecological resilience: Paut *et al.* (2020) refer to economic risk reduction, while Gilley *et al.* (1997) mention the reduction of soil erosion. Chen *et al.* (2018) conclude that strip intercropping can be a successful adaptation strategy to water scarcity. Furthermore, positive effects on biodiversity are described (Brooker *et al.*, 2016). Measures to promote diversity and abundance of agricultural fauna also improve important ecosystem services such as natural regulation of pest organisms and pollination in agricultural ecosystems (Alarcón-Segura *et al.*, 2022; Albrecht *et al.*, 2020; Holland *et al.*, 2017). Moreover, intercropping systems increase the frequency and diversity of arthropods without significant yield losses (Brandmeier *et al.*, 2021).

However, small-scale diversification presents significant disadvantages regarding labor cost when using conventional agricultural machinery. Digital technologies, especially agricultural robotics, are attributed with the potential to offset these disadvantages, as the use of autonomous systems diminishes the importance of economies of scale (Lowenberg-DeBoer *et al*., 2019). Technologies such as artificial intelligence and robotics offer promising solutions for more sustainable and efficient food production (Ashwini *et al*., 2024). These advancements can also facilitate reduced pesticide use through targeted application and alternative pest management strategies (Gerhards *et al*., 2022). These innovations enable precise crop and resource management, potentially reducing costs and environmental impacts. Therefore, following the twin transition theory, field robots and other precision technologies are being investigated as potential enablers of strip intercropping and other small-scale diversified farming systems (Ditzler & Driessen, 2022; Sparrow & Howard, 2021; Spykman *et al*., 2023).

The adoption of these innovative approaches depends on various factors, including farmer acceptance (Spykman *et al*., 2021; Gabriel & Gandorfer, 2022), economic viability, but also consumer attitudes towards food commodities produced with different farming methods (Pfeiffer *et al*., 2020; Spykman *et al*., 2022; Wilmes *et al*., 2022; Zeddies *et al*., 2024). Society at its base is composed of individual people, each with their own needs, beliefs, and perspectives. Because of this diversity, it is essential to identify and understand different groups within the population. Recognizing these distinct groups allows for more targeted and effective communication, ensuring that messages resonate appropriately with each segment (Zeddies & Busch, 2025). Besides socio-demographic characteristics, consumer behavior can help distinguish consumer segments. The literature provides different value and attitude scales for typification of consumers in terms of food and ecological impacts of food production (Haws *et al*., 2014; Shimp & Sharma, 1987), but also regarding other attitudes, e.g., towards technology use (Edison & Geissler, 2003). Despite consumers often claiming that they would support more sustainable products, purchase numbers of those products do not reflect the expressed intentions. Terlau and Hirsch (2015) describe this 'attitude-behavior gap' as the discrepancy between consumers' expressed purchase intentions for sustainable products and their actual buying behavior, which is influenced by individual, social, and situational factors. They identify key barriers such as price, limited availability, information overload, habitual consumption routines, and psychological factors related to decision-making processes (Terlau & Hirsch, 2015). Consumer segmentation provides a promising approach to address this problem because it enables the identification of heterogeneous motivations, constraints, and contextual drivers across groups and the design of targeted intervention bundles (e.g., tailored messaging, incentive structures, product and distribution adjustments) (Schäufele & Janssen, 2023).

This study employs a discrete choice experiment, an established method in preference research, to explore the intersections of digital technology use, environmental effects, landscape, and consumer price sensitivity in agricultural products. The aim is to analyze consumer preferences and preference heterogeneity for different farming systems in Germany. The data were collected from September 22 to October 15, 2023, yielding a total sample of 2,022 respondents. The integration of indirect welfare dimensions, including environmental impacts and the form of agricultural management, into the discrete choice experiment combines several interdisciplinary perspectives. The extant literature on the valuation and consumer welfare provided by specific agroecosystems via choice experiments is still limited and fragmented. Alcon *et al.* (2020) is among the few studies addressing this topic. Unlike other studies applying consumer discrete choice experiments, which typically focus on product attributes such as taste, packaging, price, conventional, organic or local production (c.f. Bazzani *et al.*, 2017) or food product labels (c.f. Kolber & Meixner, 2023), and some additional information treatment (c.f. Jean *et al.*, 2025), this study concentrates on product attributes related to environmental impacts of specific agricultural practices. These attributes bear a resemblance to 'credence' attributes, which are characteristics of a product or service that consumers are often unable to verify or assess even after purchase and use. These attributes are frequently judged based on trust or belief (Fernqvist & Ekelund, 2014). Although Fernqvist and Ekelund (2014) identified some studies addressing credence characteristics related to production methods, these are primarily understood in terms of new preservation technologies or genetic modifications (GMO) and typically refer to specific products. From farmers' perspective with respect to agri-environmental aspects such as fertilizer use, application of pesticides, or restrictions on cropping, there have been a systematic review of over 120 discrete choice experiments studies forming a base on future design of possible agri-environmental programs (Schulze *et al.*, 2024). A more recent work examined Italian farmers' preferences for adopting agriculture 4.0 technologies using a choice experiment analysis (Fragomeli *et al.*, 2025). Therefore, a multitude of choice experiments have been conducted on the production side, addressing the adoption of agri-environmental applications or digital technologies. The contribution of the following paper is to bridge the gap to the demand side and to determine whether consumers, grouped by socio-demographic characteristics, values and attitudes, support a transition to different farming systems using a discrete choice experiment. The novelty of this approach is that consumer preferences are not determined by the choice of a specific product but are instead characterized by the attributes of agricultural cultivation and management practices associated with agri-food products. These attributes of agricultural production reflect a welfare-enhancing agricultural system in its entirety. A consumer segmentation analysis helps to identify different consumer types, providing a comprehensive understanding of consumer preferences which are useful for a successful implementation and communication for different farming systems such as strip intercropping.

Thus, the paper aims to capture the public's perspective and acceptance of alternative crop production systems with digital technologies (e.g., autonomous machinery) using a choice experiment, against the background of sustainability goals as described by the twin transition theory. In addition to the general consumer preferences regarding sustainable production systems, segmentation can partially explain the attitude-behavior gap by providing guidance for appropriate, targeted communication with different consumer groups enhancing acceptance for changes towards more sustainability. The remainder of the paper will describe the methodology, followed by the results of the choice experiment and the consumer segmentation, a discussion, and finally a conclusion.

## 1. Materials and methods

The discrete choice experiment was a component of a comprehensive online survey of German consumers (>17 years) that was conducted from September 22 to October 15, 2023. Access to a consumer panel was enabled through collaboration with a field service provider. Utilizing a consumer panel allows for the separation of personal data from content data, thereby ensuring adherence to research ethics. The panel facilitated a pre-stratification process to ensure that the sample was representative of the German population in terms of age, gender, size of residential area and federal state. In addition to various socio-demographic variables, data on personal connections to agriculture, as well as value and attitude scales for a typification of consumers were collected. Following data validation by eliminating speeders or straight-liners, the final survey sample consisted of 2,022 participants.

Discrete choice experiments (DCEs) are widely used to analyze consumers preferences in cases when the behavior of interest involves discrete responses or qualitative choice. They enable researchers to estimate the effects of attributes on preferences and are based on random utility theory (RUT) (Louviere *et al.*, 2008). RUT assumes that an individual $q$ maximizes his utility, when choosing between $J$ alternatives. Hereby, the utility $U_{iq}$ of the i*th* alternative for the q*th* individual is composed of a systematic component $V_{iq}$, and a random, unobserved component $\varepsilon_{iq}$ (Louviere *et al.*, 2000, Hensher *et al.*, 2015):

$$U_{iq} = V_{iq} + \varepsilon_{iq} \qquad (1)$$

Typically, a DCE is composed of a set of choice sets, with each choice set composed of two or more alternatives. All alternatives in a choice set are defined by the same set of attributes, yet the expressed level per attribute may differ between choice sets. Consequently, a choice set provides survey respondents to choose between different combinations of attribute manifestations (or levels). When survey respondents are shown a choice set, they should select the alternative that most appeals to them. The process is iterated several times, with each choice set containing a different set of alternatives (Street & Burgess, 2007).

The choice experiment was part of an interdisciplinary joint research project by the Bavarian State Research Center for Agriculture (LfL) and the University of Passau which aimed to contribute to solving the challenges in biodiversity and soil conservation, economic competitiveness, and societal acceptance that the agricultural sector currently faces (www.future-crop-farming.de). Consequently, the attributes of the DCE were selected based on their anticipated environmental impact, such as effects on biodiversity and soil erosion (Alcon *et al.*, 2020), as well as their impact on agricultural management, including autonomous machinery. Therefore, the subsequent six attributes, accompanied by their respective levels in parentheses, were incorporated into the DCE:

- Biodiversity (less/unchanged/more).
- Soil erosion (less/unchanged/more).
- Chemical pesticide use (less/unchanged/more).
- Agricultural machinery (manned tractor/small autonomous robot/large autonomous robot).
- Landscape (strip intercropping/medium-sized fields/large-sized fields).
- Prices € 80/€ 100/€ 120/€ 140/€ 160) for cereal products, sugar, sweets, edible oils.

The base price for food groceries from specific agricultural crops (e.g., cereal products, sugar, sweets, edible oils) was derived from the German population's household goods basket divided by the average household size and was estimated to about 100 € monthly (Destatis, 2023). The fixed task (FT), which can be used for testing specific product configurations and internal validity (Sawtooth Software Inc., 2016), served as the key design for realistic scenarios regarding the attribute selection for the different farming systems (Figure 1): Combination 2 corresponds to the current status quo in

Bavarian agriculture: medium-sized fields with manned production (tractor) and unchanged environmental aspects in terms of biodiversity, soil erosion and the use of chemical pesticides at a base price of € 100. Combination 3 depicts a 'desired' target scenario, namely higher biodiversity, less soil erosion, and reduced use of pesticides. This could hypothetically be achieved through the strip intercropping approach and an autonomous large robot at an assumed higher product price of € 140 due to higher production cost. Combination 1 is an alternative future scenario with production on medium-sized fields by large autonomous robots. This would involve less pesticides, but more soil erosion and less biodiversity due to more intensive mechanical soil management. This scenario assumes that the negative effects of robots will not be mitigated through further technical development. The resulting consumer price for fixed task combination 1 is estimated at € 120, which is 20% higher than the base price.

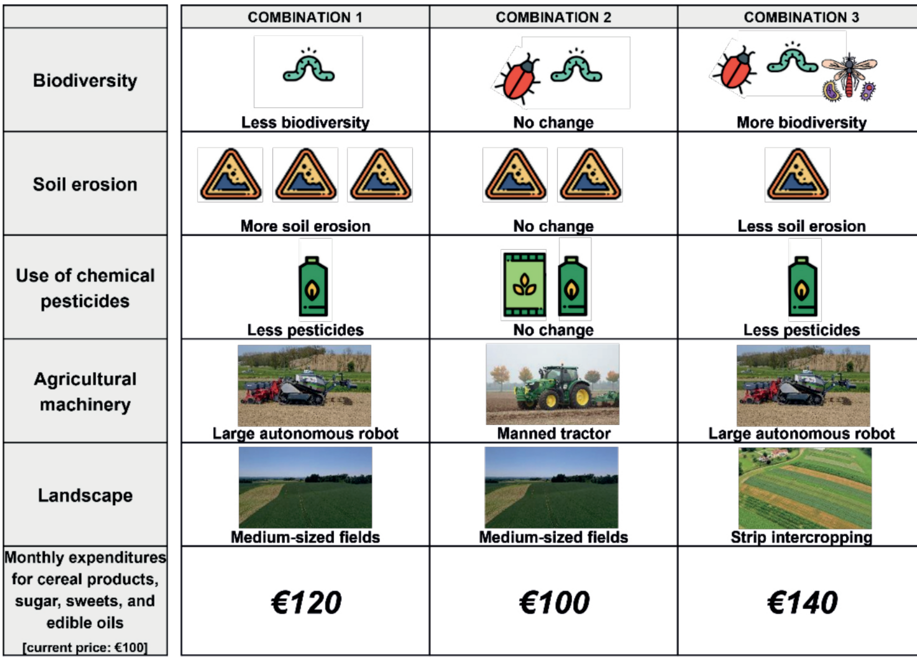
Based on the defined attributes and levels, a controlled random design with four questionnaire versions was generated using the random task generation method 'balanced overlap' in Lighthouse Studio 9.16.0 (Sawtooth Software Inc., 2024). Within the online survey pertinent images and icons were used to illustrate all attributes and levels for better visualization for the respondents (see Figure 1). At the beginning of the online survey, participants were randomly assigned to one of the four questionnaire versions and were provided with an explanatory passage translated from German.

Conventional food production can lead to environmental pollution, which can be reduced by changing the methods of production. Such site-adapted production methods enable for example a reduction of environmental risks by increasing biodiversity, protecting against soil erosion, less use of synthetic chemical pesticides, a more diverse landscape, and the use of modern and autonomous machinery. Below you will find three suggestions for combinations of farming systems, which, however, may also involve an increase in monthly expenditure on food (assuming the current base price for monthly groceries: € 100). Please indicate your preferred option in each case.

After this introduction, respondents had to choose six times between three different farming systems.

The DCE data were analyzed using Hierarchical Bayes (HB) modelling to estimate individual utilities for different farming systems. HB estimation techniques have become state-of-the art in marketing theory and practice to grasp individual heterogeneity in choice data (Goeken *et al*., 2021; Voleti *et al*., 2017). In addition, latent class analysis (LCA) was used to identify consumer groups with heterogenous preferences regarding farming systems.

*Figure 1 - Example of a choice set (fixed task - FT) used in the DCE*




The estimated HB model employs a hierarchical structure with two levels: An upper-level assuming a multivariate normal distribution for participants' part-worth utility values and a lower-level using a multinomial logit approach to analyze participants' probabilities of choosing specific attributes (Sawtooth Software Inc., 2021a). The model parameters are estimated through a Monte Carlo Markov Chain procedure, typically involving thousands of iterations to ensure robust results (Sawtooth Software Inc., 2021a). LCA was conducted to segment individuals based on response patterns and to identify subgroups with differing preferences. An optimal solution is achieved if the respondents' preferences are homogenous within one segment, but heterogenous between the segments. The latent class estimation process is iterative and involves the following steps: First, estimates of each segment's utility values are selected randomly. Next, each segment's estimated utility is used to fit each respondent's data and the relative probability that each respondent belongs to each segment is calculated. In the subsequent iterative process, the utility values of each segment and the probability of segment membership for each respondent are improved (Sawtooth Software Inc., 2021b). The optimal number of segments is determined using multiple fit criteria, including

Aikake Information Criterion (AIC), Bayesian Information Criterion (BIC), and Log-Likelihood (Sawtooth Software Inc., 2021b). While the performance of these criteria can vary with sample size (Morgan, 2014; Nylund *et al.*, 2007), analyzing their relative changes helps identify the best-fitting model (Nylund-Gibson & Choi, 2018). When results are inconclusive based on these indicators, analysis of all candidate solutions is recommended to select the most interpretable one (Nylund-Gibson & Choi, 2018; Swait, 1994). Utilities between segments were compared using zero-centered differences, allowing for analysis of relative attribute importance and preference for specific attribute levels (Sawtooth Software Inc., 2021b).

Following the LCA, socio-demographic variables like age, education level, and income as well as three different factor scales of value and attitude-based typification served to differentiate the consumer segments. The following typification, which have been proven effective in the literature and have been extensively tested in studies, were used in the survey in the form of five-point Likert scales, ranging from 'strongly agree' = –2 to 'strongly disagree' = +2. This coding scheme indicates that negative values correspond to higher levels of agreement, and vice versa. Such tested items collectively interpret a 'latent' variable that, for example, establishes a specific value range for an individual. Using factor analysis, the responses to the individual items can be condensed into an individual standardized factor score and used as a metric predictor variable (Gabriel *et al.*, 2024):

- Green Consumption Value (GCV) with six items to reflect respondents' tendency towards environmentally friendly shopping behavior (Haws *et al.*, 2014).
- Consumer Ethnocentrism (CES) with four items to express consumers' preference for local and regional production (Shimp & Sharma, 1987; Jiménez-Guerrero *et al.*, 2014).
- Attitude towards technology (ATT) with nine items to measure openness towards new technologies and basic technical know-how (Edison & Geissler, 2003).

These three scales allow for a characterization regarding sustainable consumption, local food production and attitudes towards technology. HB and LCA analyses were performed using Lighthouse Studio 9.16.0 (Sawtooth Software Inc., 2024). LCA results were then transferred to SAS Studio 3.8 (SAS Institute Inc., 2023) for analysis of socio-demographic and attitude-based typification differences between segments. Socio-demographic variables were dummy-coded and tested for significant group differences using the Pearson $Chi^2$ Test. In case of a significant outcome (p-value < 0.1), pairwise $Chi^2$ Tests were carried out to identify which segments statistically differ from each other. For the not normally distributed attitude-based typification, the Kruskal-Wallis-Test (H-Test) was chosen to compare central tendencies of multiple independent samples (i.e., the identified segments). If the H-Test yielded a significant outcome (p-value < 0.1), the post-hoc Dwass-Steel-Critchlow-Fligner (DSCF)-Test helped identifying which segments differ statistically significant from each other.

## 2. Results

### 2.1. *Sample characteristics*

Table 1 shows the socio-demographic statistics for the total sample of 2,022 respondents in comparison to the German population (Destatis, 2024), confirming that the sample can be considered nationally representative in nearly all surveyed characteristics. Table 1 also illustrates the comparison of the four randomly selected survey subgroups for the discrete choice experiment regarding socio-demographic variables. The Pearson Chi$^2$ Test of independence reveals no p-value smaller than 0.05 for any considered variable, indicating that there are no significant differences between these groups. This confirms that the random assignment of survey participants to the subgroups was appropriate.

*Table 1 - Distribution of socio-demographic variables in the randomly selected survey subgroups, total sample and the German population*

| **Variable** | **Categories** | **Randomly selected survey subgroups in absolute numbers** | | | | **Total sample** | **GNS**[1] |
|---|---|---|---|---|---|---|---|
| | | **Group 1** | **Group 2** | **Group 3** | **Group 4** | **%** | **%** |
| Gender | Female | 253 | 256 | 249 | 288 | 51.7 | 50.6 |
| | Male | 236 | 251 | 230 | 251 | 47.9 | 49.4 |
| | Non-binary | 2 | 2 | 2 | 2 | 0.4 | n/a |
| Age | 18-30 | 87 | 93 | 75 | 88 | 17.0 | 21.2 |
| | 31-40 | 80 | 87 | 84 | 97 | 17.2 | 17.7 |
| | 41-50 | 70 | 74 | 90 | 95 | 16.3 | 16.2 |
| | 51-60 | 115 | 117 | 89 | 110 | 21.3 | 20.7 |
| | ≥61 | 139 | 138 | 143 | 151 | 28.2 | 24.3 |
| Income | <1,000 € | 49 | 49 | 66 | 66 | 11.4 | 8.6 |
| | 1,001-2,000 € | 140 | 134 | 114 | 149 | 26.6 | 24.7 |
| | 2,001-3,000 € | 107 | 120 | 119 | 119 | 23.0 | 23.5 |
| | 3,001-4,000 € | 77 | 93 | 87 | 113 | 18.3 | 16.2 |
| | 4,001-5,000 € | 65 | 55 | 51 | 48 | 10.8 | 10.8 |
| | >5,000 € | 53 | 58 | 44 | 46 | 9.9 | 16.1 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Level of education | No qualific./SNVQ[2] | 70 | 59 | 64 | 80 | 19.9 | 22.2 |
| | Secondary school VQ[3] | 144 | 151 | 136 | 167 | 43.5 | 43.1 |
| | High school (Abitur)[4] | 122 | 138 | 111 | 132 | 36.6 | 34.7 |
| | Vocational training/univ.[5] | 155 | 161 | 170 | 162 | | |
| Inhabitants (size of residence) | <5,000 | 68 | 68 | 71 | 73 | 13.8 | 13.0 |
| | 5,001-20,000 | 130 | 118 | 122 | 141 | 25.3 | 24.9 |
| | 20,001-100,000 | 128 | 148 | 136 | 148 | 27.7 | 27.3 |
| | >100,000 | 165 | 175 | 152 | 179 | 33.2 | 34.8 |
| | n | 491 | 509 | 481 | 541 | | |

[1] GNS: German national statistics (Destatis, 2024). [2] SNVQ = Secondary school non-vocational qualification, corresponds to the German 'Hauptschulabschluss' (low education); [3] VQ = Vocational qualification, corresponds to the German 'Mittlere Reife'; [4] High education. [5] Comparison with national statistics not possible, only limited to the previous three education categories.

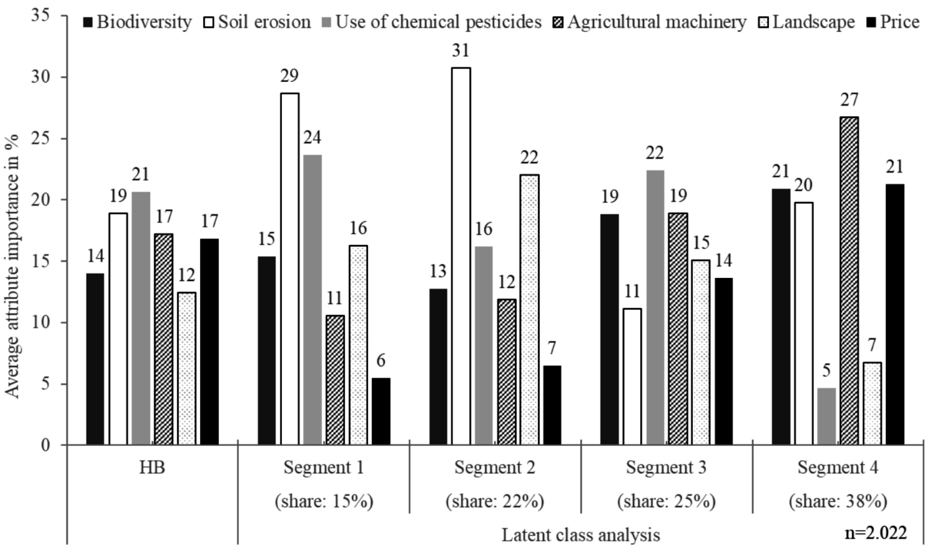
## 2.2. *Attribute importance and latent class analysis*

The estimated HB model has a mean root likelihood (RLH) of 0.675 which can be considered as good (Sawtooth Software Inc., 2021a). To identify the number of segments in the LCA, various fit criteria (AIC, BIC, Log-Likelihood) were checked. Their values suggested the four-segments solution as appropriate because the improvements in these criteria were particularly large from the three- to four-segments solution. The comparison of the four- and five-segments solution resulted in no substantial improvements or even deterioration of the criteria. For this reason, the four-segments solution was screened for interpretability (Swait, 1994). It proved to be reasonably interpretable and was therefore selected for further analysis. The shares of the four-segments solution are as follows: 14.9% for segment 1, 22.1% for segment 2, 25.0% for segment 3, and 38.0% for segment 4.

Figure 2 illustrates the results of the attribute importance from the HB estimation and the latent class analysis. The importance of the individual attributes is determined based on the range of the part-worth utility values (difference between the highest and lowest) of one attribute and sums up to 100% across all attributes. The larger the range, the more important the attribute is for preference formation. The HB estimation shows that the use of chemical pesticides is attributed to the highest importance on average at 21%, closely followed by soil erosion (19%). Both price and agricultural machinery follow at 17% each. Biodiversity and landscape receive slightly less importance compared to the aforementioned attributes, at 14% and 12%, respectively. In addition, Figure 2 illustrates differences in the attribute importances of the identified segments. Segments 1 and 2 consider soil erosion to be the most important characteristic. At the same time, consumers in these segments place less importance on the price compared to the other segments.

Segments 1 and 3 attach great importance to the attribute use of chemical pesticides. Segment 2 finds the attribute landscape more important than the other segments. The most important attribute for the largest segment 4 is agricultural machinery, followed by biodiversity and the price attribute. The use of chemical pesticides, on the other hand, is not decisive for segment 4. Segment 3 also reveals a high importance for agricultural machinery and biodiversity but places less importance to the attribute soil erosion.

*Figure 2 - Average attribute importance for HB and latent class analysis in %*




## 2.3. *Part-worth utilities*

A further analysis identifies the average relative part-worth utilities from the HB estimation for the respective attributes of the total sample and the four identified segments (Table 2). All part-worth utilities of an attribute add up to 0 as effects coding is used. Accordingly, positive values represent a higher part-worth utility within an attribute in relation to the other (negative) attribute levels; the respective highest part-worth utility for each attribute and each segment is printed in bold-face in Table 2. On average, participants perceive a higher relative utility from more biodiversity, less soil erosion, and less use of chemical pesticides than for the respective opposite levels or the status quo (i.e., no change). Similarly, for the technological aspect, the manned tractor receives a higher part-worth utility than the two autonomous robots at almost equal negative part-worth utilities. Regarding the landscape, consumers perceive a higher relative part-worth utility in strip intercropping than in large or medium-sized fields.

*Table 2 - Part-worth average utility values of attribute levels (zero-centered difference)*

| Attribute | Level | HB | Segment | | | |
|---|---|---|---|---|---|---|
| | | | 1 | 2 | 3 | 4 |
| Biodiversity | Less (–) | –28.06 | –40.82 | –47.40 | 34.13 | –54.56 |
| | No change (=) | 7.02 | –10.47 | 18.51 | **39.40** | –16.32 |
| | More (+) | **21.05** | **51.29** | **28.89** | –73.53 | **70.88** |
| Soil erosion | Less (–) | **49.18** | **72.50** | **66.18** | 17.14 | **78.34** |
| | No change (=) | –5.20 | 27.06 | 52.06 | –41.99 | –40.10 |
| | More (+) | –43.98 | –99.57 | –118.24 | **24.85** | –38.24 |
| Use of chemical pesticides | Less (–) | **38.30** | **67.59** | –4.98 | **74.91** | 2.59 |
| | No change (=) | 10.65 | 6.65 | **51.04** | –15.34 | **12.64** |
| | More (+) | –48.96 | –74.24 | –46.05 | –59.57 | –15.23 |
| Agricultural machinery | Manned tractor | **59.11** | **35.88** | **43.86** | **64.47** | **98.95** |
| | Large autonomous robot | –29.24 | –27.46 | –27.27 | –49.02 | –37.72 |
| | Small autonomous robot | –29.87 | –8.42 | –16.59 | –15.45 | –61.22 |
| Landscape | Large-sized fields | –19.56 | –15.38 | –55.30 | **30.86** | –19.42 |
| | Medium-sized fields | 2.26 | **56.53** | –21.47 | –59.70 | **21.06** |
| | Strip intercropping | **17.31** | –41.15 | **76.77** | 28.84 | –1.64 |
| Price | | –122.92 | –41.23 | –48.73 | –102.14 | –159.48 |

For segments 1, 2 and 4, a reduction in soil erosion is preferred compared to the status quo or a higher soil erosion. While the first two segments are the least price-sensitive ones, the largest segment 4 has the most negative utility value for price. A high utility from more biodiversity is also evident in segments 1, 2 and 4 compared to the other respective levels. Segment 3, on the other hand, prefers the status quo of biodiversity. Regarding chemical pesticides, segments 2 and 4 prefer the status quo over 'less use'. Conversely, segments 1 and 3 clearly prefer less use of chemical pesticides. All segments have a high preference towards traditional use of machinery with a manned tractor. Strikingly, segment 4 is less opposed to large autonomous robots than to small autonomous ones. In the other three segments, the pattern is reversed. Segment 2 is the only segment which prefers strip intercropping compared to large- or medium-sized fields. Segment 3 seems indifferent between large-sized fields and strip intercropping but rejects medium-sized fields. Segments 1 and 4 draw a higher utility from medium-sized fields compared to the other two landscape options.

### 2.4. *Segment characterization*

Table 3 presents the socio-demographic composition of the four segments, highlights differences between them, and aids in their characterization. Statistically significant differences between the segments arise from age (younger or older than 40), level of education (secondary school or lower vs. vocational training, high school or higher), disposable income (less or more than 4,000 €), farmers in the personal network, and all three attitude-based typification. By contrast, no significant differences are observed for gender (male vs. female), size of place of residence (number of inhabitants lower or higher than 20,000), or whether respondents have experience in agriculture or a related sector. For the attitude- and value-based scales, mean scores per segment are displayed and negative values reflect higher approval. These scales range from –2, reflecting highest approval to the respective attitude, to +2, reflecting lowest approval to the respective attitude. In case of a significant outcome of the Chi$^2$ Test for the dummy-coded variables, pairwise comparison between segments is conducted in the same manner. For the attitude- and value-based scales, the post-hoc DSCF in case of significant outcomes of the non-parametric Kruskal-Wallis-Test allow for segment comparisons.

Segment 1 is characterized by younger respondents with a higher education, and the highest share of respondents who reported to have farmers in their personal network among all segments. Segment 1 comprises individuals with above-average technical affinity (ATT) and a high commitment towards green consumption (GCV). Segment 2 is comparable to segment 1 with regard to education levels and the presence of farmers in participants' personal networks. However, participants in segment 2 have the highest disposable income among all segments. Besides a high valuation of 'green consumption', like segment 1, segment 2 also considers regional

*Table 3 - Dummy-coded socio-demographic composition of segments and test statistics for segment comparison*

| | | Segments (shares in %) | | | | Chi² Test statistic |
|---|---|---|---|---|---|---|
| **Variable** | | **1** | **2** | **3** | **4** | **(p-values)** |
| Gender | Male | 46.8 | 47.2 | 48.0 | 49.6 | 1.01 (0.7982) |
| Age** | <40 years | 40.2[b] | 34.4[ab] | 29.8[a] | 34.5[bc] | 9.13 (0.0276) |
| Level of education*** | Lower education | 36.5[a] | 39.4[a] | 48.4[b] | 44.3[b] | 14.1 (0.0028) |
| Inhabitants (size of residence) | ≤20,000 | 42.5 | 37.8 | 39.7 | 38.1 | 2.17 (0.5382) |
| Income* | <4,000 € | 79.4[ab] | 75.4[a] | 82.2[b] | 79.4[ab] | 6.76 (0.0799) |
| Experience in agricult. or rel. sector | | 10.3 | 8.5 | 8.1 | 9.1 | 1.25 (0.7400) |
| Farmers in personal network*** | | 23.9[b] | 22.2[b] | 14.8[a] | 18.1[a] | 13.73 (0.0033) |
| | | **Segments (mean scores)** | | | | **H-Test** |
| **Attitude- and value-based scales** | | **1** | **2** | **3** | **4** | **(p-values)** |
| ATT*** | | –0.07[a] | –0.02[a] | 0.17[b] | –0.07[a] | 18.39 (0.0004) |
| GCV*** | | –0.19[a] | –0.19[a] | 0.31[b] | 0.06[c] | 106.67 (<.0001) |
| CES*** | | –0.11[ac] | –0.24[a] | 0.21[b] | 0.04[bc] | 36.75 (<.0001) |

Significance level Chi² and Kruskal-Wallis-Test (H-Test): <0.1*, <0.05**, <0.01***. Pairwise Chi² and DSCF post-hoc Tests: segments with the same superscripts [a, b, c] do not differ significantly from each other. Attitude and value-based scales: negative values reflect higher approval.

production (CES) highly relevant. Next, segment 3 shows the most significant differences in pairwise comparisons with the other segments. It is composed of predominantly senior individuals and is characterized by the lowest levels of education and disposable income compared to the other segments. Significantly fewer participants in segment 3 have farmers in their personal network than in segments 1 and 2. All attitude- and value-based scales have positive values in segment 3, indicating the lowest commitment towards green consumption and local production as well as lower levels of technological affinity relative to all other segments. Segment 4, finally, is characterized by an average level of education and a strong affinity towards technology. However, its members do not show a strong commitment towards 'green consumption' and regionality.

## 3. Discussion

Similar to Alcon *et al.* (2020), the study at hand investigates social preferences for welfare-enhancing agricultural systems, such as strip intercropping, and demonstrates a societal demand for more sustainable agroecosystem outcomes in terms of biodiversity, prevention of soil erosion, and reduction of chemical pesticide use. In addition, different management options, including farming systems and autonomous machinery, are also examined. The relative importance of the six attributes analyzed in the DCE ranged from 12% for landscape to 21% for chemical crop protection, implying that society recognizes multiple dimensions of farming systems as relevant. Using latent class analysis, four distinct segments with marked differences in attribute importance and part-worth utilities were identified.

Concerning the attitude-behavior gap, results might be more biased towards a more environmentally friendly agricultural production (e.g., less use of chemical pesticides, more biodiversity) than consumers would support. However, the study was more focused on scenario analyses (e.g., using Hierarchical Bayes modelling) relying on part-worth utilities rather than willingness-to-pay assumptions. This procedure reduces sensitivity to design errors and improves validity for heterogeneous preferences (Hein *et al.*, 2022). In addition, the performed segmentation can partially reduce the gap by aligning measures with the specific barriers of each segment (e.g., knowledge deficits can be addressed by education). Still, the attitude-behavior gap cannot be closed by information provision alone, since situational, structural and psychosocial barriers also strongly shape behavior (Sheeran, 2002; Kollmuss & Agyeman, 2002). Segmentation therefore is not a panacea, but it increases the relevance and costeffectiveness of policy and market interventions by matching them better to the needs and levers of distinct consumer groups (Schäufele & Janssen, 2023).

The preferences for the use of autonomous machines in the production of grocery commodities, such as large and small autonomous robots, are lower compared to conventional manned tractors in all identified segments. Wilmes *et al.* (2022) observed similar reservations, as the use of digital technologies negatively impacted willingness-to-buy from the corresponding farms in their study. However, the authors found that the relationship turned positive when introducing environmental arguments. On the other hand, Zeddies *et al.* (2024) found attitudes towards agricultural robots generally positive among the German public, with information about possible environmental benefits increasing those positive perceptions. The strong preference towards 'traditional' image of farming suggests a general lack of visibility of autonomous agricultural technology in the public sphere (Pfeiffer *et al.*, 2020) and does not necessarily imply a general rejection of field robots. To counteract this, positive environmental impacts of robots and a consumer-friendly information strategy could enhance public trust in these technologies (Wilmes *et al.*, 2022; Zeddies & Busch, 2025).

The findings further underscore that consumer acceptance of sustainable farming systems is shaped not only by ecological objectives but also by the framing of attributes and socio-environmental experiences, both of which merit closer attention in the design of policy and communication strategies. Thus, the balance between ecological objectives and technological innovation is perceived very differently across consumer groups. The identified consumer segments 1 and 4 might view technologies such as field robots as promising solutions. Segment 3, conversely, might associate them with risks, e.g., for the 'institution' of family farming and job security in agriculture (Zeddies & Busch, 2025), or prioritize environmental considerations and cost-related aspects instead. These heterogeneous perceptions underscore that the societal acceptance of agricultural innovation cannot be taken for granted and depends strongly on how tradeoffs are framed in public discourse.

Finally, the implementation of the twin transition theory in agriculture highlights significant tradeoffs between advancing sustainability goals and deploying digital technologies. In farming contexts like crop cultivation, rapid adoption of precision agriculture tools such as GNSS-guided tractors and drone-based monitoring entails substantial upfront material and energy costs from manufacturing and installation, alongside supply-chain impacts like rare earth mineral extraction, which may partially offset anticipated sustainability gains from optimized inputs (Brunori, 2022). These tradeoffs manifest along temporal, spatial, and societal dimensions, as highlighted in Myshko *et al.* (2024) on the twin transition in agri-food systems: A discrepancy exists between the temporal fluctuations in emissions resulting from the implementation of digital and mechanical infrastructure and the potential for long-term reductions in resource utilization, including water and mineral fertilizers. Spatially, localized environmental pressures – for example, soil compaction from heavy machinery or the accumulation of electronic waste – may contrast with aggregate reductions in greenhouse gas emissions at regional or global scales. Societally, the diffusion of digital technologies in agriculture tends to be skill-biased, privileging farmers with higher levels of digital literacy and education. This has the potential to result in the exclusion of more vulnerable groups from the benefits of the twin transition.

## Conclusion

The results of the DCE indicate that strategies for introducing new farming technologies and different farming systems, such as strip intercropping, must consistently emphasize their confirmed or anticipated environmental benefits in order to foster legitimacy and social acceptance. The introduction of these innovations into agriculture therefore requires more than merely demonstrating efficiency gains; it also depends on clearly linking them to ecological improvements and broader societal goals. In practice, this calls for target group specific policy and communication strategies, as societal acceptance of sustainable and digital technologies is segment-dependent and cannot be achieved through uniform measures. Tailored information campaigns, transparent labeling, and cocreation formats, such as on farm demonstrations, field days or living labs, can help connect visible changes in production practices to tangible ecosystem outcomes and thereby strengthen public support. The observed reservations toward autonomous machinery imply that policy initiatives on technology must be accompanied by proactive communication about their environmental and social implications, including issues of occupational safety, labor displacement, and data governance. Finally, the discussion of twin transition tradeoffs indicates that digitalization policies should be systematically integrated with environmental policy and with measures that promote regional development and social inclusion, to avoid exacerbating spatial and socioeconomic disparities. This includes investing in rural digital infrastructure, strengthening independent advisory systems, and ensuring that support schemes do not disproportionately favor large, capital-intensive farms with high digital readiness. From a theoretical perspective, the study contributes to the literature on technology acceptance and sustainable consumption by jointly modeling ecological and technological attributes within a discrete choice experiment. It relates to the acceptance of agricultural innovation from a multi-dimensional perspective, thereby extending existing models that focus predominantly on either environmental or technological factors in isolation. Moreover, the estimated preference structures can serve as a basis for deriving willingness-to-pay in future studies, providing more concrete insights into societal willingness-to-pay for sustainable and digital technologies. However, it is important to acknowledge several limitations to this study. First, as is typical of most choice experiments, the results are based on stated rather than revealed preferences, which may overstate support for environmentally friendly options and underrepresent situational constraints in real purchasing contexts. Second, the study focuses on a specific national and cultural context and a limited set of attributes, which restricts the generalizability of the segment structure and preference patterns to other countries or technological configurations. Given the context- and time-dependency of preferences, as well as the rapid advancements in digital technology, further studies are necessary to achieve a more profound understanding of the evolution of societal acceptance of different farming systems. This understanding is imperative for the formulation of effective strategies to promote the adoption of sustainable and digital farming practices.

## Declaration of generative AI use

During the preparation of this article, the authors used Perplexity, and DeepL Write to improve grammar and language and to search for available literature. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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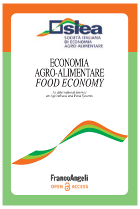


# High-Altitude, High Value? Consumer Preferences and Willingness to Pay for Mountain Wines

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*Abstract*

This study examines consumers' willingness to pay (WTP) for mountain wines and assesses the potential impact of extending the EU quality term "mountain product" to the wine sector. A discrete choice experiment was conducted with 256 wine consumers from the Veneto region, Italy. Participants were presented with various wine options featuring different attributes, including a mountain designation, organic certification, and price. The multinomial logit model was used to analyse consumer preferences and estimate WTP.
Consumers have a positive willingness to pay for mountain wines and for organic wines, with the two labels contributing independently to consumer utility.
Price, mountain designation, and organic certification were the most influential factors in the decision-making process. In addition, environmental awareness and the perception of mountain wines had a significant impact on consumer choice. These findings provide actionable insights for policymakers and producers, highlighting the potential of the "mountain product" label as a tool for sustainable rural development.

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## Introduction

As several studies have shown, "mountain products" are perceived by consumers as high-quality, authentic, and healthy, as products that result from the sustainable use of local resources and promote the preservation of biodiversity, traditions, and the socio-economic fabric of mountain areas (Baritaux *et al.*, 2011; Schjøll *et al.*, 2010; Zuliani *et al.*, 2018; Bonadonna *et al.*, 2022; Staffolani *et al.*, 2023; Zanchini *et al.*, 2023). However, consumers often have difficulty recognising agricultural and food products from these areas on the market (Schjøll *et al.*, 2010; Bentivoglio *et al.*, 2019; Cei *et al.*, 2023). To enhance and promote mountain areas, the European legislator has taken various measures, the best known of which is the optional quality designation "mountain product", introduced at European level by Regulation (EC) 1151/2012 and later supplemented by Delegated Act (EU) 665/2014. The adoption of an EU legal definition for "mountain products" reduces the risk of misleading consumers and disadvantaging genuine mountain producers (Santini, Guri and Gomez y Paloma, 2013), serves as a tool to enhance mountain areas themselves, and guarantees the authenticity of the products, thus supporting the economic system of these areas (Mazzocchi and Sali, 2022; Pagliacci *et al.*, 2022; Finco *et al.*, 2017; Sanjuán and Khliji, 2016). Since 2017, there have been 1,585 registered "mountain products" in Italy, with 42.5% concentrated in the Piedmont region (Masaf, 2024). The most represented supply chains are those of milk and dairy products, fruit, vegetables and cereals (both processed and unprocessed), and processed meat. However, wine products cannot benefit from this opportunity, despite increasing production in mountain areas due to climate change and evolving agricultural practices (Oliveira *et al.*, 2021). The exclusion of the wine sector by the legislator within the framework of the regulation for mountain areas is controversial in the scientific community.

According to other authors (Linder *et al.* 2022; Schäufele-Elbers, Ricci and Sidali, 2024), extending the optional quality term "mountain product" to the wine sector would increase consumers' willingness to pay for these products, thereby supporting local investment in mountain agriculture, preventing depopulation trends, and strengthening rural communities.

The existing literature on mountain wine purchase and consumer evaluation is limited compared to other mountain food products. Some research indicates that consumers are increasingly interested in wines with geographical, organic, and sustainability credentials (Schäufele and Hamm, 2017; Capitello *et al.*, 2021; Chandra, Moschini and Lande, 2025; Dominici *et al.*, 2025), but there is little empirical evidence on consumer willingness to pay (WTP) for wines explicitly labelled as "mountain products". Furthermore, research on consumer valuation and perception of mountain wines in the context of existing geographical indicators (GI) and quality certifications remains underdeveloped. Notably, earlier studies have found that consumer perception improves when GI food products indicate they are produced in a mountainous region (Mancini *et al.*, 2019; Endrizzi *et al.*, 2021).

Although previous studies have investigated consumer preferences for mountain food products and, more generally, for wines with sustainability or geographical characteristics, none has specifically examined consumers' willingness to pay for wines labelled as mountain products. The existing literature has primarily focused on the perception and evaluation of mountain products, such as dairy, meat, or other agri-food products (Baritaux *et al.*, 2011; Schjøll *et al.*, 2010; Cei *et al.*, 2023; Mazzocchi & Sali, 2022), and on consumer preferences for wine attributes such as origin, terroir, and organic certification (Schäufele & Hamm, 2017; Mauracher *et al.*, 2019; Capitello *et al.*, 2021). However, these studies have not been integrated to assess whether the quality term "mountain product", which currently cannot be applied to wine under EU Regulation 1151/2012, influences consumers' evaluation and willingness to pay in the wine sector. In other words, although the cited sources provide important conceptual and methodological foundations, they do not empirically quantify how consumers evaluate the potential extension of the "mountain product" designation to wine, nor do they examine how it interacts with other quality indicators such as organic certification or environmental attitudes.

The lack of research on whether consumers would value and pay a premium for mountain wine presents an opportunity to explore the potential economic and policy benefits of extending the EU mountain label to this sector.

Our study was designed to address this gap by conducting a discrete choice experiment that isolates the effect of the hypothetical mountain label on consumer preferences and willingness to pay.

This study investigates consumer willingness to pay for mountain wines and assesses the impact of a possible extension of the EU "mountain product" quality term to the wine sector. We also hypothesise that environmentally conscious consumers and those with positive perceptions of mountain wines will show higher willingness to pay for the "mountain product" label.

The study was conducted on a sample of Italian consumers, with a particular focus on residents of the Veneto region. Italy is one of the largest wine producers (OIV, 2024), with renowned wine-growing regions. As climate change shifts viticulture to higher altitudes, mountain wines are becoming an important category within the industry. The Veneto region was chosen due to its status as the leading wine-growing region in Italy and its position among the top regions for wine consumption (Istat, 2020). Veneto was selected as a case study not only because it is Italy's leading wine-producing region, but also because of a paradox that characterises its wine market. Despite being among the Italian regions with the highest number of native grape varieties, the Veneto wine sector has traditionally favoured the production of conventional wines for highly competitive international markets, rather than promoting the specificity of its native varieties. This strategic focus has contributed to its economic success but has also increased exposure to global market volatility.

Furthermore, niche wine segments, such as mountain wines, can play a stabilising role during market crises. As observed during the COVID-19 pandemic, regions with stronger local or proximity markets (e.g., Friuli Venezia Giulia) were better able to cushion the effects of sudden demand shocks. Developing and promoting niche markets for mountain wines could therefore strengthen the resilience of the Veneto wine sector, while supporting the sustainability and distinctiveness of its mountain viticulture. Niche and mass-market strategies differ in focus and approach but can coexist and complement each other (Hammervoll *et al.*, 2014).

The research question focuses on whether such a designation would increase consumer preference and willingness to pay for mountain wines, thereby supporting the sustainability of mountain viticulture.

The study will quantify the relative importance of the mountain label compared to other well-established labels, such as organic certification. Participants were presented with different wine options featuring various attributes, including the presence or absence of a mountain designation, organic certification, and other key product characteristics. This approach enables an in-depth understanding of consumer trade-offs and the factors influencing their purchasing decisions.

Understanding consumer perception and valuation of these wines in Italy, a country with a strong wine culture (OIV, 2024), provides valuable insights into potential market acceptance and strategic positioning.

The results indicate that consumers exhibit a willingness to pay a premium for mountain wines, and for organic wines, with the two labels contributing independently to consumer utility. These findings contribute to the literature by providing empirical evidence on the market potential of mountain wine and the impact of labelling strategies on consumer choice (Anagnostou *et al.*, 2025). From a policy perspective, the study highlights the potential benefits of extending the EU "mountain product" label to the wine sector, supporting both mountain viticulture and rural economic development. From a business perspective, wineries in mountain regions could use this label to differentiate their products and attract environmentally conscious consumers.

This research contributes to the discourse on geographical labelling and sustainable marketing strategies for mountain agriculture, offering new insights into consumer behaviour and policy implications.

The remainder of the paper is structured as follows. The next section presents the data and methods, detailing the choice experiment and data collection approach. This is followed by an analysis of the findings, highlighting consumer preferences and willingness to pay for mountain wine. The discussion section connects these results to the existing literature and explores their implications for marketing, policy, and sustainability. Finally, the study concludes with recommendations for future research and potential policy considerations regarding the expansion of the EU mountain product label to include wine.

## 1. Materials and methods

### 1.1. *Data gathering*

To address the research questions, we conducted an online questionnaire with a convenience sample of Italian wine consumers. The online survey method facilitates easier data collection and processing. Additionally, online questionnaires provide a flexible range of options for question design.

Consumers were selected using screening questions before completing the questionnaire. The "conditio sine qua non" were: (1) legal drinking age in Italy (at least 18 years old), (2) consumption of wine at least once a month, and (3) residence in the Veneto region. If any of these conditions were not met, the respondent was excluded from the survey. Additionally, those who always answered "no purchase" in the selection experiment were excluded as invalid responses. The final number of consumers surveyed was 256.

While this number can be considered modest for large-scale segmentation analyses, it is adequate for discrete choice modelling aimed at estimating average preferences and marginal willingness to pay values. Similar sample sizes have been employed in previous discrete choice experiment studies on wine (Bazzani *et al*., 2024).

The questionnaire was structured in three sections: (i) attitudinal questions capturing environmental values and perceptions of mountain agriculture, (ii) the discrete choice experiment (DCE), and (iii) sociodemographic information. The attitudinal section preceded the DCE to avoid contamination of self-reported attitudes by the experimental task, following established best practices in stated-preference research (De-Magistris & Gracia, 2016). Although this sequencing may increase attribute salience, it allows consistent estimation of interaction effects between attitudes and choice behaviour.

Consumer attitudes and perceptions were investigated through a series of questions using previously empirically tested and validated scales.

The final section collected socio-demographic data (age, gender, educational attainment, employment status, and income level), which was subsequently used in the analysis. Including this data allows for a full interpretation of the results and enables observation of how certain consumer characteristics are related to and influence the decision-making process.

The questionnaire was tested before distribution to identify any issues with question comprehension or the questionnaire's structure. After reviewing the various elements and making necessary corrections, the online distribution of the questionnaire began.

To assess consumer perception of mountain wines and the potential implementation of the "mountain product" quality term, the study was structured in several phases. The first phase identified the tool to pursue the defined objectives (discrete choice experiment). In the next phase, the product, its attributes, and the related attribute levels to be implemented and analysed in the study were defined. Based on these elements, the choice experiment was designed and then incorporated into the questionnaire. To set up the choice experiment mentioned above we implemented multiple tools: we used the Ngene software to design the choice experiment and QualtricsXM to create and distribute the questionnaire.

### 1.2. *The choice experiment*

The product examined in the study is a wine described by both constant (Table 1) and variable (Table 2) attributes. The choice of grape variety, and therefore of growing area and organoleptic characteristics, was based on selecting a product suitable for mountain viticulture and recognised as such by professionals and consumers (Fondazione Edmund Much, 2022). The identification of the variable attributes was based on current literature on consumer behaviour towards wine products. Various studies have shown the central importance of attributes such as price, place of origin, grape variety, production method and harvest year (Mauracher *et al.*, 2019; Stanco *et al.*, 2020). Although attributes such as brand, bottle design, the presence of sustainability certifications, and the presence or absence of additives or sulphites were also of interest, they were not considered in this study (Galati *et al.*, 2019; Mauracher *et al.*, 2019; Migliore *et al.*, 2020; Stanco *et al.*, 2020).

The product used in the selection procedure was defined based on these aspects. As previously mentioned, the wine simultaneously has attributes that may or may not differ in level between the alternatives. Specifically, elements such as grape variety, production area, presence of protected designation of origin, organoleptic characteristics, and alcohol content did not vary across

*Table 1 - Constant attributes of the analyzed product*

| **Attribute** | **Description** |
|---|---|
| Wine type | White wine |
| Grape variety | Müller Thurgau |
| Cultivation area | Province of Bolzano |
| Protected designation of origin | Alto Adige DOC – Südtirol DOC |
| Organoleptic Characteristics | Dry, fresh, elegant minerality and with hints of sage, thyme and white peach |
| Net contents | 0,75 L |
| Alcohol by volume | 12% vol. |

the different choice scenarios (Table 1). In contrast, the attributes that differed in level between the alternatives were the optional quality term "mountain product", production method, harvest year, and purchase price (Table 2). The first of these attributes used to describe the product is the optional quality term. However, according to Regulation (EC) No 1151/2012, this quality term cannot currently be applied to wine products, as also indicated in the questionnaire. This term was hypothetically applied to any wine in the study produced at an altitude of more than 500 m a.s.l. (in accordance with Regulation (EC) No 257/1999), while excluding wines produced in vineyards located in valley bottoms. The "mountain product" label used in this experiment was hypothetical, as there is currently no official EU label for wine. Therefore, the study may be subject to hypothetical bias, a common issue in stated preference methods, where respondents tend to overestimate their willingness to pay for socially desirable or sustainability-related attributes. This limitation has been acknowledged in the literature and is typical of wine consumption evaluation studies that use hypothetical statements to assess emerging labelling systems (Bazzani *et al.*, 2024; Vecchio & Annunziata, 2021).

The second variable attribute used in the choice experiment concerns the production method. Specifically, a wine was defined as organic if it was produced from grapes sourced exclusively from certified organic farming and its vinification involved the use of certified organic wine products in accordance with Regulation (EC) 889/2008, as amended by Regulation (EC) 203/2012, along with limited use of sulphites. In contrast, wines without this label were produced from grapes grown using conventional viticulture and conventional oenological practices. The year of harvest is the third variable attribute analysed in the study. The attribute values correspond to the 2018 and 2019 harvests, which are the most recent options available on the market for this product. Finally, the price attribute ranges from €9.00 to €18.00 per bottle, reflecting the established market prices for the same product.

*Table 2 - Variable attributes of the analyzed product and relative variation levels*

| **Attribute** | **Level** |
|---|---|
| "Mountain product" quality term | YES - NO |
| Organic production method | YES - NO |
| Vintage | 2018 - 2019 |
| Price (€/Bottle 0.75 L) | 9.00 - 12.00 - 15.00 - 18.00 |

The choice cards were designed using Ngene software. The selected design consists of 12 different scenarios, each offering three choice alternatives. The first two correspond to the previously described product (Table 1); they differ in the characteristics of the previously identified variable features (Table 2). The third alternative is the "no choice" option, introduced to make the choice situation more realistic for the consumer. Based on the code used, this experimental design was programmed to be orthogonal (orth = OOD) and, more specifically, optimal orthogonal in the differences (OOD), following the principles defined by Street *et al*. (2005).

The design consists of 12 different choice scenarios (tasks) and has a D-optimality value greater than 90% (Figure 1).

*Figure 1 - Example of choice scenario*

As shown in Table 3, this type of design maximises the differences in attribute values between the alternatives and simultaneously maximises the information provided by respondents (Design, 2009).

*Table 3 - Conversion of levels in Ngene*

| Attribute | Level | Level in Ngene |
|---|---|---|
| "Mountain product" quality term | YES - NO | 1 - 0 |
| Organic production method | YES - NO | 1 - 0 |
| Vintage | 2018 - 2019 | 2018 - 2019 |
| Price (€/Bottle 0.75 L) | 9.00 - 12.00 - 15.00 - 18.00 | 9.00 - 12.00 - 15.00 - 18.00 |

Finally, Table 4 shows the design obtained by using Ngene for the different tasks of the choice experiment.

*Table 4 - Design obtained using Ngene*

| | Alternative 1 | | | | Alternative 2 | | | |
|---|---|---|---|---|---|---|---|---|
| **Task** | **Mountain** | **Organic** | **Vintage** | **Price** | **Mountain** | **Organic** | **Vintage** | **Price** |
| 1 | 0 | 1 | 2018 | 12.00 | 1 | 0 | 2019 | 15.00 |
| 2 | 1 | 0 | 2018 | 9.00 | 0 | 1 | 2019 | 12.00 |
| 3 | 1 | 0 | 2018 | 12.00 | 0 | 1 | 2019 | 15.00 |
| 4 | 1 | 1 | 2019 | 9.00 | 0 | 0 | 2018 | 12.00 |
| 5 | 0 | 1 | 2019 | 9.00 | 1 | 0 | 2018 | 12.00 |
| 6 | 0 | 0 | 2019 | 12.00 | 1 | 1 | 2018 | 15.00 |
| 7 | 1 | 1 | 2018 | 18.00 | 0 | 0 | 2019 | 9.00 |
| 8 | 0 | 1 | 2018 | 15.00 | 1 | 0 | 2019 | 18.00 |
| 9 | 0 | 0 | 2018 | 15.00 | 1 | 1 | 2019 | 18.00 |
| 10 | 1 | 1 | 2019 | 18.00 | 0 | 0 | 2018 | 9.00 |
| 11 | 1 | 0 | 2019 | 15.00 | 0 | 1 | 2018 | 18.00 |
| 12 | 0 | 0 | 2019 | 18.00 | 1 | 1 | 2018 | 9.00 |

## 2. Results

### 2.1. *The sample*

To ensure response reliability, several data quality checks were conducted before analysis. Observations with unrealistically short completion times, which could indicate inattention, were removed. Participants who consistently selected the same alternative across all choice sets were also excluded. Additionally, a comprehension question following the DCE instructions ensured that participants understood the meaning of the "mountain product" label and the structure of the task. Only participants who passed this check were included in the final sample. These procedures align with recommended best practices for online discrete-choice experiments (Cummings & Taylor, 2019) and support the validity of our findings.

The sample obtained through the questionnaire, directed exclusively to people residing in the Veneto Region, is made up of 256 wine consumers (Table 5). Of these, 133 are female (52%) and 122 are male (48%). Only one respondent preferred not to provide any information in this regard. The mean age for the sample is 41 years, with a standard deviation of 13 years, while the median age is 42 years. Still referring to age, the sample was also divided into three age groups (18-34 years, 35-50 years and 51-68 years).

The average level of education is particularly high. In fact, just under 90% of respondents hold at least a high school diploma. More than 40% of the sample have a university degree or a higher qualification, such as a master's degree or a postgraduate degree.

On the other hand, if we look at the employment status of the respondents, we can see that around 80% are employed. The number of family members was on average 3.2 people, while the median value is 3 people. The analysis of the economic situation shows that 48% earn between €1000 and €2000. Around 20% of respondents stated that they had a monthly net income of at least €2000. 28% preferred not to provide any information on this.

Within the questionnaire, respondents were also asked to indicate the type of wine generally purchased based on colour, structure, alcohol content and effervescence (Table 6). In particular, the data collected demonstrate how consumer choice is equally redistributed between white wines (45%) and red wines (47%). Medium-bodied wines (47%) are preferred to both light-bodied wines (27%) and full-bodied wines (26%). From the point of view of alcohol content, wines with values included between 12% vol. and 13% vol. (65%) are the most appreciated by the consumer. Finally, still wines (63%) represent the most popular choice in terms of effervescence.

*Table 5 - Sample characteristics*

| | **Level** | **N** | **%** |
|---|---|---|---|
| Gender | Female | 133 | 51.9 |
| | Male | 122 | 47.7 |
| | Not reported | 1 | 0.4 |
| Age | 18-34 | 98 | 38.3 |
| | 35-50 | 74 | 28.9 |
| | 51-68 | 84 | 32.8 |
| Educational level | None | 0 | 0.0 |
| | Primary school | 1 | 0.4 |
| | Middle school diploma | 28 | 10.9 |
| | High school diploma | 113 | 44.2 |
| | University degree | 103 | 40.2 |
| | PhD | 6 | 2.3 |
| | Other | 5 | 2.0 |
| Employment status | Employed | 207 | 80.9 |
| | Not employed | 47 | 18.3 |
| | Other | 2 | 0.8 |
| Number of family members | 1 | 22 | 8.6 |
| | 2 | 59 | 23.0 |
| | 3 | 59 | 23.0 |
| | 4 | 86 | 33.6 |
| | 5 | 25 | 9.8 |
| | 6 | 5 | 2.0 |
| Attitude towards spending | I have to pay close attention to what I spend and sometimes my income is not enough for necessary purchases | 5 | 1.9 |
| | With a bit of caution, I can afford even a few small luxuries from time to time | 171 | 66.8 |
| | I have no financial problems and when I want to buy something I do it | 55 | 21.5 |
| | I prefer not to answer | 25 | 9.8 |
| Net monthly income | Less than 1000 € | 11 | 4.3 |
| | Between 1000 € and 2000 € | 122 | 47.7 |
| | Between 2000 € and 3000 € | 30 | 11.7 |
| | Between 3000 € and 4000 € | 16 | 6.2 |
| | More than 4000 € | 5 | 2.0 |
| | I prefer not to answer | 72 | 28.1 |

*Table 6 - Consumer preferences related to certain wine characteristics*

| **Attribute** | **Level** | **N** | **%** |
|---|---|---|---|
| Colour | White | 116 | 45.3 |
| | Rosé | 20 | 7.8 |
| | Red | 120 | 46.9 |
| Structure | Light-bodied | 68 | 26.5 |
| | Medium-bodied | 121 | 47.3 |
| | Full-bodied | 67 | 26.2 |
| Alcohol by volume | Less than 12 %vol | 40 | 15.6 |
| | Between 12 %vol and 13 %vol | 165 | 64.5 |
| | Greater than 13% vol | 51 | 19.9 |
| Type of wine (effervescence) | Still | 161 | 62.9 |
| | Sparkling | 70 | 27.3 |
| | Fizzy | 25 | 9.8 |

Consumer attitude was also analysed in relation to the concept of environmental sustainability. Specifically, this topic was assessed by including a tool known as the GREEN scale (Haws *et al.*, 2014) in the questionnaire. This scale consists of six distinct items, enabling the estimation of associated green consumption values (Table 7). In this study, respondents evaluated each item using a 5-point Likert scale ranging from 1 (“strongly disagree”) to 5 (“strongly agree”). The scale reflects the extent to which consumers consider the environmental consequences of their purchasing decisions and are willing to engage in environmentally responsible consumption, even when this involves personal inconvenience.

The analysis of the collected data shows that consumers in the sample tend to place particular importance on choosing products that are not harmful to the environment. This importance is reflected in their tendency to associate their decisions and actions with an assessment of potential environmental impact or with the possibility of consuming and wasting environmental resources. At the same time, purchasing habits are partially influenced by the potential impact on the environment.

*Table 7 - GREEN scale (Haws et al., 2014)*

| **Items** | **Min.** | **Max.** | **Mean** | **Std** | **Median** |
|---|---|---|---|---|---|
| It is important to me that the products I use do not harm the environment | 1 | 5 | 4.16 | 0.73 | 4 |
| I consider the potential environmental impact of my actions when making many of my decisions | 1 | 5 | 3.74 | 0.86 | 4 |
| My purchase habits are affected by my concern for our environment | 1 | 5 | 3.59 | 0.85 | 4 |
| I am concerned about wasting the resources of our planet | 1 | 5 | 3.90 | 0.86 | 4 |
| I would describe myself as environmentally responsible | 1 | 5 | 3.87 | 0.83 | 4 |
| I am willing to take inconvenient actions that are more environmentally friendly | 1 | 5 | 3.64 | 0.91 | 4 |

These observations show that consumers place particular importance on the role of agriculture in preserving and maintaining the mountain environment and its resources. These consumers associate the term "mountain wine" with a product made from local grape varieties and produced with few additives. Moreover, consumers appear almost indifferent to factors such as the location and altitude of cultivation when considering mountain wines. It is also notable that greater finesse in aromas and flavours, as well as the use of more manual labour in vineyard cultivation and harvesting, do not significantly influence the value consumers attribute to these wines. Based on these observations, consumers are also especially interested in extending the optional quality term "mountain product" to wines produced in these areas.

*Table 8 - Perception of mountain wines*

| **Items** | **Min.** | **Max.** | **Mean** | **Std** | **Median** |
|---|---|---|---|---|---|
| Wines from mountain areas must be more delicate in terms of aromas and flavours | 1 | 5 | 3.20 | 0.79 | 3 |
| Grapes for mountain wines must be grown on small farms | 2 | 5 | 3.49 | 0.76 | 3 |
| Mountain vineyards must be terraced | 1 | 5 | 3.27 | 0.72 | 3 |
| Mountain vineyards should be high altitude | 1 | 5 | 3.21 | 0.84 | 3 |
| Mountain vineyards should be at least in highland | 1 | 5 | 3.42 | 0.78 | 3 |
| Agriculture should preserve the mountain environment | 1 | 5 | 4.26 | 0.67 | 4 |
| Wine producers in mountain areas should use fewer additives | 1 | 5 | 3.83 | 0.80 | 4 |
| viticulture in mountain areas should use local varieties | 1 | 5 | 4.07 | 0.69 | 4 |
| Mountain wine should be made using more manual labour | 1 | 5 | 3.40 | 0.8 | 3 |
| The total volume of wine production should be limited in mountain areas | 1 | 5 | 3.30 | 1.0 | 3 |
| The optional "mountain product" quality term should also be extended to wines | 1 | 5 | 3.88 | 0.76 | 4 |

## 2.2. *Elicitation of consumer preference structure*

According to Lancaster theory (Lancaster, 1966), discrete choice models assume that the total utility consumers derive from a product can be decomposed into the marginal utilities associated with the product's attributes. Accordingly, in our model, the utility function (U) that individual n derives from choosing option j in choice situation t can be specified as follows:

$$U_{njt} = \beta_p Price_{njt} + \beta_1 Mountain_{nj}t + \beta_2 Organic_{njt}t + \beta_3 Vintage_{njt} + \varepsilon_{njt.}$$

$Price_{njt}$ represents the purchase price of the wine,

$Mountain_{njt}$ is a dummy variable equal to 1 when the optional "mountain product" quality term is present and 0 otherwise,

$Organic_{njt}$ is a dummy variable indicating organic certification, and

$Vintage_{njt}$ identifies the harvest year (2018 = 1; 2019 = 0). The term $\varepsilon_{njt}$ is an independently and identically distributed error term following a Type I extreme value distribution.

The opt-out alternative ("no purchase") is explicitly included in the choice set and is modeled through an alternative-specific constant:

$$U_{n0t} = ASC_{optout} + \varepsilon_{n0t}$$

The alternative-specific constant ASCoptout captures the average utility difference between choosing one of the wine alternatives and opting out of the choice task. A negative value of this parameter indicates a higher propensity to select one of the purchase alternatives rather than the no-buy option.

The model is estimated as a Multinomial Logit (MNL), which provides a parsimonious and robust framework for estimating average preferences and marginal willingness-to-pay (WTP) values in discrete choice experiments with moderate sample sizes (Tait *et al.*, 2016). Although the MNL assumes homogeneous preferences across individuals, it is well suited to the exploratory objective of this study, which focuses on identifying aggregate preference structures rather than individual-level heterogeneity.

In this specification, utility is defined relative to a normalized reference alternative, and all estimated coefficients should therefore be interpreted as relative effects on choice probabilities rather than absolute levels of utility. The inclusion of the opt-out alternative ensures that the model explicitly captures the buy versus no-buy decision, thereby improving the behavioral realism of the choice task.

The model was estimated using the mlogit package in R (Croissant, 2020). The estimated coefficients represent average marginal utilities at the population level (Jaeger & Rose, 2008). Willingness-to-pay measures were derived as the negative ratio between the attribute-specific coefficients and the price coefficient, consistent with standard practice in discrete choice modeling.

The MNL model estimates the effects of various attributes on respondents' choice decisions in a discrete choice experiment (Table 9).

*Table 9 - Results from MNL*

| **Attribute** | **Coefficients** | **Std. Error** | ***z* values** |
|---|---|---|---|
| Intercept | 0.002 | 0.041 | 0.063 |
| Price | –0.112*** | 0.008 | –12.680 |
| Mountain | 0.320*** | 0.022 | 14.269 |
| Organic | 0.290*** | 0.022 | 12.977 |
| Year 2018 | 0.034 | 0.020 | 1.628 |
| Optout | –2.668*** | 0.130 | –20.474 |
| Log-Likelihood: –2816.8 | | | |
| McFadden $R^2$: 0.072601 | | | |
| Likelihood ratio test: $\chi^2 = 441.02$ ($p < 0.001$) | | | |

The alternative-specific constant associated with the opt-out option is negative and statistically significant, indicating that respondents derive higher utility from choosing one of the wine alternatives rather than opting out of the choice task. This suggests that the attributes included in the model capture key factors influencing decisions

The positive and significant coefficient for the "Mountain" attribute suggests that respondents strongly prefer mountain-related options. The large z-value indicates a robust effect. In addition, the positive and significant coefficient for "Organic" suggests that respondents prefer organic products to non-organic alternatives. This indicates a potential willingness to pay more for organic options.

The coefficient for the 2018-year variable is positive but not statistically significant. This indicates that there is no strong evidence that choices differed significantly in 2018 compared to other years in the dataset.

The estimated coefficient for the price attribute is negative and significant. This means that as the price increases, the likelihood of choosing a given alternative decrease. The consumer is therefore more likely to choose the alternative with a lower price. This is expected, as higher prices generally lead to lower demand.

The model achieved a McFadden pseudo-$R^2$ of 0.0726, which is within the range commonly reported for discrete choice experiments (0.02–0.10; McFadden, 1974; Hensher *et al.*, 2015). Although pseudo-$R^2$ values are not directly comparable to those from linear regression models, this level of fit indicates that the estimated model provides a satisfactory representation of respondents' choice behaviour.

In addition to explaining the random utility model, these coefficients can also be used to estimate the consumer's willingness to pay by associating this aspect with specific attribute levels. In this case, willingness to pay can be determined as the negative ratio between the coefficients of the attribute *r* and the price coefficient $\beta_{price}$ (1).

$$WTP = -\frac{(\beta_l - \beta_{ref})}{\beta_{price}} \tag{1}$$

Where $\beta_l$ represents the estimated coefficient for the attribute level *l*, while $\beta_{ref}$ corresponds to the coefficient for the reference level, the value of which is zero in the case of *dummy coding*. Finally, $\beta_{price}$ identifies the estimated coefficient relating to the price attribute.

Given that the model was specified as a Multinomial Logit (MNL) with fixed coefficients, the estimated WTP values represent average marginal valuations across respondents. The standard errors and 95% confidence intervals were calculated using the Delta Method (Hole, 2007), based on the model's variance-covariance matrix.

Therefore, applying the equation reveals that the marginal willingness to pay for the presence of the optional "Mountain product" quality term is €5.70 per bottle (Table 10). Similarly, the estimated marginal willingness to pay for wines produced using an organic method is €5.18 per bottle.

*Table 10 - Estimated Willingness to Pay*

| **Attribute** | **Level** | **WTP (€/bottle)** | **Std. Error** |
|---|---|---|---|
| Mountain | Yes | 5.70*** | 0.85 |
| Production method | Organic | 5.18*** | 0.82 |

The estimation of a second MNL model also made it possible to verify whether the attribute levels related to the presence of the optional quality term and the organic production method add value to the product independently or, on the contrary, overlap in the quantification of the willingness to pay.

In parallel, additional models were implemented to assess the relationship and impact of socio-demographic variables on consumers' decisions and their willingness to pay. The results from these models show that the various socio-demographic variables do not significantly influence the value consumers associate with the term "mountain product". However, the data indicate that female consumers and those without economic concerns are more willing to pay a higher price for organically produced wines.

The study also examined how consumers' attitudes towards environmental sustainability influence the previously estimated willingness-to-pay values. In this context, the observations collected using the green scale described above were used. This variable, after being centred and standardised, was added to the data set and then analysed with mlogit (Croissant, 2020).

The results of the model (Table 11) show that the attitude towards environmental sustainability contributes significantly to explaining and quantifying the willingness to pay in relation to the term "mountain product" and the organic production method.

*Tab. 11 - Mlogit output: GREEN scale*

| **Attribute** | **Coefficients** | **Std. Error** | ***z* values** |
|---|---|---|---|
| Intercept | 0.012 | 0.043 | 0.294 |
| Price | –0.117*** | 0.009 | –12.895 |
| Mountain | 0.336*** | 0.023 | 14.608 |
| Organic | 0.307*** | 0.023 | 13.345 |
| Year 2018 | 0.034 | 0.021 | 1.607 |
| Mountain:Green | 0.133*** | 0.022 | 6.133 |
| Organic:Green | 0.165*** | 0.022 | 7.607 |
| Optout | –2.707*** | 0.132 | –20.424 |
| Log-Likelihood: –2772.1 | | | |
| McFadden $R^2$: 0.087314 | | | |
| Likelihood ratio test: $\chi^2 = 530.4$ ($p = < 0.001$) | | | |

The estimated coefficients indicate that consumer attitudes toward environmental sustainability systematically moderate the utility derived from product attributes. In particular, the positive and statistically significant interaction terms show that consumers with stronger pro-environmental values assign higher utility to both the mountain product label and organic certification. This implies that environmental awareness amplifies the marginal effect of these credence attributes on choice probabilities. Importantly, the results suggest that the mountain product label and organic certification appeal to a similar consumer segment in terms of environmental orientation. Rather than attracting distinct groups of consumers, both attributes are valued more strongly by individuals with higher pro-environmental consumption values, indicating a convergence in the profile of consumers who respond positively to sustainability-related labels. In parallel, the role of perceptions of mountain wines was analyzed using a comparable modeling approach. The perception index, constructed from multiple items and subsequently mean-centered and standardized, was interacted with the labeling attributes to assess whether product-related beliefs further shape willingness to pay. The results confirm that more favorable perceptions of mountain wines increase the marginal utility associated with both the mountain product label and organic certification, reinforcing the role of cognitive evaluations alongside value-based attitudes in shaping consumer choice.

*Tab. 12 - Mlogit output: Perception of mountain wine*

| **Attribute** | **Coefficients** | **Std. Error** | ***z* values** |
|---|---|---|---|
| Intercept | 0.011 | 0.042 | 0.249 |
| Price | –0.116*** | 0.009 | –12.851 |
| Mountain | 0.334*** | 0.023 | 14.581 |
| Organic | 0.305*** | 0.023 | 13.315 |
| Year 2018 | 0.034 | 0.021 | 1.610 |
| Mountain:Wine | 0.140*** | 0.022 | 6.377 |
| Organic:Wine | 0.135*** | 0.022 | 6.188 |
| Optout | –2.698*** | 0.132 | –20.435 |

Log-Likelihood: –2780.6

McFadden $R^2$: 0.084515

Likelihood ratio test: $\chi^2 = 513.4$ (p = < 0.001)

The results of the model analysis (Table 12) show that the perception of mountain wines significantly influences willingness to pay, as was also found in the environmental sustainability model. In particular, the utility factor attributed by the consumer to the choice option can increase or decrease depending on their expressed perception of mountain wines. This may alter the consumer's choice compared to other alternatives, as it affects the decision-making process.

In addition to the baseline model, we estimated a set of parsimonious interaction specifications aimed at testing theoretically grounded hypotheses regarding the role of consumer attitudes and multiple quality labels.

First, environmental attitudes (measured through the GREEN scale) and perceptions of mountain wines were interacted separately with the mountain product and organic labels, in order to assess whether these attitudinal dimensions systematically moderate preferences for credence attributes. These interactions capture heterogeneity in preferences driven by value orientation and product-related beliefs, without introducing higher-order or compounded attitudinal constructs.

Second, given the increasing policy relevance of multi-label strategies, we explicitly tested whether the joint presence of the "mountain product" quality term and organic certification generate complementarities, redundancies, or neutral effects in consumer utility. To this end, an interaction term between the mountain label and organic certification was included in the model. This approach builds directly on the literature on multiple quality labels (Stiletto and Trestini, 2022) and allows us to assess whether the informational content conveyed by the two labels is perceived by consumers as reinforcing or overlapping in the wine sector.

At the same time, the first-order interactions between labeling attributes and consumer attitudes remain statistically significant. Both environmental attitudes and positive perceptions of mountain wines increase the marginal utility associated with the mountain product and organic labels, confirming that attitudinal orientation acts as a meaningful moderator of preferences without requiring higher-order interaction terms.

## 3. Discussion

The findings of this study contribute to the growing body of research on consumer preferences for geographical and sustainability-based wine labelling, showing a significant positive effect of the mountain product label on consumer choice. This result is consistent with research by Linder *et al.* (2022), who found that including a mountain designation in wine labelling can enhance consumer interest and willingness to pay for such products. Similar findings have already been reported in studies focusing on other products, such as milk, dairy products, and meat (Cei *et al.*, 2023; Mazzocchi and Sali, 2022; Staffolani *et al.*, 2023; Zanchini *et al.*, 2023). In particular, there is clear consumer interest in the mountain product label, even when it is not associated with other quality attributes or production method indicators.

The analysis of the collected data and the coefficients estimated using the mlogit function (Croissant, 2020) enabled a deeper exploration of consumer interest in mountain wines. In particular, these analyses showed that consumers associate agriculture with the care and preservation of the mountain environment. They also believe that mountain wines should be made from indigenous grape varieties, thereby linking the wine to the territory and reinforcing its status as a local product. Furthermore, consumers place great importance on the reduced use of additives in the production process, prioritising this factor over elements such as vineyard altitude or aromatic composition. This finding highlights a proactive consumer attitude towards environmental sustainability, as also reflected in the Green Scale values from the questionnaire (Haws *et al*., 2014).

Consumers exhibit a willingness to pay a premium for mountain wines and for organic wines, with the two labels contributing independently to consumer utility. These findings are consistent with previous studies that have highlighted consumers' positive perceptions of mountain products (Schjøll *et al*., 2010; Zuliani *et al*., 2018) and their willingness to pay more for products associated with sustainability and local origin (Schäufele & Hamm, 2017; Cei *et al*., 2023). Overall, mountains evoke a broadly positive collective imagination among consumers. Mountain territories are perceived as carriers of positive values, and mountain products are regarded as inherently valuable (Mazzocchi and Sali, 2020).

The significant willingness to pay for mountain wine also aligns with research on the value of geographical indications (GIs) in consumer decision-making (Costanigro *et al*., 2014; Mauracher *et al*., 2019). Like protected designation of origin (PDO) labels, the mountain label serves as a quality cue for consumers, reinforcing the perception that wines produced in high-altitude regions have unique and desirable characteristics. However, unlike PDOs, which primarily emphasize terroir, the mountain product label signals broader sustainability and regional authenticity aspects, which are increasingly valued by contemporary consumers. The effect of multiple quality labels (such as PDO, organic, and mountain product) on consumer behaviour must be analysed across different products and regions. Stiletto and Trestini (2022) argue that providing extensive information is not always the most effective strategy for firms.

An important contribution of this study lies in the explicit assessment of how multiple quality labels jointly affect consumer choices in the wine sector. Contrary to expectations of strong complementarities, the interaction between the mountain product label and organic certification is not statistically significant, suggesting a neutral effect. This finding aligns with evidence from other agri-food contexts, such as cheese products (Stiletto and Trestini, 2022), and indicates that the informational content conveyed by the two labels is perceived as distinct rather than overlapping.

From a policy and managerial perspective, this result implies that extending the "mountain product" quality term to wine would add value independently of existing organic certification schemes. Rather than crowding out or duplicating the informational role of organic labels, the mountain designation appears to function as a separate quality cue, reinforcing the case for its inclusion within the EU quality policy framework. At the same time, the positive moderating role of environmental attitudes and mountain wine perceptions highlights the importance of targeted communication strategies aimed at environmentally conscious consumers.

Another noteworthy finding is the interaction between environmental consciousness and the mountain product label (Laca *et al.*, 2020). Consumers with stronger pro-environmental attitudes were more likely to express willingness to pay a premium for mountain wines. This supports previous research indicating that environmentally conscious consumers prefer products with sustainability credentials (Haws *et al.*, 2014; Migliore *et al.*, 2020). In particular, young consumers tend to choose products with the mountain product label more frequently (Bonadonna *et al.*, 2022), likely due to associations with recreational activities and a generally greener lifestyle (Mazzocchi and Sali, 2024).

Additionally, the study shows that the perception of mountain wines influences willingness to pay (WTP), suggesting that consumer education and marketing strategies highlighting the environmental and social benefits of mountain viticulture could further increase demand. To quantify the value consumers place on the "mountain product" label, the marginal willingness to pay for its presence was estimated at €5.70 per bottle. This indicates that, all else being equal, the term generates a positive consumer valuation. This value is partly explained, as already noted, by consumers' positive attitudes towards environmental sustainability. However, despite consumer support for extending the "mountain product" label to wines, regulatory challenges persist. At present, wine is excluded from the list of products eligible for this designation under Regulation (EC) No 1151/2012 and Delegated Act (EU) No 665/2014. As a result, consumer recognition of the term in the market remains difficult to achieve, reinforcing the need for policy intervention.

From a policy perspective, these findings provide strong empirical support for extending the EU "mountain product" label to include wine. Previous research has identified a regulatory gap in labelling policies for mountain wines (Finco *et al.*, 2017), and our study contributes to this discussion by demonstrating the potential market benefits of such an extension. By formally recognising mountain wines, policymakers could help sustain viticulture in high-altitude regions, prevent rural depopulation, and support economic resilience in mountain communities. In conclusion, this study contributes to the literature by providing empirical evidence on the market potential of mountain wines and the role of labelling strategies in consumer decision-making.

## Conclusions

Beyond confirming a positive willingness to pay for mountain wines, this study offers several implications for policy design, producer strategies, and market communication. The finding that the “mountain product” label contributes independently to consumer utility suggests that its informational content is not redundant with existing quality schemes, such as organic certification or geographical indications. This reinforces the potential role of the mountain designation as a complementary policy instrument, capable of enhancing consumer information without increasing label complexity or causing informational overload.

From a regulatory perspective, extending the optional “mountain product” quality term to the wine sector could support clearer and more transparent communication of production conditions specific to mountain viticulture. Such an extension would recognize the structural constraints and environmental characteristics of high-altitude wine production, contributing to the preservation of mountain landscapes, traditional practices, and regional identity. At the same time, the voluntary nature of the quality term may limit its enforceability under existing consumer protection and competition rules. Policymakers should therefore carefully consider the trade-off between accessibility for producers and the strength of regulatory oversight, particularly in comparison with more stringent certification-based schemes.

For wine producers, the results suggest that adopting a mountain designation can serve as an effective differentiation strategy in increasingly competitive markets. By signaling environmental stewardship, territorial specificity, and production in challenging conditions, the mountain label may help justify price premiums and attract consumer segments that value authenticity and sustainability. Producers operating in high-altitude areas could benefit from emphasizing the distinctive characteristics associated with mountain wines, including their perceived links to biodiversity, traditional viticultural practices, and environmentally responsible production methods.

From a marketing and communication standpoint, the findings highlight the importance of conveying the meaning and value of mountain wines in a clear and credible manner. Promotional strategies should focus on authenticity, territorial identity, and sustainability-related attributes, aligning with broader trends in consumer demand for environmentally responsible and place-based food products. In this context, collaborations with tourism initiatives, local institutions, and regional branding strategies may further enhance the visibility and perceived value of mountain wines by embedding them within a broader cultural and environmental experience.

Overall, this study contributes to the literature on quality labeling and credence attributes by providing evidence on the role of the mountain product designation in the wine sector. While the analysis focuses on a specific regional context, the results offer insights that may be relevant for other mountain areas and agri-food products facing similar challenges. Future research could extend this work by examining consumer responses across different countries, wine types, or regulatory frameworks, as well as by exploring the long-term market effects of introducing mountain-specific quality labels.

## Limitation and future research

Despite the results, several limitations of this study should be acknowledged. First, the sampling strategy relied on a convenience sample collected online, which resulted in an uneven distribution of respondents. As is common in online surveys, younger and more educated individuals are likely overrepresented, a group that may exhibit higher awareness of environmental and sustainability-related issues. Consequently, the findings should be interpreted as reflecting the preferences of a digitally active segment of Italian wine consumers rather than being fully generalizable to the entire population.

Relatedly, the geographic scope of the study is limited to the Veneto region. While this area represents a relevant and economically important wine-producing context, extending the analysis to other regions would help assess the robustness of the results and evaluate the broader market potential of mountain wine labeling across different territorial and cultural settings. Future research employing probabilistic or stratified sampling frameworks and cross-regional designs would be particularly valuable in this respect. A further limitation concerns the sample size, which restricts the possibility of conducting detailed subgroup analyses. Nevertheless, the sample provides sufficient variation to estimate aggregate-level preferences and willingness-to-pay measures with acceptable precision. Consistent with previous discrete choice experiment studies on wine consumer preferences (e.g., Bazzani *et al.*, 2024), the results should therefore be interpreted as representative of broad preference structures rather than specific consumer segments. Larger and more diverse samples could allow future studies to explore preference heterogeneity in greater depth. While more flexible modeling approaches such as the Mixed Logit model allow for a richer representation of unobserved taste heterogeneity, the primary objective of this study was to identify average preference patterns and assess the relative importance of key product attributes.

A further limitation of this study relates to the interpretation of willingness-to-pay (WTP) estimates derived from the econometric model.

While the analysis allows the estimation of marginal WTP for specific product attributes, it does not model overall market participation or simulate total demand. Therefore, although consumers may express a higher willingness to pay for certain attributes (such as mountain wine labelling), this does not necessarily translate into increased overall sales, as some consumers may switch to alternative products at higher price levels. Future research could address this limitation by combining attribute-based WTP estimation with market simulation approaches to better capture potential changes in total demand and market outcomes.

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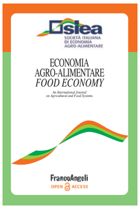


# Consumer segments and determinants shaping meat consumption in Slovakia

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## *Abstract*

The paper focuses on the analysis of meat consumption patterns and the level and structure of consumption of individual types of meat, on segmenting consumers according to consumption patterns and determining the key factors affecting meat consumption. The study is based on data obtained through an electronic questionnaire survey conducted in 2020 on a sample of 1,409 Slovak consumers. Descriptive statistics, cluster analysis and principal component analysis (PCA) were used to process the data. The results indicate a relatively high overall meat consumption, but with an unbalanced structure between individual types of meat. Based on these consumption patterns, four consumer segments were identified: consumers preferring poultry meat, consumers with a high consumption of all types of meat, consumers oriented mainly towards pork meat and consumers combining poultry meat and pork meat. The analysis of factors affecting meat consumption identified three main components. The first component represents a key factor, including items such as freshness, quality, aroma, meat content, appearance, country of origin, perishability, previous experiences, price, producer and health aspects. The second component represents a composition factor, consisting of factors related to nutritional attributes. The last component is a sales and promotion factor, related to product availability, packaging, and marketing attributes. The study provides insights for the food and meat processing industry in creating targeted marketing strategies related to health and sustainable aspects of consumption, as well as for public policymakers. Results also contribute to expanding the existing theoretical framework in the field of consumer behavior.

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## Introduction

The current meat industry is undergoing important changes, influenced by market trends related to environmental, ethical, social and health aspects of meat production and consumption. Consumer interest in sustainability and concerns about climate change are leading to ecological solutions and fuelling the debate about responsible meat consumption. Meat is considered an important part of the human diet and plays a key role in nutrient intake (Collier *et al*., 2021). From a nutritional point of view, meat is a valuable source of high-quality protein, minerals, especially iron, zinc and selenium, B-complex vitamins, but also various bioactive compounds such as taurine, carnitine, carnosine, ubiquinone, glutathione and creatine, which are involved in several metabolic processes (Geiker *et al*., 2021; Wood, 2023). Due to its nutritional composition, meat contributes to proper human development and is an important part of a balanced and healthy diet (Stadnik, 2024; Leroy *et al*., 2023), especially during childhood and adolescence (Almeida *et al*., 2023). Meat and meat product consumption has a significant impact on consumer health, the environment and the food system. Consumer decisions, therefore, significantly influence the demand and shape of the meat market. However, for a comprehensive understanding of meat consumption patterns and factors influencing consumer behaviour, systematic research on this issue is necessary.

## 1. Background

Meat consumption contributes to the reduction of nutritional deficiencies, thereby supporting human health and immunity (Singh *et al*., 2023). Some studies aimed at meat health effects point to a connection between the exclusion of meat from the diet and an increased risk of certain health problems related to the human psyche, such as depression, anxiety and self-harm (Dobersek *et al*., 2020). On the other hand, some studies point to a negative impact on consumer health resulting from excessive meat consumption, particularly processed meat products. The relationship between the consumption of unprocessed red meat and the risk of various chronic diseases, especially cancer, cardiovascular diseases and type 2 diabetes, was examined in a study by Lescinsky *et al*. (2022), which showed that excessive meat consumption may be associated with an increased risk of the aforementioned diseases. However, it is important to emphasize that the relevant evidence for the claims is still weak, because a high degree of heterogeneity between studies, related to differences in the consideration of factors such as gender, age, smoking, other dietary habits, meat preparation method, socioeconomic status and regional dietary habits. Based on the above, these factors could be key determinants influencing the relationship between meat consumption and human health (Lescinsky *et al.*, 2022). Additional studies show that an increased risk of developing or worsening certain chronic diseases, especially cancer, cardiovascular disease, type 2 diabetes, obesity, inflammatory bowel disease, non-alcoholic fatty liver disease, and fertility disorders, is associated with excessive consumption of processed red meat (Libera *et al.*, 2021). Although meat has an important place in human nutrition, in recent years, the topic of meat consumption and its effects on health has become very controversial and discussed in the public sphere (Nungesser and Winter, 2021; Parlasca and Qaim, 2022). The meat industry faces various challenges associated with social demands and criticism (Chaib *et al.*, 2023), while the discussions touch not only on the health aspects of consumption, but also on the environmental issues of production and consumption (Font-i-Furnols, & Guerrero, 2022). Moreover, current consumer trends, changing eating habits and the focus on healthy or sustainable diet further highlight these challenges, which have an important influence on consumer perception and decisions (Veiga *et al.*, 2023; Font-i-Furnols, & Guerrero, 2022). Clare *et al.* (2022) point out that the manner and content of information that meat industry actors communicate to consumers can significantly influence perceptions of the health and environmental aspects of meat consumption and the formation of dietary patterns. The authors also state that scientific knowledge about health and environmental risks can be questioned and the benefits of consuming meat and meat products can be emphasized. However, according to a wide array of studies, increasing meat and meat product consumption leads to environmental risks (Turnes *et al.*, 2023). Valli *et al.* (2022) identified that consumers' concerns related to the impact of meat production and distribution on the environment can significantly determine consumer choice. High meat consumption is associated with negative environmental consequences (Markoni *et al.*, 2023), mainly because meat production is one of the biggest contributors to global warming and environmental degradation (Stewart *et al.*, 2021). Henry *et al.* (2019) add that the meat industry is one of the most significant drivers of global deforestation and biodiversity loss. Furthermore, it has been stated that animal-based food products have a high ecological footprint (Marinova, & Bogueva, 2019) and are responsible for more than half of greenhouse gases from all agri-food sector producers (Crippa *et al.*, 2021). Moreover, increasing meat production does not have a positive impact on the environment mainly due to antibiotics, but also pesticides used in the production of plants intended for animal fattening (Marzban *et al.*, 2023). Excessive meat production also contributes to environmental changes and negatively affects animal welfare, greenhouse gas emissions, land and water use (Van der Weele *et al.*, 2019). Furthermore, in recent years, there have been strong public concerns about animal welfare (Gebska *et al.*, 2020) as well as a growing interest among consumers in supporting sustainable food systems (Garcez de Oliveira Padilha *et al.*, 2021). As such, in order to support sustainable meat production, organic meat alternatives are made available to consumers (Font-i-Furnols, 2023). However, it is also necessary to highlight the positive environmental effects of livestock, especially in well-managed agroecological systems. Livestock can convert non-edible biomass, return plant nutrients into the land, increase soil fertility and sequestrate carbon, so these systems can improve overall ecosystem services (Thompson *et al.*, 2023). Traditional pastoral socio-ecological systems can also provide significant environmental benefits. Fernandez-Gimenez *et al.* (2022) emphasize that these systems support a variety of ecosystem services, including biodiversity conservation, soil health maintenance and sustainable land use. Certain studies also highlight the positive ecological aspects of traditional livestock farming. Troiano *et al.* (2021) show that traditional free-range livestock can help maintain the biodiversity of mountain pastures and stabilize the structure of plant and animal communities. Nevertheless, for the time being, the current level of global meat consumption is not consistent with the goals of sustainable food systems. In addition, global demand for meat is expected to continue to grow, which may increase pressure on the environment (Hayek *et al.*, 2021; Springmann *et al.*, 2016; Williams *et al.*, 2021; Parlasca, & Qaim, 2022).

Sustainable food systems in the context of the meat market clearly relate to changing meat consumption patterns. Reducing meat consumption, especially red processed meat, can subsequently have a positive impact on the environment, animal welfare, but also on consumer health. This shift can be a tool for reducing negative environmental impacts related to climate change (Ivanova *et al.*, 2020) and biodiversity loss (Selinske *et al.*, 2020), but also for preventing health problems (Willett *et al.*, 2019), particularly in high-income countries (Sun *et al.*, 2022). In addition, the availability of healthy, high-quality and safe meat can also contribute to sustainable consumer behaviour in the meat market (Yang, 2022). In this context, Oliveira *et al.* (2021) find that beef meat produced in mountain areas is perceived by consumers as more natural, higher quality and healthier.

Changing eating habits are linked with reducing meat and meat products consumption and supporting the consumption of healthy and sustainable foods (Lourenco, 2022). The meat industry can be significantly affected by the consumer trend of flexitarianism, which is related to the conscious reduction in meat consumption and partial replacement with other meat substitutes, mainly plant-based which have similar sensory properties to meat and respond to changing consumer needs adhering to sustainable principles

(Andreani *et al.*, 2023). Croney and Swanson (2023) emphasize that the complete exclusion of meat and meat products from the diet is not appropriate and can cause negative consequences for human health, but also for food equality, justice and the economic viability of actors in the meat market. However, meat is an important part of human diets, and thus, for achieving changes in eating habits, it is crucial to understand individual consumer behavior (Szczebyło *et al.*, 2022). Meat consumers and their future behavior are determined by many factors, and it is therefore necessary to understand their current preferences and consumption patterns.

In the context above, the consumption of meat and meat products is debatable, especially from the perspective of health and sustainability, as well as future developments and expectations regarding increasing consumption. Against this background, the paper examines meat consumption patterns in the Slovak Republic, focusing on consumer segmentation according to the consumption of individual types of meat, as well as factors influencing current meat consumption. This intention provides novelty and fills a research gap, especially in identifying different consumer segments based on the level of meat consumption with respect to individual types of meat, poultry, pork and beef. The theoretical contribution of the research is a comprehensive understanding of the dynamics of consumer behavior on the Slovak meat market. The research extends existing theories of consumer behavior with new segmentation approaches in meat consumption and identifies key factors determining consumer behavior based on answers to the following research questions:

Research question no. 1: What is the consumption of meat and meat products by Slovak consumers, categorized by individual types of meat?

Research question no. 2: What are the key factors influencing the purchase and consumption of meat and meat products?

## 2. Materials and methods

### 2.1. *Data collection*

The study is based on data obtained through a consumer survey aimed at exploring meat and meat products consumption patterns by different types of meat. The research also included the identification of consumer clusters with regard to the level of consumption of different types of meat and meat products.

The consumer survey was conducted on a sample of 1,409 respondents in Slovakia in 2020. Respondents were invited to participate in the survey via an electronic questionnaire using Google Forms and distributed by emails and social media. The snowball sampling method was used for data collection. The sample is characterized by a higher representation of younger, urban, and more educated respondents compared to national demographic statistics, reflecting the online data collection method. Respondents involved in the questionnaire survey were divided into seven categories (Table 1).

*Table 1 - Socio-demographic profile of sample*

| **Socio-demographic characteristics** | | % |
|---|---|---|
| **Gender** | Women | 58.98 |
| | Men | 41.02 |
| **Age** | 18-25 years | 38.82 |
| | 26-35 years | 22.07 |
| | 36-50 years | 21.79 |
| | Over 51 years | 17.32 |
| **Education** | Elementary | 3.41 |
| | Secondary | 47.48 |
| | University | 49.11 |
| **Residence** | Rural | 45.49 |
| | Urban | 54.51 |
| **Economic status** | Employed | 48.90 |
| | Entrepreneur | 8.87 |
| | Student | 31.16 |
| | Retired | 7.59 |
| | Unemployed | 0.78 |
| | Maternity leave | 2.70 |
| **Number of household members** | 1 member | 5.82 |
| | 2 members | 20.30 |
| | 3 members | 27.33 |
| | 4 members | 30.02 |
| | 5 members | 11.92 |
| | More than 5 members | 4.61 |
| **Monthly household income** | Up to 1,000 euros | 17.74 |
| | 1,001-2,000 euros | 49.61 |
| | 2,001-3,000 euros | 23.70 |
| | 3,0001-4,000 euros | 4.83 |
| | More than 4,001 euros | 4.12 |

*Source*: Own research.

2.2. *Measures and analysis*

The questionnaire was developed specifically for this study based on previous literature and studies on meat consumption and consumer behavior (Font-i-Furnols, & Guerrero, 2014; Popescu, 2013). Respondents reported the average number of portions of different types of meat and meat products consumed per week (Table 2). Based on these data, weekly consumption in grams was calculated for each respondent and then converted to annual consumption for different types of meat. Consumption was therefore assessed separately for each type of meat and meat products. Subsequently, consumption of meat and meat products by different types of meat was compared with the recommended consumption regarding the health recommendations, which are set by the Public Health Authority of the Slovak Republic. The annual reccomended consumption for pork meat is 22.2 kg, for poultry is 15.0 kg, and for beef meat is 17.4 kg. Based on this comparison, respondents were categorized according to whether they had an insufficient level of consumption (below the recommended doses), adequate consumption (±10% of recommended doses) or excessive consumption of different

*Table 2 - Standardized portion sizes used for measuring meat consumption*

| **Meat product** | **Portion size** |
|---|---|
| Poultry meat | 150 grams |
| Beef meat | 150 grams |
| Pork meat | 150 grams |
| Poultry sausages | 150 grams (approx. 4 pieces) |
| Beef sausages | 150 grams (approx. 4 pieces) |
| Pork sausages | 150 grams (approx. 4 pieces) |
| Fish | 150 grams |
| Poultry ham | 50 grams |
| Pork ham | 50 grams |
| Salami | 50 grams |
| Traditional sausages | 50 grams |
| Bacon | 50 grams |
| Canned meat (predominantly pork) | 150 grams |
| Canned meat (predominantly poultry) | 150 grams |
| Fish canned | 150 grams |

*Source*: Own research.

types of meat (above the recommended doses). The obtained data became a prerequisite for creating consumer segmentation and profiling of individual segments.

The survey also focused on exploring factors influencing the purchase and consumption of meat and meat products, and included 24 factors that were selected by the authors based on previous studies (Font-i-Furnols, & Guerrero, 2014; Pourová, & Stehlík, 2002; Udomkun *et al.*, 2018; Predanocyová *et al.*, 2018) and their own ideas, considering the strong meat culture among Slovak consumers. The factors were evaluated on a 10-point scale with 1 representing no importance and 10 high importance, which provides greater differentiation of respondents' attitudes compared to 5- or 7-point scales and have also been used by other authors (Stávková *et al.*, 2018; Antošová, & Stávková, 2023). The evaluated factors were freshness of the product, quality, product fragrance, meat content, product appearance, country of origin, perishablility, previous experience, price, manufacturer, health aspect, saturated fatty acid content, salt content, nitrate content, water content, fat content, energy value, protein content, content of emulsifiers, product promotion, appearance of the packaging, package size, preparation speed and ecological aspect (organic food).

Data were processed using Microsoft Excel and evaluated in the statistical programs IBM SPSS and XLSTAT 2022.4.1. PCA was used to reduce the number of examined components in the set of observed data. The correlation matrix was appropriate for component extraction before extraction, according to the Kaiser-Meyer-Olkin (KMO) measure, which demonstrated excellent sampling adequacy (KMO = 0.954) and Bartlett's test of sphericity, which was statistically significant ($p < 0.001$). To improve the interpretability of the component structure, the solution was rotated using Varimax rotation with Kaiser normalization. Additionally, the scale demonstrated feasible internal consistency with a Cronbach's alpha of 0.959, proving the validity of the construct being measured.

To determine consumer segments based on distance from the recommended intake of selected types of meat (poultry, beef and pork meat), a two-step cluster analysis was conducted. A maximum of 15 clusters were tested, and the number of clusters was automatically calculated using Bayesian Information Criterion (BIC) and the log-likelihood distance measure. With an average silhouette of 0.60, the final solution showed good cluster quality, indicating satisfactory separation and cohesion. According to predictor values, the strongest discriminating variable was poultry (1.00), followed by beef (0.85) and pork (0.68). Subsequently, chi-square test of independence was utilized to study whether demographic characteristics significantly differed among the identified segments. A similar approach was implemented in other studies (Šedík *et al.*, 2019; Mackenzie *et al.*, 2025).

## 3. Results

### 3.1. *Meat consumption and meat consumer segments in Slovakia*

The results of the study showed that in the Slovak Republic, meat culture is prevalent, as only 2.48% of consumers do not consume any type of meat. The amount of meat and meat products consumed, as well as its diversity between different types of meat were identified in the research. This overview was obtained by calculating individual meals of selected food products.

The average amount of meat and meat products consumed per week was indicated by consumers in portions and subsequently converted to annual consumption in kilograms.

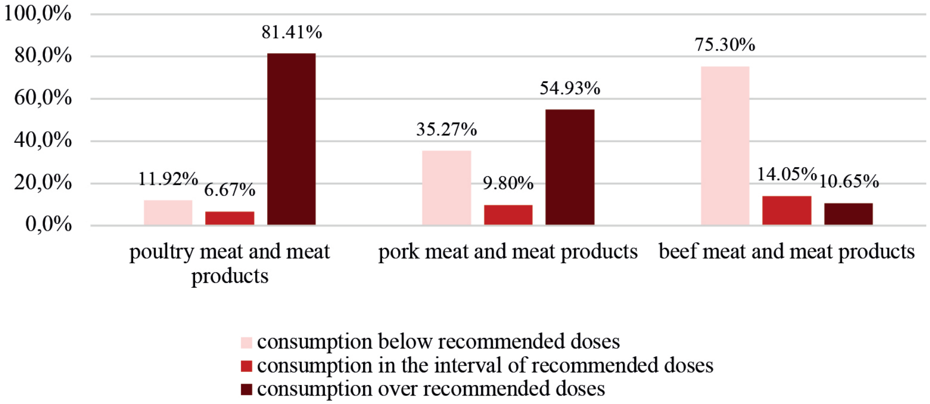
Following the above and based on the results obtained, it can be stated that 81.4% of consumers show excessive consumption of poultry meat and meat products in comparison with the recommended doses resulting from diet rationalization, which represents consumption higher than 16.5 kg per year. On the other hand, it should be emphasized that an adequate amount of poultry meat and meat products according to the recommended doses was consumed by 6.7% of consumers, which corresponds to an annual consumption in the range of 13.5 to 16.5 kg. Insufficient consumption was recorded in 11.9% of consumers, who did not reach the recommended interval of consumption of the studied meat (Figure 1).

Regarding the consumption of pork meat and meat products, the results show that the recommended consumption interval was achieved by 9.8% of consumers participating in the questionnaire survey, which represents an annual consumption of 20 to 24 kg. Excessive consumption of pork meat and meat products was recorded by 54.9% of respondents, which, in combination with an unhealthy lifestyle, lack of exercise and overall malnutrition, can lead to negative health consequences. On the other hand, insufficient consumption according to the recommended doses was recorded by more than 30% of consumers, with their annual consumption being less than 20 kg (Figure 1).

The last type of meat studied was beef, with 75.3% of consumers not reaching the recommended consumption interval, representing an annual consumption of less than 15.5 kg. The positive finding was that 14.0% of respondents reached the recommended interval with annual consumption ranging from 15.5 to 19.0 kg of beef. Excessive consumption of beef and meat products was recorded in 10.6% of consumers (Figure 1).

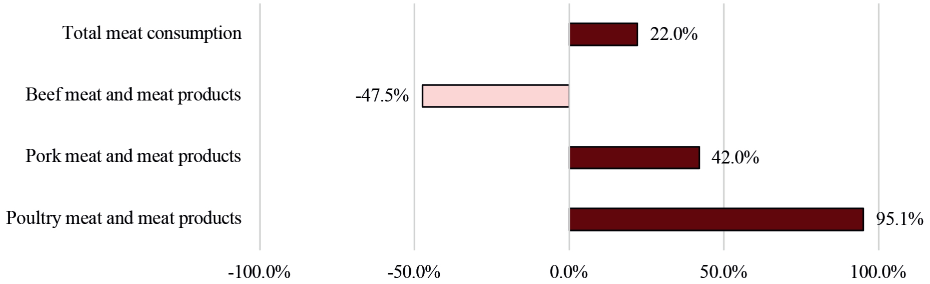
The average annual meat consumption per respondent in the questionnaire survey was found to be 69.9 kg, which means that the recommended dose in terms of diet rationalization was exceeded by approximately 22%.

*Figure 1 - Consumption of individual types of meat in terms of recommended doses*




*Source*: Own research.

*Figure 2 - Comparison of recommended and real consumption of individual types of meat by consumers involved in consumer research*




*Source*: Own research.

According to the consumption of individual types of meat, it was found that the consumption of poultry and pork was above the recommended doses, with poultry being exceeded by approximately 95% and pork by 42%. On the contrary, the consumption of beef and meat products was insufficient, falling behind the recommended interval by almost 50% (Figure 2). The average weekly consumption of meat and meat products per consumer was estimated at approximately 1.4 kg, with pork accounting for 45.1% of the total consumption, poultry 41.8% and beef 13.1%. The weekly consumption of the average Slovak consumer involved in the survey consisted of 365g of poultry meat, 100g of poultry sausages, 80g of poultry ham, 20g of other poultry products (e.g. canned foods containing poultry), 230g of pork, 100g of pork sausages, 80g of pork ham, 200g of other pork products (salami, sausage, bacon, stuffing, liver, canned foods containing pork), 140g of beef and 40g of other beef products.

Based on the examined consumption patterns of Slovak consumers, four consumer segments were identified. In these segments, the actual consumption of meat and meat products by different types was compared with the recommended doses resulting from food rationalization. Based on the results, the clusters were characterized as follows: Cluster 1 characterized by the consumption of poultry meat and meat products, Cluster 2 characterized by the consumption of all types of meat and meat products, Cluster 3 characterized by the consumption of pork meat and meat products, and Cluster 4 characterized by the consumption of poultry meat and meat products together with pork meat and meat products. The following Table 3 presents the structure of these clusters and the level of meat consumption by different types of meat.

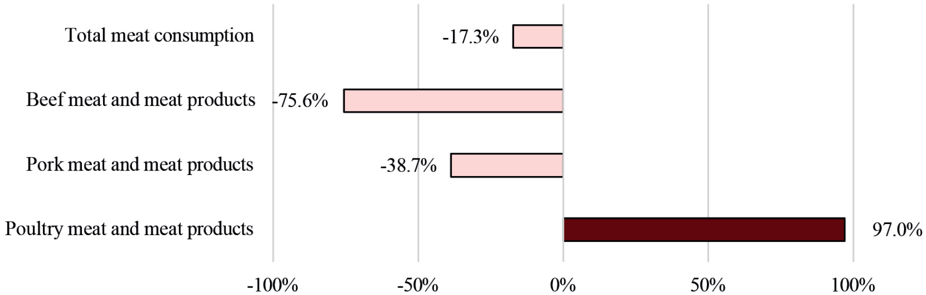
*Table 3 - The level of meat and meat products consumption per consumer in individual segments according to individual types of meat*

| | Cluster 1 | Cluster 2 | Cluster 3 | Cluster 4 |
|---|---|---|---|---|
| | 30.20% | 21.18% | 18.63% | 29.99% |
| **Consumption of poultry meat and meat products** | | | | |
| Consumption below recommended doses (lower than 13.4 kg/year) | 0.00% | 0.00% | 64.06% | 0.00% |
| Consumption in interval of recommended doses (13.5-17.5 kg/year) | 0.00% | 0.00% | 35.94% | 0.00% |
| Consumption over recommended doses (more than 17.6 kg/year) | 100.00% | 100.00% | 0.0% | 100.00% |
| **Consumption of pork meat and meat products** | | | | |
| Consumption below recommended doses (lower than 19.9 kg/year) | 78.55% | 13.40% | 46.88% | 0.00% |
| Consumption in interval of recommended doses (20- 25 kg/year) | 21.45% | 6.19% | 10.55% | 0.00% |
| Consumption over recommended doses (more than 25.1 kg/year) | 0.00% | 80.41% | 42.57% | 100.00% |
| **Consumption of beef meat and meat products** | | | | |
| Consumption below recommended doses (lower than 15.4 kg/year) | 100.00% | 0.00% | 81.25% | 100.00% |
| Consumption in interval of recommended doses (15.5-19.5 kg/year) | 0.00% | 54.64% | 13.28% | 0.00% |
| Consumption over recommended doses (more than 19,6 kg/year) | 0.00% | 45.36% | 5.47% | 0.00% |

*Source*: Own research.

The first cluster comprised 30.2% of the total number of respondents involved in the consumer survey. It was found that in this segment, the consumption of poultry meat and meat products was above the recommended doses. On the contrary, the consumption of pork and beef meat and meat products was insufficient compared to the recommended doses resulting from a rational diet. The average annual consumption of meat and meat products per respondent from the segment was 47.4 kg, which represented approximately 17.3% below the recommended dose. Excessive consumption of poultry was recorded at 29.5 kg per year, which corresponded to almost double the recommended doses. Pork meat and products were consumed on average 13.6 kg per year, while consumption was 38.7% below the recommended values. Beef and beef products were consumed in an amount of 4.2 kg per year, which meant that the recommended intake was only 24.1% (Figure 3). The average weekly consumption of respondents from this segment was distributed as follows: 415 g of poultry meat, 70 g of poultry sausages, 80 g of poultry ham, 5 g of other poultry products; 125 g of pork, 30 g of pork sausages, 35 g of pork ham, 70 g of other pork products (salami, bacon, sausage, liver, canned food containing pork); 75 g of beef and 10 g of other beef products.

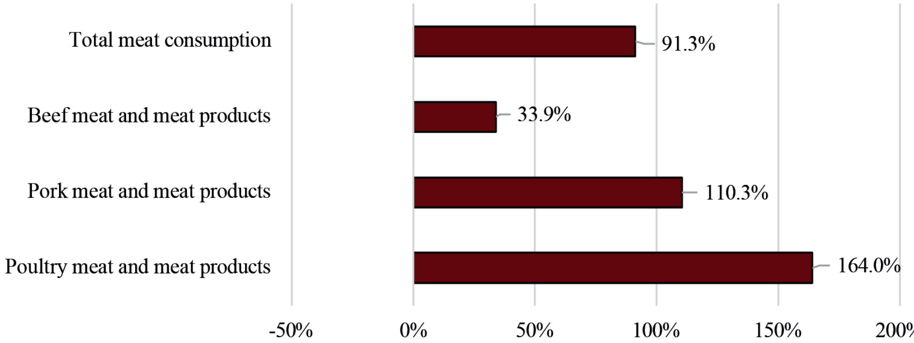
*Figure 3 - Consumption of the average consumer from a segment characterized by the consumption of poultry meat and meat products*




*Source*: Own research.

The second cluster represented 21.2% of consumers participating in the consumer survey. It was found that this segment included consumers with sufficient consumption of poultry and beef, while the majority (86.6%) also reported adequate consumption of pork meat and meat products. In general, it was found that the second segment included consumers consuming all types of meat. The average annual consumption of meat and meat products per respondent from the segment was 109.6 kg, which represented an excess of the recommended dose by 91.3%. By individual types of meat, it was found that consumers in this segment consumed 39.6 kg of poultry meat and meat products, 46.7 kg of pork and products, and 23.3 kg of beef and products. For all these types of meat, the excess of the recommended doses was more than 30% (Figure 4). The average weekly consumption of the respondents from this segment was as follows: 405g of poultry meat, 185g of poultry sausages, 120g of poultry ham, 50g of other poultry products; 275g of pork, 175g of pork sausages, 120g of pork ham, 325g of other pork products (salami, bacon, sausage, liver, canned food containing pork); 310g of beef and 135g of other beef products.

*Figure 4 - Consumption of the average consumer from a segment characterized by the consumption of all types of meat*

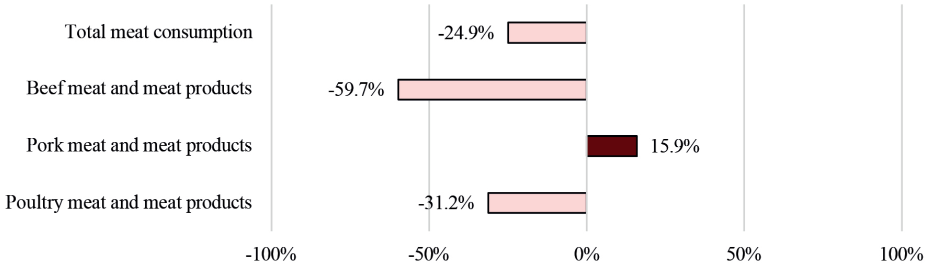



*Source*: Own research.

The third identified cluster represented 18.6% of all consumers involved in the consumer survey. It was found that this segment included consumers with different levels of consumption of individual types of meat. Excessive consumption of pork meat and meat products was recorded in 53.1% of respondents. On the contrary, the majority of consumers did not consume sufficient amounts of poultry meat or meat products (64.1%) and beef meat or meat products. The average annual consumption of meat and meat products per respondent from the segment was 43.1 kg, which represented approximately 25% below the recommended intake. According to individual types of meat, excessive consumption of pork was identified at the level of 25.1 kg per year, which represented 15.9% higher consumption compared to the recommended intake. Poultry consumption was only 10.3 kg per year, so consumption fell behind the recommended intake by more than 30%. Beef meat and beef meat products were consumed in an amount of 7 kg per year, which corresponded to only 40.2% of the recommended intake (Figure 5). The average weekly consumption of the respondents from this segment was as follows: 160 g of poultry meat, 17 g of poultry sausages, 20 g of poultry ham, 3 g of other poultry products; 205 g of pork, 80 g of pork sausages, 60 g of pork ham, 145 g of other pork products (salami, bacon, sausage, liver, canned food containing pork); 110 g of beef and 20 g of other beef products.

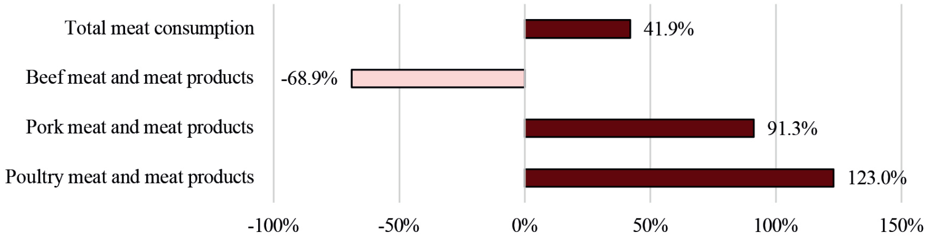
The fourth cluster represented 30.0% of consumers involved in the consumer survey. It was found that this segment included consumers with excessive consumption of poultry and pork meat and meat products. On the other hand, none of the consumers in this segment reached the recommended level of consumption of beef meat and meat products. The consumption pattern found thus corresponded to the behavior of the average Slovak consumer according to the data of the Statistical Office of the Slovak Republic. The average annual consumption of meat and meat products per respondent reached 81.3 kg, which exceeded the recommended dose by more than 40.1%. For poultry meat and meat products, consumption was recorded at 33.4 kg per year, which represented more than double the recommended doses. Similarly, pork also showed excessive consumption, with an average annual consumption of 42.5 kg exceeding the recommended dose by more than 90%. In contrast, the consumption of beef meat and meat products reached only 5.4 kg per year, which represents only about 30% of the recommended intake (Figure 6). The weekly consumption of the average consumer in this segment was 415 g of poultry meat, 110 g of poultry sausages, 100 g of poultry ham, 20 g of canned poultry meat; 320 g of pork, 120 g of pork sausages, 110 g of pork ham, 270 g of other pork products; and approximately 100 g of beef and beef products.

*Figure 5 - Consumption of the average consumer from a segment characterized by the consumption of pork meat and meat products*




*Source*: Own research.

*Figure 6 - Consumption of the average consumer from a segment characterized by the consumption of poultry meat and meat products and pork meat and meat products*




*Source*: Own research.

Table 4 presents the structure of consumers in clusters according to demographic criteria, along with statistically identified dependencies between segments based on the chi-square test of square contingency. The results showed that in the first, third and fourth segments, women prevailed among consumers of meat and meat products, while in the second segment, characterized by the consumption of all types of meat, men dominated. The differences between these segments were statistically significant ($p < 0.0001$). In terms of age, differences between segments were also confirmed ($p < 0.0001$). In the first segment, which was characterized by higher consumption of poultry meat, young consumers under 25 were most often represented. The level of education showed a moderate effect on the distribution of respondents in the segments ($p = 0.0009$). In the first segment, consumers with higher education were most often represented, while in the second and fourth segments, consumers with secondary education predominated. Results also showed that the place of permanent residence has influenced the consumption of meat ($p = 0.0042$). Urban consumers prevailed in the first, second and third segments, while in the fourth segment, consumers from villages. Slight differences between segments were also noted in the number of household members ($p = 0.0406$). The second segment had more than 20% of consumers living in households with five or more members, while in the other segments this group was represented at a maximum of 16%. An interesting finding was that the third segment consisted of more than 50% of households with one or two members. In terms of economic activity, only slight differences were noted between the segments ($p = 0.0002$). The largest proportion of consumers in the second segment were employees, while in the first segment there was a significant representation of students, which corresponded to the age distribution of this segment. Regarding the income of the households where the respondents

*Table 4 - Demographic structure of consumers by clusters*

| | Cluster 1 | Cluster 2 | Cluster 3 | Cluster 4 | p-value |
|---|---|---|---|---|---|
| **Gender** | | | | | |
| Man | 25.54% | 62.89% | 33.98% | 47.33% | < 0.0001 |
| Woman | 74.46% | 37.11% | 66.02% | 52.67% | |
| **Age** | | | | | |
| Up to 25 years | 48.67% | 35.40% | 35.94% | 31.55% | < 0.0001 |
| 26-34 years | 19.04% | 25.09% | 21.88% | 22.57% | |
| 35-50 years | 20.72% | 20.96% | 21.09% | 24.76% | |
| More than 51 years | 11.57% | 18.55% | 21.09% | 21.12% | |
| **Achieved education** | | | | | |
| Elementary | 1.92% | 2.75% | 5.08% | 4.13% | 0.0009 |
| Secondary | 41.45% | 53.26% | 45.70% | 52.67% | |
| University | 56.63% | 43.99% | 49.22% | 43.20% | |
| **Permanent residence** | | | | | |
| City (<20,000 people) | 21.44% | 25.77% | 21.48% | 23.79% | 0.0042 |
| City (>20,000 people) | 36.63% | 32.65% | 31.25% | 24.03% | |
| Village | 41.93% | 41.58% | 47.27% | 52.18% | |
| **Number of household members** | | | | | |
| 1 | 6.27% | 6.87% | 5.86% | 4.37% | 0.0406 |
| 2 | 19.28% | 17.87% | 21.88% | 20.87% | |
| 3 | 26.51% | 23.37% | 32.03% | 28.16% | |
| 4 | 32.77% | 29.55% | 27.34% | 30.58% | |
| 5 | 12.29% | 17.53% | 8.20% | 9.95% | |
| More than 5 | 2.88% | 4.81% | 4.69% | 6.07% | |
| **Economic status** | | | | | |
| Employed | 43.13% | 54.30% | 46.48% | 53.64% | 0.0002 |
| Retired | 4.82% | 6.87% | 10.16% | 9.95% | |
| Self-employed | 8.19% | 11.00% | 7.81% | 8.50% | |
| Student | 40.24% | 25.77% | 30.47% | 24.51% | |
| Maternity leave | 2.89% | 1.37% | 4.30% | 2.43% | |
| Unemployed | 0.73% | 0.69% | 0.78% | 0.97% | |
| **Household's income** | | | | | |
| Up to 1,000 € | 20.00% | 16.15% | 17.19% | 16.99% | < 0.0001 |
| 1,001-2,000 € | 51.08% | 38.83% | 53.91% | 53.40% | |
| 2,001-3,000 € | 19.52% | 28.87% | 22.65% | 24.27% | |
| 3,001-4,000 € | 4.10% | 8.93% | 3.52% | 3.64% | |
| More than 4,001 € | 5.30% | 7.22% | 2.73% | 1.70% | |

lived, statistically significant differences were identified between the segments ($p < 0.0001$). A similar distribution of income categories was recorded in the first, third and fourth segments, with the majority of consumers living in households with an income of up to €2,000. In contrast, the second segment included more than 40% of consumers from households with a combined income exceeding €2,000.

### 3.2. *Factors influencing meat consumption in Slovakia*

The research analyzed factors influencing the consumption of meat and meat products, with consumers evaluating 24 selected determinants. Subsequently, hidden relationships between these factors were identified through the application of principal component analysis (PCA). Based on the results, three latent components were extracted that influence purchasing behavior and the subsequent consumption of meat and meat products (Table 5), confirming the assumption about the existence of differences in the evaluation of the factors under study.

The first component included factors related to freshness, quality, aroma, meat content, appearance, country of origin, perishability, previous experiences, price, producer and health aspects. As these factors can be considered essential in consumers' decisions on the purchase and subsequent consumption of meat and meat products, this component was defined as a "key factor" determining the purchase and consumption of meat and meat products. The second component consists of aspects related to the content structure of the products, namely the content of saturated fatty acids, salt, nitrates, water, fat, energy value, protein and emulsifiers. This set of determinants was designated as the "composition factor", since its variables characterize the nutritional and technological properties of meat and meat products. The third component combined factors such as promotion, appearance and size of packaging, speed of preparation and information about the certified organic origin of the product. These aspects reflect the marketing activities of producers and processors aimed at promoting sales, so this component was defined as the "sales and promotion factor", which affects respondents' decision-making process.

The results showed that consumer decisions about the purchase and subsequent consumption of meat and meat products are influenced by broader value orientations. In terms of the importance of the identified latent components, it can be stated that qualitative factors and attributes related to trustworthiness are key for consumers. Composition factors indicate a health-oriented approach to meat and meat products choices and may be significant for a certain segment of consumers, especially for consumers oriented towards healthy eating. The last group of factors refers to marketing and situational factors, which may play a complementary role in the purchase and consumption process.

*Table 5 - Factors affecting meat consumption (PCA)*

| Factors | Key factor | Composition factor | Sales and promotion factor |
|---|---|---|---|
| Freshness of the product | 0.890 | 0.245 | 0.128 |
| Quality | 0.813 | 0.301 | 0.012 |
| Product fragrance | 0.785 | 0.285 | 0.213 |
| Product appearance | 0.773 | 0.223 | 0.224 |
| Proportion of meat | 0.761 | 0.427 | 0.013 |
| Country of origin | 0.745 | 0.341 | 0.191 |
| Perishability | 0.695 | 0.245 | 0.371 |
| Previous experience | 0.682 | 0.151 | 0.337 |
| Manufacturer | 0.666 | 0.350 | 0.275 |
| Price | 0.627 | 0.067 | 0.359 |
| Health aspect | 0.572 | 0.454 | 0.343 |
| Saturated fatty acid content | 0.193 | 0.826 | 0.266 |
| Salt content | 0.240 | 0.813 | 0.240 |
| Nitrate content | 0.178 | 0.797 | 0.183 |
| Water content | 0.354 | 0.764 | 0.123 |
| Protein content | 0.302 | 0.750 | 0.155 |
| Fat content | 0.290 | 0.747 | 0.277 |
| Energy value | 0.244 | 0.733 | 0.326 |
| Content of emulsifiers | 0.404 | 0.727 | 0.099 |
| Product promotion | 0.141 | 0.234 | 0.839 |
| Package size | 0.236 | 0.173 | 0.825 |
| Appearance of the packaging | 0.351 | 0.158 | 0.719 |
| Preparation speed | 0.171 | 0.272 | 0.692 |
| Ecological aspect (organic food) | 0.183 | 0.461 | 0.589 |

*Source*: Own research.

## 4. Discussion

The paper explores consumer trends in meat consumption, with a particular focus on the determinants shaping consumption patterns of meat and meat products. The consumer study in Slovakia further points out that the most preferred types of meat are poultry meat and meat products as well as pork meat and meat products. These results were confirmed by other studies, and it could be concluded that actual consumer behavior indicates poultry to be the most consumed meat followed by beef (Masuku *et al.*, 2013). Similarly, Babu *et al.* (2010) stated that poultry meat is preferred by most of the rural households when compared to pork and beef and Schmid *et al.* (2017) identified that pork and poultry are the most often consumed types of meat by consumers. Conversely, Kubíčková and Šerhantová (2005) emphasize that beef is bought and consumed less often, while Ndwandwe and Weng (2017) added that the consumer attitude was influenced by a combined effect of several factors including the supply of various types of meat, price of individual types of meat and moreover Christian and cultural orientation of consumers.

Based on the meat consumption, the study identifies four segments depending on the amount of consumption and consumer preference of individual types of meat. A similar consumer study aimed at segmentation was conducted by Kayser *et al.* (2013) and identified three segments depending on the amount of consumption of meat and meat products and their results show that "Low Meat Consumers" consume mainly poultry, the "Average Meat Consumers" and the "Heavy Meat Consumer" prefer pork meat and meat products. In contrast, the consumption of beef and other meat (e.g. lamb, game) did not differ significantly among the three groups and is relatively on the low level, which aptly aligns with these findings.

This study also identified three latent factors that determine the level of meat consumption. Until recently, there have been no consumer studies carried out by using multivariate statistical analysis (factor analysis), but there were several studies aimed at factors determining meat consumption. For instance, Nagyová *et al.* (2012) and Becker *et al.* (2000) confirm that freshness is one of the most important aspects for consumers buying food, especially meat and meat products. Quality has also been identified in several studies as an important factor in the purchase and consumption of meat and meat products and is most often associated with taste, appearance, color, texture, juiciness, or fat marbling (Drey *et al.*, 2017). The importance of the price factor is also confirmed by Kubíčková and Šerhantová (2005), who stated that price has always shaped consumer habits and eating habits. With reference to the price factor, Souček and Turčínková (2015) and Zhang *et al.* (2018) added that the effect of price is significant mainly for people with a lower purchase price who focus on cheaper types of meat and meat products, while Schmid *et al*. (2017) points out that beef prices are high. The country of origin was also identified by other studies as a decisive factor in the purchase and consumption of meat and meat products (Bernué *et al*., 2003; Náglová, & Špička, 2017). Revoredo-Giha *et al*. (2011) pointed out that consumers perceive Scottish beef as a differentiated product independent of price, placing a strong emphasis on the origin and quality of the meat. According to Flaudrops *et al*. (2015) it is important to determine the origin of meat, in connection with the safety of consumption and the existing scandals in the agrifood industry as well. Garmyn (2020) also emphasize that at the point of purchase, consumers often notice color, marbling, leanness, packaging, and price of meat and then these aspects are determining for meat purchase and consumption. On the other hand, the less important factor affecting purchase and consumption of meat and meat products are the aspect of organic food, factors related to product packaging and marketing sales support (Kubíčková, & Šerhantová, 2005). As a corollary, Perea (2023) further emphasizes that understanding variables such as cultural and religious values, health and environmental concerns is essential for a proper understanding of consumer behavior and preferences in meat consumption.

## Conclusions

In conclusion, this paper provides valuable insights into the meat and meat product consumption trends in the Slovak Republic and consumption patterns of Slovak meat consumers with an emphasis on the amount of consumed meat and factors affecting meat consumption. The study identified four consumer segments created based on the consumed amount and preference for individual types of meat. Moreover, this consumer study revealed key factors determining meat consumption in Slovakia. It is important to note that these current patterns of meat and meat product consumption in the studied sample do not correspond to the recommended consumption level set by the Public Health Authority of the Slovak Republic.

Following the mentioned findings, the study has its theoretical implications. The identification of four consumer segments, as well as key factors for meat consumption offers a theoretical foundation for future studies on consumer behavior in the meat market. Moreover, from a scientific perspective, the study contributes to understanding the preferences and behavior of consumers for meat consumption, with a focus on different types of meat. From a practical perspective, this research emphasizes the necessity of solving imbalances in meat consumption. For one, study findings are beneficial for companies in the meat industry. Particularly, insights into segment behavior and the identification of latent factors influencing consumption can be used in creating marketing strategies and developing new meat products regarding aspects of health and sustainability. The study and its results can also be valuable for policymakers. By implementing educational and information campaigns reflecting meat consumption patterns of identified consumer clusters, it is possible to increase consumer awareness of the recommended levels of consumption of individual types of meat, as well as the environmental impacts of meat production and consumption. The suggestions would not concern the complete exclusion of meat from consumers' diets, but a shift towards responsible and adequate consumption that considers health and environmental challenges.

However, it is necessary to point out the limitations of this study. The key limitation is the reliance on self-reported data obtained from a consumer survey. Moreover, the study's territorial scope, sampling strategy and lack of key demographic controls such as religion may limit the generalizability of the findings to other regions or populations.

Future research should expand territorial coverage and use probability or quota sampling to improve representativeness and generalizability of obtained results. In addition, the research should address religion and other cultural-demographic controls to test confounding and refine segmentation across subpopulations.

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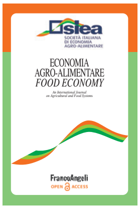


# AI and Consumer Perception of Expertise: A Conceptual Framework for Studying Algorithmic Trust in Wine Recommendations

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*Abstract*

Artificial intelligence (AI) is transforming how consumers in credence-based markets search for, interpret, and trust product information. In the wine sector, where authenticity and quality depend on symbolic and experiential cues, AI-driven recommendation systems increasingly act as new intermediaries. This paper develops a conceptual framework explaining how consumers perceive algorithmic expertise and form trust in AI-generated wine recommendations. Integrating theories of information asymmetry, signalling, source credibility, and trust in automation, the framework identifies AI transparency and source framing as key drivers of perceived expertise and trustworthiness. These perceptions, moderated by literacy, cultural orientation, and risk, influence purchase intention and reliance on AI advice. The study highlights AI as both a signalling and screening institution that can reduce but also redistribute information asymmetries in agri-food markets. The paper concludes with methodological and policy directions for ensuring transparent and consumer-centred AI adoption in the food and wine industries.

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## Introduction

The rapid digitalisation of agri-food markets is transforming the way consumers search for, evaluate, and select products. Artificial intelligence (AI) systems increasingly act as intermediaries between producers and consumers by generating product recommendations, quality predictions, and personalised advice. From e-commerce platforms suggesting "wines you may like" to AI-driven chatbots capable of mimicking sommelier expertise, algorithmic agents are becoming key actors in shaping consumption decisions (Festa *et al.*, 2025; Cao, 2025). At the same time, AI systems not only transform the channels through which consumers access products but also transform the nature of expertise and trust that underpin consumer decisions (Glikson & Woolley, 2020; Longoni & Cian, 2022). These technologies analyse vast datasets, predict preferences, and personalise communication at a scale and speed previously unattainable, thereby redefining how value and meaning are co-created between producers, intermediaries, and consumers (Paschen *et al.*, 2020; Pizzi *et al.*, 2021).

In the agri-food sector, where authenticity, quality, and provenance are essential to consumer choice, AI-driven recommendation systems introduce both opportunities and risks. Beyond its role as a technological tool for information processing, AI increasingly operates as a quasi-social actor, shaping how consumers perceive expertise, authority, and trust. Through conversational interfaces, recommendation narratives, and anthropomorphic cues, AI systems actively participate in the social construction of expertise rather than merely transmitting information (Lindgren & Holmström, 2020; Munnuka *et al.*, 2022; Mariani *et al.*, 2023).

This means that, on the one hand, algorithms can reduce information asymmetries by helping consumers navigate complex product assortments and interpret multidimensional quality cues, such as origin, sustainability, or expert ratings (Akerlof, 1970; Darby & Karni, 1973). On the other hand, they may create new forms of opacity and dependence, as consumers often cannot verify how or why a particular product is recommended (Miller, 2019). The resulting "black-box" effect raises questions about transparency, fairness, and accountability in digital decision environments (Glikson & Woolley, 2020; Von Eschenbach, 2021).

In agri-food and wine markets, such opacity is particularly problematic because authenticity, origin, and quality are central credence attributes that cannot be independently verified by consumers (Caswell & Mojduszka, 1996; Charters, 2006). When recommendation logic remains opaque, consumers may struggle to assess whether algorithmic advice reflects genuine product characteristics, commercial incentives, or hidden biases, potentially undermining confidence in digital intermediaries and trust in food systems more broadly (McCluskey & Loureiro, 2003; Reitano *et al.*, 2024).

Trust therefore becomes a central determinant of consumer acceptance of algorithmic advice, particularly because AI systems operate simultaneously as technical decision tools and as socially perceived sources of expertise. Previous research on trust in automation demonstrates that transparency, perceived expertise, and perceived benevolence are critical antecedents of user trust (Hoff & Bashir, 2015). In recommendation systems, trust formation is further complicated by the dual nature of AI as both a technological tool and a social actor (Castelo *et al.*, 2019; Lee & See, 2004). Consumers may anthropomorphize digital assistants, attributing human-like competence or warmth, yet simultaneously fear loss of control or bias. Such ambivalence gives rise to phenomena of algorithm aversion – a tendency to reject algorithmic output after observing error – and, conversely, algorithm appreciation, where algorithms are perceived as more objective and consistent than humans (Dietvorst *et al.*, 2015; Logg *et al.*, 2019; Pizzi *et al.*, 2021).

Understanding this transformation is particularly important in markets characterised by information asymmetries and credence attributes, such as the wine sector. Many of a wine's quality attributes – such as terroir, craftsmanship, or cellar ageing – cannot be fully assessed prior to purchase or even after consumption (Hanf, 2000; Cardebat & Livat, 2016). Consumers traditionally rely on expert ratings, origin labels, and storytelling to infer quality (Orth *et al.*, 2007; Ashton, 2013; Mora & Livat, 2013; Kaimann *et al.*, 2023). Today, digital recommendation systems, blockchain traceability platforms, and AI-enhanced virtual sommeliers increasingly mediate these signals, raising questions about how algorithmic expertise is perceived relative to human expertise (Wien & Peluso, 2021; Kramer *et al.*, 2024; Kopsacheilis *et al.*, 2024; Velasco *et al.*, 2024; Tassiello *et al.*, 2025). Recent systematic reviews further confirm that consumer responses to AI in agri-food systems are shaped by perceptions of transparency, fairness, and expertise attribution, rather than by technical performance alone (Reitano *et al.*, 2024; Reitano *et al.*, 2025).

Wine quality, authenticity, and origin cannot be verified before purchase and are difficult to assess even after consumption (Hanf, 2014). Consequently, consumers have historically relied on human experts and established reputation mechanisms to infer quality and reduce uncertainty. With AI systems assuming advisory and evaluative functions traditionally held by experts, a new question arises: How do consumers perceive and construct trust in algorithmic expertise?

Addressing this question requires re-examining the foundations of consumer trust in digital contexts. While marketing research has long recognised trust as a key driver of online purchase behaviour (Gefen *et al.*, 2003), little is known about how trust operates when the source of information is a non-human, algorithmic system.

Prior research on trust in AI and recommendation agents remains conceptually fragmented, often treating cognitive evaluations (such as accuracy or competence) and affective responses (such as comfort, warmth, or anxiety) in isolation rather than as jointly shaping trust formation (Benbasat & Wang, 2005; McKnight *et al.*, 2011; Glikson & Woolley, 2020). As a result, existing studies offer limited conceptual guidance on how these cognitive and affective mechanisms interact in algorithmic recommendation contexts, or on how such processes can be empirically examined in a systematic manner.

The introduction of AI therefore challenges established constructs of credibility, authenticity, and authority in markets traditionally grounded in human expertise and narrative mediation. In sectors such as wine – where emotional, cultural, and symbolic values coexist with technological innovation – understanding this transformation matters not only for theory but also for managerial and policy decision-making (De Toni *et al.*, 2022; Pizzi *et al.*, 2021). It remains unclear whether AI systems are perceived as expert, objective, or alien sources of advice, and how these perceptions shape purchasing behaviour, willingness to pay, and perceived authenticity.

The purpose of this paper is to address this gap by developing a conceptual framework for analysing consumer perceptions of expertise and trust in AI-based wine recommendation systems. Drawing on theories of information asymmetry, signalling, and source credibility, the paper proposes that consumers interpret algorithmic advice through both cognitive (perceived competence, transparency) and affective (trust, authenticity) dimensions. It also discusses how methodological innovations – ranging from digital experiments and vignette studies to eye-tracking and sentiment analysis – can enhance our understanding of consumer responses to AI-generated recommendations. By integrating theoretical and methodological insights, the paper aims to contribute to the growing debate on how digital technologies reshape consumer behaviour in the agri-food sector, highlighting the need for responsible and transparent use of AI in guiding consumer choice.

## 1. Theoretical Background

Understanding consumer behaviour toward AI-driven recommendation systems in the agri-food sector requires integrating insights from multiple theoretical traditions. The literature on information asymmetry, signalling, source credibility, and trust in automation provides a complementary foundation for analysing how consumers assess expertise and develop trust in digital intermediaries. This chapter outlines the conceptual premises of these theories and explains how they converge in the context of algorithmic mediation.

### 1.1. *Information Asymmetries and Credence Goods in the Agri-Food Sector*

Markets for agri-food and wine products are often characterised by information asymmetries between producers and consumers (Akerlof, 1970). Consumers cannot directly observe critical quality attributes such as production methods, sustainability practices, or authenticity before purchase. These credence attributes remain uncertain even after consumption (Darby & Karni, 1973). As a result, purchasing decisions rely heavily on indirect signals – labels, certifications, expert scores, or price – as proxies for underlying quality.

The wine sector exemplifies this dynamic. Although intrinsic attributes like taste or aroma can be experienced, much of wine's perceived value stems from extrinsic cues such as reputation, origin, or expert evaluation (Lockshin *et al.*, 2005; Cardebat *et al.*, 2014; Ashton, 2014; Livat *et al.*, 2019). Because these signals function as quality heuristics, their credibility depends on consumers' trust in the institutions or individuals who provide them. Traditionally, wine critics, sommeliers, and guides have played a crucial role in reducing uncertainty and aligning perceptions between producers and consumers. In economic terms, these experts act as information intermediaries who perform screening and signalling functions, thereby mitigating market inefficiencies caused by asymmetric information.

AI-based recommendation systems increasingly function as additional algorithmic signals, complementing or partially substituting traditional cues by aggregating and interpreting multiple quality indicators on behalf of consumers. Recent studies also show that algorithmic transparency improves user confidence and acceptance, especially when explanations are simple and human-centric (Miller, 2019; Longoni & Cian, 2022). However, when signals are overly technical or inconsistent, they can increase skepticism or cognitive fatigue (Pieters, 2008). From this perspective, AI systems act as new signalling institutions, shaping perceptions of trustworthiness in markets where traditional human intermediaries are being replaced or augmented by digital ones.

### 1.2. *Source Credibility and Perceived Expertise in Consumer Decision-Making*

Within consumer behaviour theory, source credibility has long been recognised as a determinant of persuasion and trust (Hovland & Weiss, 1951; Ohanian, 1990). The perceived expertise, trustworthiness, and attractiveness of the information source shape consumers' evaluations and willingness to act on recommendations. When the source of advice is an algorithm rather than a human expert, these dimensions translate into assessments of system competence (accuracy, domain knowledge) and reliability (consistency, transparency, and fairness), which jointly determine whether AI-based advice is perceived as credible (Lee & See, 2004; Hoff & Bashir, 2015; Shin, 2021).

In the wine market, where symbolic and experiential dimensions intertwine, the expert's authority often substitutes for direct knowledge or experience (Ashton, 2013; Cardebat & Livat, 2016; Kaimann *et al.*, 2023). The consumer's confidence in a rating or recommendation is therefore closely tied to the expert's perceived legitimacy and competence.

However, the growing digitalisation of food and wine communication has blurred traditional boundaries of expertise. Online reviews, peer platforms, and algorithmic recommender systems increasingly complement – or even replace – human experts (Dubois, 2025). This shift challenges the conventional understanding of expertise as a function of human judgement and professional training. Instead, expertise becomes algorithmically mediated, shaped by data-driven models that emulate human evaluation processes. The consequence is a redefinition of what constitutes credible expertise and how consumers perceive authority in digital environments.

As such, AI-based recommendation systems represent a novel type of communicator – non-human, data-driven, and adaptive. Consumers evaluate such systems using similar psychological heuristics to those they apply to human experts (Dietvorst *et al.*, 2015; Castelo *et al.*, 2019; Logg *et al.*, 2019). When the AI system displays consistent accuracy, appropriate reasoning, and domain-specific knowledge, it is perceived as competent; when it demonstrates fairness, ethical behaviour, and transparency, it is perceived as trustworthy (Glikson & Woolley, 2020). In the agri-food sector in general, and the wine sector in particular – where emotional and cultural associations play an essential role, source framing affects consumer reactions (Kim & Sundar, 2012).

In the agri-food sector in general, and the wine sector in particular, where emotional and cultural associations play an essential role, source framing – whether an AI is presented as a neutral tool or as a "virtual sommelier" – affects consumer reactions (Kim & Sundar, 2012; Moeskops, 2022; Beverland, 2006).

### 1.3. *Algorithmic Trust and AI Explainability*

Recent research on trust in AI extends traditional notions of credibility to encompass the perceived reliability, transparency, and fairness of algorithmic systems (Glikson & Woolley, 2020). Trust in AI differs from interpersonal trust in that it is grounded less in social relationships and more in cognitive evaluations of system performance, predictability, and alignment with user goals (Lee & See, 2004; Verma *et al.*, 2021). In human-machine interaction, trust develops when users perceive an automated system to be competent, reliable, and appropriately aligned with human intentions, while excessive trust can lead to complacency and insufficient trust can result in underuse or outright rejection (Hancock *et al.*, 2011; Hoff & Bashir, 2015).

In consumer decision contexts, these dynamics manifest as algorithm aversion and algorithm appreciation. Consumers may reject algorithmic advice after observing small mistakes – even when the system performs objectively better than humans (Dietvorst *et al.*, 2015) – yet in other situations they prefer algorithmic recommendations for tasks perceived as objective, data-driven, or analytical (Logg *et al.*, 2019). The balance between these tendencies depends heavily on transparency, framing, and user experience (de Visser *et al.*, 2018; Longoni & Cian, 2022).

A central challenge underlying these divergent responses is the opacity of machine learning systems, which limits users' ability to understand how recommendations are generated and to assess whether algorithmic outputs align with their preferences, values, or expectations (Miller, 2019; von Eschenbach, 2021). To mitigate this "black-box" problem, the field of Explainable AI (XAI) seeks to translate complex algorithmic operations into intelligible, human-understandable explanations that support user understanding, perceived control, and appropriately calibrated reliance (Ribeiro *et al.*, 2016; Lee & See, 2004; Shin, 2021). Experimental studies demonstrate that the framing and transparency of AI-generated advice critically shape user acceptance: recommendations presented as collaborative or human-augmented ("AI-assisted expert") tend to elicit higher trust and adoption than those described as fully autonomous (Langer *et al.*, 2023; Longoni & Cian, 2022; Kim & Sundar, 2012). Transparent explanations also serve as cognitive aids, reducing uncertainty and increasing the perceived fairness and control of automated systems (Eiband *et al.*, 2018; Verma *et al.*, 2021).

Trust in automation is therefore context-dependent and co-evolutionary as it evolves over time through interaction, feedback, and performance consistency (de Visser *et al.*, 2018; Hoff & Bashir, 2015). In the agri-food sector, and particularly in the wine industry, trust in AI intersects with emotional, cultural, and moral dimensions such as authenticity, provenance, and sustainability – elements that historically underpinned human expertise and artisanal value (Beverland, 2006; Pizzi *et al.*, 2021).

In these settings, consumers may simultaneously value efficiency, precision, and personalization while seeking the reassurance of human-like judgment, narrative, and taste. The interaction between algorithmic precision and perceived human warmth thus becomes central to the formation of trust in AI-mediated experiences (Kim & Sundar, 2012; Moeskops, 2021). As recommendation systems evolve from impersonal databases to "virtual sommeliers" capable of storytelling and contextual reasoning, they redefine what counts as expertise in markets where emotion, culture, and identity are integral to consumption (Arakawa *et al.*, 2024).

### 1.4. *Gaps and Conceptual Opportunity*

Despite growing attention to AI in marketing and consumer research, empirical and conceptual studies focusing on algorithmic trust in credence goods remain scarce. The wine sector provides an especially fertile ground for such investigation: it combines high symbolic value, multi-dimensional quality attributes, and deep-rooted traditions of expert mediation. These characteristics amplify the relevance of trust and expertise attribution, as consumers must navigate complex sensory, cultural, and reputational cues when evaluating wine quality.

The integration of AI recommendation systems into this domain raises novel questions about how consumers form perceptions of algorithmic expertise, how trust operates in digital decision environments, and how transparency and framing influence behavioural outcomes.

This paper therefore builds on the theoretical intersections between information asymmetry, source credibility, and algorithmic trust to develop a conceptual framework explaining consumer responses to AI-generated wine recommendations. In particular, the framework focuses on cognitive effort, perceived expertise, and perceived trustworthiness as the core mechanisms through which consumers evaluate algorithmic advice in a credence-goods context. Cognitive effort captures the information-processing costs associated with interpreting AI outputs, perceived expertise reflects competence attributions toward the system, and perceived trustworthiness represents the relational acceptance of algorithmic recommendations under conditions of uncertainty. The next section presents this framework and outlines the key constructs and relationships that support the formation of trust and perceived expertise in algorithmic contexts.

## 2. Conceptual Framework: Algorithmic Expertise and Consumer Trust

### 2.1. *Overview*

The emergence of artificial intelligence (AI) in consumer decision environments has transformed how individuals evaluate information, attribute expertise, and form trust. In agri-food markets – consumers frequently rely on intermediaries to interpret complex quality cues and reduce uncertainty (Akerlof, 1970; Darby & Karni, 1973) – in particular in a credence-based category such as wine. As AI systems increasingly replace or complement traditional experts, understanding the antecedents and mechanisms of algorithmic trust becomes paramount.

Building on the theoretical foundations of information asymmetry, signalling theory, source credibility, and trust in automation, the framework proposed here explains how consumers perceive AI-based recommendation systems as competent, trustworthy, or reliable sources of advice. Specifically, it suggests that AI transparency and source framing shape consumer perceptions of expertise, trustworthiness, and ease of understanding, which together determine behavioural outcomes such as purchase intention, reliance on AI advice, and satisfaction. These relationships are moderated by individual and contextual factors including digital literacy, product knowledge, cultural orientation, and perceived risk (Gefen *et al.*, 2003; Hoff & Bashir, 2015; Awad *et al.*, 2020).

### 2.2. *AI Transparency and Explainability*

Transparency refers to the degree to which an AI system communicates how its recommendations are generated. Research in human-AI interaction shows that transparent systems elicit greater perceived competence and fairness, provided that explanations are understandable and matched to user expertise (Miller, 2019; Glikson & Woolley, 2020). In recommendation systems, explainability enhances user trust when it helps consumers form a coherent "mental model" of how the algorithm functions (Verma *et al.*, 2021; Kunkel *et al.*, 2019). Conversely, excessive or overly technical detail can create confusion, raise cognitive effort, and paradoxically reduce trust (Longoni & Cian, 2022; Angelov *et al.*, 2021).

In the context of credence goods, AI transparency performs a function analogous to quality signals in traditional signalling theory (Spence, 1973; Connelly *et al.*, 2011). A transparent algorithm effectively signals the reliability of its data sources and decision logic. Consumers interpret this signal as an indicator of expertise and integrity – attributes that mitigate uncertainty about product authenticity or suitability (Schnackenberg & Tomlinson, 2016; Macready *et al.*, 2020). Thus, transparency and explainability are not simply ethical imperatives but also strategic trust-building mechanisms.

## 2.3. *Source Framing and the Human-AI Comparison*

How the source of a recommendation is framed strongly influences perceived expertise and trust. Studies in algorithmic decision-making demonstrate that consumers evaluate identical advice differently depending on whether it is presented as coming from a human expert or an AI system (Dietvorst *et al.*, 2015; Logg *et al.*, 2019). After witnessing algorithmic error, users tend to show algorithm aversion, preferring human judgment despite equal or superior algorithmic accuracy (Dietvorst *et al.*, 2015). However, when algorithms are framed as collaborative or human-augmented, consumers often exhibit algorithm appreciation, perceiving such systems as both competent and objective (Longoni & Cian, 2022).

This framing effect aligns with classical source-credibility theory, which states that perceived expertise and trustworthiness are the primary determinants of persuasive impact (Hovland & Weiss, 1951; Ohanian, 1990). Anthropomorphic framing, i.e., portraying the AI as a "virtual sommelier" or "digital assistant", can elicit warmer responses and greater engagement, while highly mechanical framing may signal cold precision but lower empathy.

Such framing choices highlight a fundamental competence–warmth trade-off: while anthropomorphic cues enhance emotional engagement and approachability, more mechanical framing may reinforce perceptions of analytical precision and objectivity. This trade-off is central to consumer acceptance of AI systems, as framing cues shape expectations about whether algorithmic advice should be evaluated primarily in terms of human-like warmth or technical competence (Cuddy *et al.*, 2008; Castelo *et al.*, 2019; Kim & Sundar, 2012).

## 2.4. *Perceived Expertise, Trustworthiness, and Cognitive Effort*

Perceived expertise represents consumers' beliefs about the AI system's competence and depth of knowledge. It is influenced by prior experience, system performance, and the quality of explanations (Glikson & Woolley, 2020). In recommendation contexts, expertise is often inferred from accuracy, personalization, and data diversity – attributes associated with analytical power rather than social experience (Paschen *et al.*, 2020).

Perceived trustworthiness extends beyond competence to include integrity and benevolence (Gefen *et al.*, 2003). Consumers trust AI systems when they believe that algorithms act in their best interest and make consistent, unbiased decisions (Hoff & Bashir, 2015). Trust is thus the mediating construct linking system attributes (e.g., transparency, framing) to behavioural outcomes.

Cognitive effort, or the mental resources required to process explanations, also affects these perceptions. Studies in information-processing theory show that when explanation formats match the consumer's literacy level, cognitive fluency enhances trust and satisfaction; when explanations are complex or contradictory, cognitive strain triggers skepticism (Miller, 2019; Pieters, 2008; Alter & Oppenheimer, 2009). This balance is particularly relevant for wine consumers, whose expertise ranges widely – from novices relying on heuristic cues to connoisseurs who may critically assess algorithmic reasoning (Mueller Loose & Lockshin, 2013; Danner *et al*., 2016).

Conceptually, these mediators are interrelated rather than independent. Lower perceived cognitive effort reduces information-processing costs, facilitating comprehension and confidence in system outputs. This, in turn, supports higher attributions of expertise, as systems that are easy to understand and interpret are more likely to be perceived as competent. Perceived expertise then functions as a key antecedent of trustworthiness, as users are more inclined to trust recommendations when they believe the underlying system is knowledgeable and reliable. Conversely, high cognitive effort may undermine expertise attributions and weaken trust formation.

### 2.5. *Behavioural Outcomes and Moderating Factors*

Trust and perceived expertise jointly determine key behavioural outcomes such as purchase intention, reliance on AI, and user satisfaction. Experimental studies indicate that transparent recommendation systems increase decision confidence, reduce perceived risk, and enhance satisfaction (Longoni & Cian, 2022; Shin, 2021). When consumers perceive AI systems as both competent and fair, they are more likely to follow algorithmic suggestions and report positive post-purchase experiences (Pizzi *et al*., 2021).

However, these relationships are moderated by several contextual factors. Digital and AI literacy strengthens the positive effect of transparency on trust because consumers with higher literacy can better interpret explanations and identify algorithmic logic (Shin, 2022). Product knowledge plays a similar role: expert wine consumers rely more on their own judgments and are therefore less influenced by algorithmic cues (Cardebat & Livat, 2016). Cultural orientation also affects algorithmic trust; cross-cultural studies demonstrate that societies with high uncertainty avoidance tend to exhibit lower acceptance of automation (Awad *et al*., 2018). Finally, perceived risk influences reliance: when purchase stakes are high, consumers may revert to human expertise even if they trust the algorithm (Hoff & Bashir, 2015; Madhavan, Wiegmann, & Lacson, 2006).

Together, these moderators highlight that algorithmic trust is not universal but contingent on cognitive, experiential, and cultural conditions – an insight essential for tailoring AI design and communication strategies in agri-food markets.

### 2.6. *Conceptual Framework and Theoretical Integration*

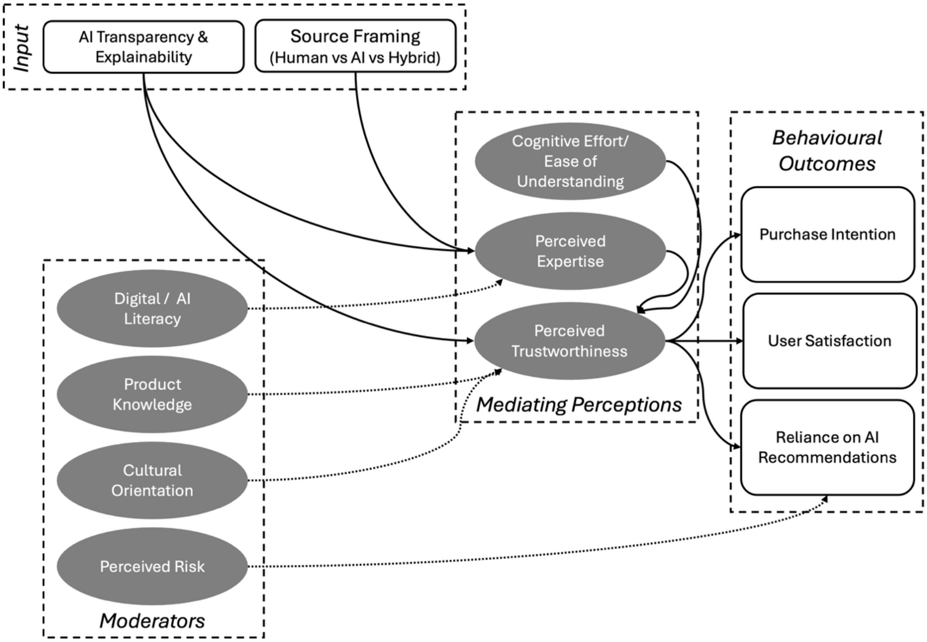
The proposed framework conceptualises AI-based recommendation systems as signalling mechanisms that reduce information asymmetry in credence-based markets (Spence, 1973; Connelly *et al*., 2011). In this view, algorithmic design features – such as transparency and source framing – function as *input signals* that communicate reliability and competence. Consumers interpret these signals through perceptions of expertise and trustworthiness, which, moderated by individual characteristics (e.g., literacy, cultural orientation, product knowledge), lead to behavioural outcomes such as purchase intention, reliance, and satisfaction (Gefen *et al*., 2003; Glikson & Woolley, 2020). Over time, consistent performance and ethical behaviour allow algorithms to accumulate what can be termed digital trust capital – that is, a reputational asset built through repeated, reliable, and transparent AI-user interactions that strengthens long-term credibility in credence-based markets (Ransbotham *et al*., 2021; Schnackenberg & Tomlinson, 2016).

In the wine sector, where authenticity, storytelling, and expertise are central to consumer choice, AI-driven recommendation tools can either reinforce or erode trust. Transparent, human-augmented systems that explain reasoning and reflect wine culture can complement traditional sommeliers, while opaque or overly technical systems risk alienating consumers who associate authenticity with human judgement (Dietvorst *et al*., 2015; Beverland, 2006; Caputo & Reardon, 2025; Shin, 2021). Digital transparency thus acts not merely as a functional feature but as a symbolic signal of integrity and authenticity, bridging the cognitive and cultural dimensions of trust in agri-food consumption.

Accordingly, the framework advances existing trust and signalling theories by positioning AI as a dual-role actor as both a signalling device communicating quality and a screening mechanism filtering information where information asymmetry persists.

The model (see below Figure 1: Conceptual Model of Algorithmic Expertise and Consumer Trust Formation) illustrates the hypothesised relationships among variables (AI transparency and source framing), mediating perceptions (expertise, trustworthiness, and cognitive effort), moderating factors (digital literacy, product knowledge, cultural orientation, and perceived risk), and behavioural outcomes (purchase intention, reliance, satisfaction). Over time, these interactions contribute to the accumulation of digital trust capital, representing the sustained credibility of algorithmic systems in credence-based markets such as wine.

*Figure 1 - Conceptual Model of Algorithmic Expertise and Consumer Trust Formation*




## 3. Methodological Approaches for Studying Algorithmic Trust

Understanding how consumers perceive algorithmic expertise requires research methods that go beyond traditional surveys or preference studies. Because trust and credibility often operate at an implicit or subconscious level, new tools from behavioural, digital, and neuroscientific research can reveal the cognitive and emotional mechanisms underlying consumer responses to AI-generated recommendations. For this reason, below methodological strategies are outlined that can be either individually or in combination applied to empirically test the conceptual framework proposed above:

### 3.1. *Experimental Approaches*

Controlled experiments offer a robust means of identifying causal relationships between AI design features (e.g., transparency, framing) and consumer responses (Dietvorst *et al*., 2015; Logg *et al*., 2019). Experimental manipulation of these variables allows researchers to isolate effects on perceived expertise, trust, and behavioural intention.

1. Scenario-based (vignette) experiments
   Participants are exposed to short, realistic descriptions of shopping or recommendation scenarios that vary in framing (e.g., "AI sommelier" vs. "human sommelier"). Such designs are efficient for exploring framing and transparency effects on perceived trustworthiness (Longoni & Cian, 2022; Castelo *et al*., 2019; Langer *et al*., 2023).

2. Conjoint or Discrete Choice Experiments (DCEs)
   Respondents choose among hypothetical wine offerings with systematically varied attributes (price, origin, recommendation source, transparency). The resulting data enable estimation of part-worth utilities for each attribute (Louviere *et al*., 2010; Mueller Loose & Lockshin, 2013), revealing trade-offs between trust-related and product-related factors.

3. Online behavioural experiments
   Simulated e-commerce interfaces record real-time behaviour – click patterns, dwell time, and recommendation acceptance – providing behavioural indicators of trust that complement stated preferences (Pizzi *et al*., 2021; Shin, 2021). These designs are particularly suited to examining algorithm aversion (Dietvorst *et al*., 2015) and algorithm appreciation (Logg *et al*., 2019) phenomena in digital purchase contexts.

### 3.2. *Digital and Neuroscientific Methods*

Because trust formation often involves non-conscious emotional processes, methods from consumer neuroscience and biometrics can provide richer insights than purely declarative measures (Plassmann *et al*., 2012; Ramsøy, 2019). Together, these methods allow researchers to connect cognitive evaluations (perceived expertise) with affective reactions (emotional trust), yielding a holistic picture of consumer-AI interaction.

1. Eye-tracking
   Measures visual attention to AI-related cues (logos, transparency icons, explanations). Fixation duration and gaze transitions indicate cognitive processing and scepticism or confidence (Pieters, 2008).

2. Facial expression and emotion recognition

Automated facial-coding systems can detect micro-expressions (e.g., surprise, confusion, satisfaction) during AI-consumer interaction, serving as affective markers of trust (Lewinski *et al.*, 2014; Ramsøy, 2019).

3. Electroencephalography (EEG) and galvanic skin response (GSR)

These physiological measures capture arousal and emotional valence linked to trust and decision confidence. For instance, higher frontal alpha asymmetry correlates with positive engagement toward transparent algorithms (Vecchiato *et al.*, 2014).

### 3.3. *Data Analytics and Machine Learning for Trust Measurement*

Digital ecosystems such as online wine platforms, social media, and AI chat interfaces generate vast behavioural and textual data that can be harnessed to study trust at scale. Computational methods enable both descriptive and predictive analysis. Text mining and sentiment analysis.

User reviews, social media discussions, or chatbot conversations can be analysed using natural language processing to identify trust-related sentiment, perceived fairness, or authenticity concerns (Camacho *et al.*, 2020; Pizzi *et al.*, 2021).

1. Network analysis

Examines how trust and influence propagate within digital communities (Jerez-Villota, 2025). This is especially relevant for recommendation ecosystems where peer and algorithmic signals interact.

2. Predictive modelling

Machine learning approaches such as random forests or gradient boosting can model determinants of algorithmic trust and forecast consumer engagement patterns (Paschen *et al.*, 2020). Combining predictive models with behavioural experiments allows for iterative testing of design interventions.

These analytical approaches move beyond self-reported trust, offering evidence from actual behaviour and longitudinal engagement.

### 3.4. *Integrative and Mixed-Method Designs*

Given the multifaceted nature of algorithmic trust, multi-method designs are particularly valuable (Venkatesh *et al.*, 2013).

- Sequential mixed-methods can begin with qualitative interviews exploring consumers' perceptions of AI expertise, followed by experimental validation.

- Parallel designs can combine biometric measures (e.g., eye-tracking) with psychometric trust scales, providing both depth and generalizability (Plassmann *et al.*, 2012).
- Cross-cultural comparative studies – building on Hofstede (2001) – can reveal how cultural dimensions (e.g., uncertainty avoidance, power distance) shape reactions to AI transparency and framing (Awad *et al.*, 2020; Awad *et al.*, 2020).

Mixed-method approaches thus enhance both the ecological validity and interpretive richness of consumer behaviour research in digital environments.

### 3.5. *Methodological Contribution*

These approaches represent a significant shift from traditional consumer research methods that rely primarily on surveys and post-hoc evaluations. Combined, these methods provide empirical means to observe how algorithmic systems operate as screening mechanisms by processing and prioritising informational cues that consumers use to interpret quality. In doing so, they allow direct testing of how AI-generated signals may reduce or reshape information asymmetries between producers and consumers. Innovative digital and experimental tools make it possible to:

- Capture real-time decision processes and emotional dynamics;
- Measure implicit trust indicators beyond conscious awareness;
- Test design interventions (e.g., transparency wording, AI-human framing) in ecologically valid settings.

For credence-based products such as wine, integrating these methods enables a more precise analysis of how algorithmic transparency and expertise framing influence trust, authenticity perception, and purchase behaviour.

Methodologically, this approach allows the core mechanisms of signalling and screening to be observed directly rather than inferred, allowing for empirically grounding of research rather than a theoretical debate.

## 4. Implications and Future Directions

### 4.1. *Theoretical Implications*

The conceptual framework developed in this paper contributes to the growing literature on consumer trust and digital transformation by extending classical theories of information asymmetry and source credibility into the domain of algorithmic mediation. Based on the combination of information asymmetry, and instruments to address it – signalling, and screening – the framework interprets AI transparency and framing as new market signals, through which digital intermediaries communicate credibility and competence. It suggests that AI-based systems function not only as technical tools for product recommendation but also as new signalling institutions that influence consumer perceptions of quality, expertise, and authenticity.

First, by applying signalling theory to algorithmic contexts, the framework positions transparency and explainability as digital analogues of traditional trust signals such as certification labels or expert endorsements. The algorithm itself becomes a signal carrier, communicating the reliability of the underlying data and the competence of its design. This redefines how trust capital is generated in markets for credence goods, shifting from personal or institutional reputation toward data-driven credibility.

Second, the model enriches the understanding of expertise in consumer behaviour research. Expertise is no longer confined to human knowledge and sensory experience but emerges as a hybrid construct, blending human curation, machine learning, and data aggregation. This "hybrid expertise" challenges traditional hierarchies of authority in the wine sector and other agri-food domains where craftsmanship and authenticity have long been associated primarily with human judgement.

Finally, by conceptualising trust capital as a measurable and transferable construct, the paper links consumer behaviour research with broader debates in institutional and digital economics, where trust is increasingly recognised as a strategic resource. The framework thus bridges behavioural, economic, and technological perspectives on how information systems shape consumer confidence and market efficiency.

### 4.2. *Managerial Implications*

For practitioners in the agri-food and wine sectors, the framework translates into concrete design and governance choices that directly shape consumer trust, perceived expertise, and acceptance of AI-based recommendation systems. Rather than treating AI adoption as a purely technical implementation, the framework highlights how managerial decisions regarding transparency, framing, personalization, and human-AI integration function as strategic signals that consumers use to screen and interpret algorithmic advice under conditions of uncertainty.

Each managerial principle outlined below reflects a practical manifestation of signalling and screening dynamics that are directly shaped by managerial design and communication choices: transparency communicates credible signals of reliability, while framing determines how effectively consumers screen and interpret AI-based advice.

1. Transparency as a trust-building feature: Systems that disclose how recommendations are generated – through simple, comprehensible explanations – are more likely to elicit trust and engagement. Transparency should be framed as empowerment, not technical detail. When positioned in this way, transparency enables consumers to engage more confidently with algorithmic advice, supporting autonomy rather than passive reliance.
2. Framing and anthropomorphism: Consumers respond differently depending on whether an AI is presented as a neutral algorithm, a virtual sommelier, or a collaborative assistant. Designing interfaces that balance competence with warmth can humanise technology without sacrificing perceived expertise.
3. Personalisation and fairness: Algorithmic recommendations must be perceived as both relevant and unbiased. Excessive personalisation can trigger privacy concerns, while opaque filtering criteria may undermine trust. Ethical data practices and consumer control options are essential.
4. Integrating AI with human storytelling: Especially in the wine sector, where narratives of terroir, craftsmanship, and heritage drive emotional value, AI systems should complement – not replace – human expression. Hybrid models that embed digital precision within authentic storytelling may offer the strongest trust cues.
5. Continuous monitoring of consumer responses: AI systems evolve through feedback loops. Monitoring user sentiment, engagement metrics, and cross-cultural differences allows producers and platforms to adapt recommendations dynamically and sustain long-term credibility.

Taken together, these implications suggest that effective AI deployment in wine markets depends less on maximizing algorithmic sophistication than on aligning system design with how consumers cognitively process information and attribute expertise and trust. Managers who actively shape these dimensions are better positioned to harness AI as a credibility-enhancing tool rather than a source of skepticism.

### 4.3. *Policy and Societal Implications*

At the policy level, ensuring the integrity of these new algorithmic signalling institutions is essential to prevent renewed information asymmetries between digital platforms and consumers and to safeguard transparency, fairness, and accountability. The European Commission's AI Act (2024) already classifies recommendation systems influencing consumer choices as requiring transparency and explainability. Similar principles are echoed in broader discussions on trustworthy AI (European Commission, 2020; Floridi *et al.*, 2018).

For policymakers, this implies three main priorities:

1. Establish clear transparency standards for algorithmic recommendation and data use in agri-food contexts.
2. Encourage industry codes of conduct for responsible AI design and consumer communication.
3. Invest in digital literacy programmes that empower consumers to interpret algorithmic information critically.

The wine sector, where authenticity, quality, and regional identity are central, can serve as a model case for implementing responsible AI practices that balance innovation with heritage and consumer protection. Ultimately, policy should safeguard the integrity of information signals whether emitted by human experts or algorithms to preserve transparency as a public good in digital markets, a principle increasingly recognised in recent governance initiatives on algorithmic transparency and accountability (Council of Europe, 2023).

### 4.4. *Directions for Future Research*

Future research should build more direct empirical bridges between the concepts of information asymmetry, signalling, and screening in algorithmic environments. While this paper conceptualises AI as a new signalling institution, the next step is to operationalise this function empirically. AI technologies themselves can serve as both object and instrument of study.

First, researchers could apply AI-driven text and sentiment analysis to social-media content related to wine brands, recommendation platforms, or virtual sommeliers. Tracking discussions, for instance, on Instagram or Vivino would allow identification of emotional tone, expressions of trust, and consumer interpretations of algorithmic versus human expertise. Such analyses could reveal how credibility signals circulate and evolve in digital communities and how consumers evaluate authenticity or bias in AI-based recommendations.

Second, machine-learning models can be used to detect and classify consumer signals (e.g., endorsement, scepticism, perceived fairness) and to study how firms respond through their own signalling behaviour. This approach would align methodological innovation directly with the theoretical roots of signalling and screening theory – AI acting simultaneously as an analytical tool and as the phenomenon under investigation.

Cross-cultural investigations examining how factors such as uncertainty avoidance and technology acceptance moderate algorithmic trust would deepen understanding of AI adoption in global agri-food markets. Longitudinal research tracking how trust in AI systems evolves with prolonged exposure and user feedback could reveal learning effects and adaptation processes over time. Extending the analysis to other credence goods – such as olive oil, spirits, or specialty coffee – would help assess the generalisability of the model beyond wine and highlight product-specific trust dynamics. Moreover, future work should explore human-AI collaboration models, examining how hybrid forms of expertise – for instance, AI supporting human sommeliers or agricultural advisors – influence both consumer perceptions and organisational decision-making.

By integrating these research directions, scholars can advance a new methodological and conceptual agenda for consumer behaviour research in the digital age that combines behavioural insight with technological understanding and ethical awareness.

## Conclusion

Artificial intelligence is transforming how information asymmetries are managed in credence-based markets. In the wine sector, where authenticity and quality are inferred through reputation and expert judgement, AI now functions as both a screening mechanism, processing complex data on quality cues, and a signalling device, communicating reliability, origin, and taste predictions to consumers.

This paper has proposed a framework linking these classical economic theories with emerging digital technologies. By situating AI within the logic of signalling and screening, it reinterprets algorithmic transparency, framing, and explainability as modern equivalents of certification labels and expert endorsements. In doing so, it shows how algorithmic systems participate in the co-creation of credibility and trust, potentially reducing – but also redistributing – information asymmetries among producers, platforms, and consumers.

Future empirical work, particularly through AI-enabled analysis of social-media discourse and emotional responses, can test how these new signals operate in practice. Such methods make it possible to observe trust formation dynamically, capturing how consumers react to algorithmic advice and how digital trust capital accumulates or erodes over time. These techniques allow researchers to capture cognitive, affective, and behavioural dimensions of consumer-AI interaction that are often inaccessible through conventional surveys. In doing so, they help bridge the gap between technological innovation and behavioural insight, enabling more nuanced analyses of consumer decision-making in increasingly automated environments.

For practitioners, the framework highlights that trust is not automatically granted to algorithms; it must be designed, communicated, and maintained.

The combination of transparency, fairness, and human-like empathy will likely determine the long-term success of AI-driven recommendation systems in the agri-food industry. For policymakers, the findings underline the importance of developing ethical and transparent governance mechanisms for algorithmic advice, in order to ensure that digitalisation enhances rather than undermines consumer autonomy.

Finally, understanding AI as an institutional actor that produces and filters quality signals anchors digital transformation within information economics theory, ensuring that innovation serves transparency, authenticity, and consumer trust.

## Declaration of Generative AI Use

During the preparation of this article, the author used ChatGPT (OpenAI, GPT-5) to support language refinement, structural editing, and consistency improvements. After using this tool, the author thoroughly reviewed and edited all content and takes full responsibility for the final version of the manuscript.

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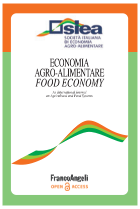


# Understanding Consumer Knowledge of Wild Edible Plants: Objective Knowledge and Customer Segmentation

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*Abstract*

Climate change poses a significant challenge to agriculture in the Mediterranean region, generating multiple food-related concerns. Wild edible plants (WEPs) may represent a partial solution as they provide a valuable genetic resource and possess notable nutritional properties. However, realising their full market potential is dependent on consumer knowledge. This study aimed to develop a scale for assessing consumers' objective knowledge of WEPs and to identify consumer segments based on that knowledge. Data were collected from consumers shopping at farmers' markets in Istria County, Croatia. The results suggested that consumers possess only basic knowledge of WEPs. They were very familiar with wild asparagus and least familiar with purslane, followed by sea fennel. Cluster analysis identified three distinct segments: high-knowledge, moderate-knowledge, and low-knowledge WEP consumers. These segments differed significantly in terms of gender, dietary restrictions, prior purchase of WEPs, household size, attitudes toward WEPs, and perceptions of the impact of climate change on WEPs.

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## Introduction

Climate change and the growing demand for food represent two interconnected and significant challenges in modern agriculture (Fanzo *et al.*, 2018). The impacts of climate change, especially intense dry periods, are expected to severely affect the Mediterranean region (Muñoz-Rojas *et al.*, 2017), leading to reduced agricultural activity and food production (Jat *et al.*, 2018). To address these challenges, sustainable solutions and practices are essential, such as the genetic improvement of plants to enhance their adaptation to current climatic conditions and human needs (del Pozo *et al.*, 2019). In this context, wild edible plants (WEPs) represent a valuable genetic resource for developing new and improved crops (Ford-Lloyd *et al.*, 2011). WEPs have traditionally been part of the culture and heritage of the Mediterranean region, used not only for food but also for medicinal purposes and ritual practices (Ceccanti *et al.*, 2018), establishing their place as an integral part of the traditional Mediterranean diet (Pieroni *et al.*, 2006; Rivera *et al.*, 2006).

Historically, WEPs have been prepared in diverse ways, including in soups, pies, jams, and liqueurs (Ceccanti *et al.*, 2018; Łuczaj *et al.*, 2012) and even used in medicinal applications, such as infusions or macerates (Benitez *et al.*, 2017). However, despite their historical importance, contemporary consumer knowledge of WEPs is limited (Łuczaj & Dolina, 2015; Łuczaj *et al.*, 2012). Consumer knowledge plays a key role in the decision-making process, particularly during information gathering (Alba & Hutchinson, 1987). In the case of WEPs, this knowledge often takes the form of traditional knowledge, as consumption is closely linked to local cuisine and cultural identity. Consequently, the erosion of WEP knowledge reflects a broader loss of cultural heritage (Turner & Turner, 2008). There are many reasons for this decline, including modern fast-paced lifestyles, depopulation of rural areas, an ageing population (Łuczaj & Dolina, 2015; Łuczaj *et al.*, 2012), and reduced interest due to the widespread availability of fast food (Aboukhalaf *et al.*, 2022; Cruz *et al.*, 2014; Hadjichambis *et al.*, 2008).

Preserving knowledge about WEPs could present an opportunity to revitalise rural areas (Chen & Qiu, 2012). Thus, developing an instrument to measure consumers' knowledge of WEPs is an important step toward understanding consumer behaviour in relation to WEP consumption. Recent studies indicate a considerable decline in consumers' traditional knowledge regarding WEPs (Hadjichambis *et al.*, 2008; Łuczaj *et al.*, 2012; Reyes-García *et al.*, 2015), highlighting the need for further research. Such studies are particularly relevant given the potential of WEPs to contribute to sustainable agricultural solutions under climate change by serving as genetic resources for crop improvement (del Pozo *et al.*, 2019; Ford-Lloyd *et al.*, 2011). Accordingly, the objectives of this paper are twofold: first, to develop a scale for measuring consumers' knowledge of WEPs, and second, to explore how this knowledge can be leveraged for consumer segmentation purposes.

## 1. Background

WEPs have traditionally formed part of the Mediterranean diet. Despite their historical importance, however, modern consumers demonstrate limited knowledge of WEPs (Łuczaj & Dolina, 2015; Łuczaj *et al.*, 2012). Consumer knowledge plays a central role in shaping the consumer decision-making process because information influences purchasing decisions (Alba & Hutchinson, 1987).

Consumer knowledge is commonly conceptualised as comprising three dimensions: objective knowledge, subjective knowledge, and familiarity (Cordell, 1997). Objective knowledge is defined as information stored in memory (Blackwell *et al.*, 2001) and is impartially measured by a third party, typically following a standardised procedure (Cordell, 1997). Subjective knowledge refers to an individual's self-assessment of their own expertise (Cordell, 1997). Objective knowledge captures what consumers actually know, whereas subjective knowledge reflects what they believe they know. Although these two types of knowledge are generally correlated, they differ in their antecedents: objective knowledge is primarily based on stored information about a product category, while subjective knowledge is more strongly influenced by personal experience (Park *et al.*, 1994). Meanwhile, familiarity refers to the level of experience a consumer has with a particular product category (Park *et al.*, 1994). Familiarity is considered the foundation of subjective and objective knowledge because it directly influences them (Chocarro *et al.*, 2009).

Knowledge about WEPs is typically framed as traditional knowledge related to the place of residence. It is most often associated with rural areas, which are considered rich sources of knowledge regarding WEP species and their uses (Benítez *et al.*, 2017; Maurer & Schueckler, 1999). This knowledge is generally transmitted orally from generation to generation (Benítez *et al.*, 2017). Traditional knowledge of WEPs is often attributed more to women, who are described as the primary custodians of such knowledge (Łuczaj, 2008), particularly in rural contexts where they have historically been responsible for food preparation and outdoor subsistence activities (Kosmaryandi, 2005). Preserving this traditional knowledge is therefore a critical contemporary task. One approach involves systematically collecting and documenting the knowledge that remains in rural communities to prevent its disappearance (Aboukhalaf *et al*., 2022; Altundağ Çakır, 2017; Ceccanti *et al*., 2018; Hadjichambis *et al*., 2008).

Due to the loss of traditional knowledge, WEPs can also be regarded as a novel food source. They are a rich source of bioactive compounds, which makes them valuable as functional foods (Pinela *et al*., 2017). Their high phytochemical content has led some authors to classify them as 'new functional foods' (Bacchetta *et al*., 2016; Ceccanti *et al*., 2018), thereby positioning them as promising innovative products for contemporary consumers. The consumption of WEPs is associated with numerous health benefits and many environmental advantages, meaning they have excellent potential for inclusion in a sustainable agroecological system (Bundela *et al*., 2023). However, knowledge remains a key determinant of consumer preferences and acceptance of functional foods (Topolska *et al*., 2021) because increasing consumer knowledge about functional foods leads to a corresponding rise in their acceptance (Baker *et al*., 2022).

The potential of WEPs lies in their capacity to contribute to a modern, sustainable agricultural system that must meet the growing demand for healthy food while minimising environmental impact (Borelli *et al*., 2020). It is therefore important to explore creative approaches to increase consumer familiarity, demand, and desirability for these plants (Borelli *et al*., 2020). To do this, it is necessary to not only conserve plant resources but also to preserve the associated bio-cultural knowledge that connects communities to natural resources and values local traditions (McCarter *et al*., 2018). Greater familiarity with WEPs is expected to strengthen both objective and subjective knowledge (Söderlund, 2002), thereby improving consumer acceptance and supporting their reintegration into contemporary diets.

## 2. Materials and methods

The results presented in this paper form part of a broader body of research linking healthy lifestyles to the consumption of WEPs within the context of climate change. The target population consisted of consumers shopping at farmers' markets. The survey was conducted from March–June 2022 across four local farmers' markets in Istria County, Croatia. A research agency was commissioned to collect the data.

Data collection followed a stationary researcher/mobile respondent approach (Veal, 2006): researchers were positioned at the entrances of the farmers' markets and approached consumers as they entered. Potential respondents were informed about the purpose of the study and assured of anonymity before being asked to provide consent to participate. Upon agreement, participants received a leaflet containing a QR code linking to the online questionnaire, as data were collected using a digital survey instrument. The questionnaire consisted of 66 questions organised into seven sections: WEP consumption, subjective knowledge, objective knowledge, food neophobia, climate change, wellness-related lifestyles, and respondents' characteristics. For sampling purposes, a minimum of 150 respondents was set to ensure sufficient data for analysis, as consumers shopping at farmers' markets represent only a small proportion of the local population (Hair *et al.*, 2009).

The data were analysed using descriptive, bivariate, and multivariate statistical techniques. Descriptive statistics (means, standard deviations, and percentages) were used to summarise the sample characteristics. Bivariate statistics were used to test the differences among clusters (chi-square and one-way ANOVA) and item-to-total correlation (Point Biserial Correlation) (Kline, 2015). Multivariate statistics were used for segmentation (cluster analysis) and to determine construct dimensionality (exploratory factor analysis) and validity (Cronbach's Alpha). Specifically, EFA was performed on the following constructs: attitude toward nature preservation, attitude toward WEPs, food neophobia, and subjective knowledge. Principal Axis Factoring with Promax rotation was employed, retaining factors with eigenvalues greater than 1.00. Moreover, cluster analysis was used to group farmers' market consumers based on their objective knowledge of WEPs. This was done by first determining the number of clusters through a hierarchical clustering technique, namely, 50 observations were randomly selected, while the Ward method, with squared Euclidean distance, was used to establish the preliminary number of clusters. A three-cluster solution was then selected based on the largest and most plausible proportionate change. Subsequently, a non-hierarchical k-means cluster analysis was performed on the full sample using the predetermined number of clusters. Cluster validity was assessed using one-way ANOVA and subjective knowledge of WEPs (Hair *et al.*, 2009; Težak Damijanić *et al.*, 2024). Subjective knowledge was measured using six items adapted from Flynn and Goldsmith (1999), rated on a five-point Likert scale (1 = strongly disagree; 5 = strongly agree). For the purposes of this paper, these items were analysed separately to determine the unidimensionality of the scale. The scale explained 78.15% of the total variance, all factor loadings exceeded 0.60, and the Cronbach's alpha coefficient was 0.955, indicating excellent internal consistency.

Variables used for profiling were sociodemographic characteristics (gender, age, profession, education, number of household members, and income), diet restrictions (no vs. yes), purchase of WEPs in the previous year (no vs. yes), farmers' market purchase frequency (several times a year or less; once a month or more often; once a week or more often), concern about climate change and its consequences (five-point Likert scale: 1 = not concerned at all; 5 = extremely concerned), and perceived climate change impact on WEPs (five-point Likert scale: 1 = strongly disagree; 5 = strongly agree). Psychological factors included three variables: attitude toward nature preservation, attitude toward WEPs, and food neophobia (Težak Damijanić *et al.*, 2024). Attitude toward nature preservation (Yadav & Pathak, 2016), attitude toward WEPs (Schunko & Vogl, 2020), and food neophobia (Piha *et al.*, 2018) were separately factor analysed to determine whether the constructs were unidimensional. Attitude toward nature preservation accounted for 73.38% of the accumulated variance, with all factor loadings exceeding .60 and a Cronbach's alpha coefficient of 0.914. Attitude toward WEPs accounted for 62.50% of the accumulated variance, with all factor loadings exceeding .60 and a Cronbach's alpha coefficient of 0.863. Food neophobia accounted for 66.15% of the accumulated variance, with all factor loadings exceeding .60, and a Cronbach's alpha coefficient of 0.881. To determine differences among the groups, standardised residuals (chi-square test) (Schwab, 2004) and post hoc comparisons (Tukey's HSD and Games-Howell tests following one-way ANOVA) (Field, 2005) were employed.

To measure objective knowledge of WEPs, the recommendations of Park *et al.* (1994) and Parmenter and Wardle (1999) were followed. First, five WEPs were selected based on two criteria: (1) traditional use in the coastal region of Croatia and (2) resilience to extreme climate-related stress (Dolina *et al.*, 2016; Ninčević Runjić *et al.*, 2024; Vitasović-Kosić, 2018). The selected species were wild asparagus (*Asparagus acutifolius* L.), wild fennel (*Foeniculum vulgare* Mill.), wild garlic (*Allium ursinum* L.), purslane (*Portulaca oleracea* L.), and sea fennel (*Crithmum maritimum* L.). These plants were identified by five agricultural experts as those best meeting the defined criteria. Then, based on a review of materials describing different WEPs, five main knowledge domains were identified (Grlić, 1990): recognition, plant distribution, nutrition and health benefits, morphology, and usage. Accordingly, five questions, one per section, were proposed to measure the objective knowledge of each WEP (see Appendix). The proposed structure and items were evaluated by five subject-matter experts, who recommended no modifications. Respondents were first asked if they recognised a WEP based on a photograph, selecting the correct plant name from the five species included in the study. Respondents who selected appropriate answers were given four statements about an individual WEP and then had to select between two options: 'true' or 'not true'. To avoid excluding respondents who were familiar with a plant but unable to recognise it from the photograph, participants were subsequently shown the plant name and asked whether they had previously heard of it. However, this item was excluded from the final scale due to its potential high correlation with the recognition question. All items measuring objective knowledge of specific WEPs were retained because they tested important aspects of objective knowledge (Parmenter & Wardle, 1999). Scoring was conducted as follows: correct identification of the plant yielded one point. For the four subsequent statements, each correct response was awarded one point, while incorrect and 'don't know' responses were scored as zero. Objective knowledge for each WEP was calculated as the sum of correct answers, resulting in a possible score ranging from 0 to 5 per species.

## 3. Results

In total, 166 responses were collected. The sample consisted predominantly of female respondents (76%) while males accounted for a much smaller portion (24%). Most respondents were between 36 and 54 (48%) and had completed higher education (55%). In terms of employment status, 57% were employed, 25% were self-employed, and approximately 8% were retired. The most frequently reported monthly net income was between €800 and €1,070 (32%). Around 56% of respondents lived in a household comprising three or four members.

Respondents were generally able to recognise specific WEPs from the provided photographs (Table 1). Most participants were also familiar with the typical habitats and morphological characteristics of these plants. This pattern may reflect the fact that knowledge of plant distribution and morphology is traditionally transmitted across generations (Benítez *et al.*, 2017). However, respondents struggled to identify the nutritional and health benefits of WEPs, as well as their culinary uses. This lack of knowledge may be explained by modern lifestyles and the abandonment of traditional dishes prepared with WEPs (Łuczaj & Dolina, 2015; Łuczaj *et al.*, 2012).

Respondents were generally unfamiliar with WEPs, except for wild asparagus (Table 2). All respondents were able to either recognise wild asparagus or to indicate that they had previously heard about it (with scores ranging from 1 to 5). Furthermore, most respondents had some knowledge of the five WEPs. In contrast, knowledge levels for the remaining species were comparatively lower. Respondents were least familiar with purslane, followed by sea fennel and wild garlic. The correlation between the item-to-total score was acceptable for all five measures (Kline, 2015).

*Table 1 - Percentage of correct answers for WEPs*

| **Objective knowledge dimensions** | **Percentage** | |
|---|---|---|
| | **Incorrect** | **Correct** |
| **WEP photograph recognition** | | |
| Purslane | 27.7 | 72.3 |
| Wild garlic | 24.1 | 75.9 |
| Wild fennel | 17.5 | 82.5 |
| Sea fennel | 38.0 | 62.0 |
| Wild asparagus | 3.0 | 97.0 |
| **Plant distribution** | | |
| Purslane | 49.4 | 50.6 |
| Wild garlic | 81.9 | 18.1 |
| Wild fennel | 32.5 | 67.5 |
| Sea fennel | 53.6 | 46.4 |
| Wild asparagus | 13.3 | 86.7 |
| **Nutritive and health benefits** | | |
| Purslane | 77.1 | 22.9 |
| Wild garlic | 66.3 | 33.7 |
| Wild fennel | 41.6 | 58.4 |
| Sea fennel | 59.6 | 40.4 |
| Wild asparagus | 25.9 | 74.1 |
| **Morphology** | | |
| Purslane | 83.1 | 16.9 |
| Wild garlic | 36.1 | 63.9 |
| Wild fennel | 38.6 | 61.4 |
| Sea fennel | 50.0 | 50.0 |
| Wild asparagus | 34.9 | 65.1 |
| **Usage** | | |
| Purslane | 60.8 | 39.2 |
| Wild garlic | 44.6 | 55.4 |
| Wild fennel | 44.6 | 55.4 |
| Sea fennel | 63.3 | 36.7 |
| Wild asparagus | 5.4 | 94.6 |

*Table 2 - Descriptives for WEP objective knowledge*

| **WEP type** | **M** | **SD** | **Item-to-total-score correlation (min)** |
|---|---|---|---|
| Purslane | 2.0 | 1.61 | 0.537 |
| Wild garlic | 2.5 | 1.46 | 0.474 |
| Wild fennel | 3.3 | 1.39 | 0.423 |
| Sea fennel | 2.4 | 1.96 | 0.737 |
| Wild asparagus | 4.2 | 1.06 | 0.431 |

To segment farmers' market consumers based on their objective knowledge of the five WEPs (purslane, wild garlic, wild fennel, sea fennel, and wild asparagus), a cluster analysis was performed. A non-hierarchical cluster analysis procedure (k-means) confirmed the three-cluster solution (Table 3). The first cluster (N = 85) represented 50% of respondents, the second cluster (N = 28) accounted for 16%, and the third cluster (N = 53) comprised 34% of the sample. Statistically significant differences were observed among the clusters across all five WEP knowledge measures. Cluster 1 demonstrated high levels of objective knowledge, Cluster 2 exhibited the lowest levels of objective knowledge, and Cluster 3 showed moderate knowledge across the five WEPs. Based on the cluster centroids, the segments were labelled accordingly as high-knowledge, low-knowledge, and moderate-knowledge WEP consumers. The analysis of variance indicated statistically significant differences among the clusters (F = 10.721; DF = 2, 163; Sig. 0.000), thereby supporting the robustness of the three-cluster solution.

*Table 3 - Results of cluster analysis*

| **Measures** | **Final Cluster Centres** | | | **F value** |
|---|---|---|---|---|
| | **1** | **2** | **3** | |
| Purslane | 3.3 | 0.6 | 1.0 | 108.104*** |
| Wild garlic | 3.4 | 0.8 | 2.1 | 72.892*** |
| Wild fennel | 3.7 | 1.4 | 3.7 | 63.606*** |
| Sea fennel | 4.1 | 0.4 | 1.0 | 217.808*** |
| Wild asparagus | 4.6 | 2.8 | 4.4 | 51.670*** |

*Note*: * significant at 0.05, ** significant at 0.01, *** significant at 0.001.

In order to determine the differences among the groups in terms of socio-demographic characteristics, diet restriction, purchase of WEPs in the previous year, and farmers' market purchase frequency, chi-square tests were conducted (Table 4). Statistically significant differences between groups were identified for gender, dietary restrictions, and purchase of WEPs in the previous year.

Within the high-knowledge cluster, there were significantly more male respondents and fewer female respondents than expected based on the overall sample distribution. Regarding dietary restrictions, fewer respondents reported food restrictions than expected, while more than expected indicated no dietary restrictions in the high-knowledge segment. In addition, the high-knowledge cluster included significantly more respondents who had purchased WEPs in the previous year and fewer who had not, compared to expected frequencies. Conversely, in the low- and moderate-knowledge clusters, there were fewer respondents than expected who had purchased WEPs and more who had not purchased them in the previous year.

*Table 4 - Chi-square results*

| **Variable** | | **Percentage** | | | **Chi square (df)** |
|---|---|---|---|---|---|
| | | **Cluster 1** | **Cluster 2** | **Cluster 3** | |
| Gender | Male | 16 | 3 | 5 | 6.410 (2)* |
| | Female | 32 | 16 | 28 | |
| Education level | High school or lower | 20 | 11 | 13 | 2.307 (2) |
| | Higher education | 27 | 9 | 20 | |
| Profession | Sel-employed | 15 | 4 | 6 | 4.699 (4) |
| | Employees and managers | 25 | 13 | 21 | |
| | Other | 7 | 2 | 6 | |
| Income | Up to €796.19 | 17 | 7 | 10 | 1.620 (4) |
| | €796.20-€1,061.72 | 17 | 6 | 9 | |
| | €1,061.73 or more | 20 | 8 | 6 | |
| Diet restriction | No | 19 | 3 | 11 | 8.140 (2)* |
| | Yes | 28 | 17 | 22 | |
| Purchase of WEPs in the previous year | No | 8 | 10 | 15 | 16.347 (2)*** |
| | Yes | 39 | 10 | 18 | |
| Farmers' market purchase frequency | Several times a year or less | 11 | 4 | 11 | 3.227 (4) |
| | Once a month or more often | 18 | 10 | 13 | |
| | Once a week or more often | 18 | 5 | 10 | |

*Note*: * significant at 0.05, ** significant at 0.01, *** significant at 0.001.

One-way ANOVA was conducted to examine differences among the three clusters with respect to age, household size, concern about climate change and its consequences, perceived climate change impact on WEPs, attitude toward nature preservation, attitude toward WEPs, and food neophobia (Table 5).

*Table 5 - Results of one-way ANOVA*

| Variable | **Cluster 1** | | **Cluster 2** | | **Cluster 3** | | **F-test (2, 163)** |
|---|---|---|---|---|---|---|---|
| | M | **SD** | **M** | **SD** | **M** | **SD** | |
| Age | 47,0 | 13,54 | 41,7 | 12,99 | 42,4 | 14,50 | 2.584 |
| Number of household members | $2{,}7_{2,3}$ | 1,17 | $3{,}7_{1}$ | 1,02 | $3{,}2_{1}$ | 1,47 | 8.779*** |
| Concern about climate change a nd its consequences | 4,0 | 1,11 | 4,3 | 0,96 | 3,9 | 1,08 | 1.078 |
| Climate change impact on WEPs | $4{,}2_{2}$ | 0,91 | $3{,}5_{1,3}$ | 1,32 | $4{,}2_{2}$ | 0,94 | 5.557** |
| Attitude toward nature preservation | 4,2 | 0,77 | 3,9 | 0,71 | 4,2 | 0,46 | 2.794 |
| Attitude toward WEPs | $4{,}2_{2,3}$ | 0,73 | $3{,}6_{1}$ | 0,74 | $3{,}8_{1}$ | 0,76 | 8.083*** |
| Food neophobia | 3,6 | 0,97 | 3,5 | 0,81 | 3,6 | 0,82 | 0.177 |

*Note*: Mean with subscripts differ at $p < 0.05$, * significant at 0.05, ** significant at 0.01, *** significant at 0.001.

Statistically significant differences were identified between the high-knowledge segment and the other two segments with respect to the number of household members and attitudes regarding WEPs. In addition, significant differences emerged between the low-knowledge segment and the other two segments regarding perceptions of the impact of climate change on WEPs. Respondents in the high-knowledge cluster had fewer household members and more positive attitudes regarding WEPs compared to those in the moderate- and low-knowledge clusters. On the other hand, the low-knowledge cluster expressed less concern about how climate change might influence WEPs compared to the two other clusters.

## Conclusions

Modern agriculture faces significant challenges arising from climate change, particularly with respect to food production. To address these challenges, various sustainable solutions and practices are being explored, including the genetic improvement of plants and their adaptation to changing climatic conditions and human needs. WEPs present one of the genetic solutions to this issue; however, a lack of consumer knowledge may pose a problem in marketing such foods. This study therefore examined consumers' objective knowledge of selected WEPs derived from traditional knowledge sources.

Overall, consumers were not familiar with the nutritional and health benefits of WEPs and their culinary uses, but they were generally able to recognise the plants and were familiar with their distribution and morphological characteristics. Wild asparagus was the best known species, while consumers were the least familiar with purslane, followed by sea fennel and wild garlic. Based on objective knowledge scores, three distinct consumer segments were identified: high-knowledge, moderate-knowledge, and low-knowledge WEP consumers. These segments differed significantly in terms of gender, dietary restrictions, prior purchase of WEPs, household size, attitudes toward WEPs, and perceptions of the impact of climate change on WEPs.

This study makes several contributions to the extant literature. First, it proposes an initial scale for measuring objective knowledge of WEPs, based on five species typical of the Mediterranean region (purslane, wild garlic, wild fennel, sea fennel, wild asparagus). Second, it demonstrates the applicability of objective knowledge as a basis for market segmentation. Third, it identifies meaningful relationships between objective knowledge and consumer characteristics, dietary restrictions, purchasing behaviour, climate change perceptions, and attitudes toward WEPs.

Several practical implications emerge from the findings. Although all three segments expressed concern about climate change and its broader consequences, low-knowledge consumers perceived the specific impact of climate change on WEPs as less significant. This suggests a need for targeted awareness campaigns highlighting the vulnerability of ecosystems and the role of WEPs within sustainable food systems. Furthermore, given respondents' limited knowledge of nutritional benefits and usage, educational and promotional initiatives should focus on communicating these attributes if WEPs are to be positioned as alternative or functional food sources. The strong familiarity with wild asparagus – likely due to sustained promotion by stakeholders – indicates that similar marketing efforts could enhance awareness of less familiar species such as purslane, sea fennel, and wild garlic.

Despite the insights that it offers, it should also be noted that this study has several limitations. The sample consisted of consumers shopping at local farmers' markets in Istria County, Croatia; therefore, the findings cannot be generalised to the overall consumer market. To address this, future research could include consumers purchasing WEPs through alternative distribution channels. Moreover, no distinction was made between customers with and without specific medical issues; therefore, future research could focus on customers with different health problems and dietary restrictions. Additionally, while this study focused on Mediterranean WEP species, future research could investigate species typical of other geographic regions to enhance cross-cultural applicability.

Objective knowledge served as the segmentation variable in this study, while socio-demographic characteristics, dietary restrictions, purchasing behaviour, climate change perceptions, attitudes toward nature preservation and WEPs, and food neophobia were used for profiling. Future studies could examine the influence of objective knowledge on purchase intentions and actual consumption behaviour. Moreover, although WEPs may serve as alternative food sources in mitigating climate change impacts, climate-related variables played a relatively minor role in this study. Future research should therefore incorporate more comprehensive climate-related constructs when analysing WEP consumption. Finally, as this study introduces a preliminary scale for measuring objective knowledge of WEPs, further research is needed to validate the instrument across larger and cross-national samples.

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## Appendix

WEPs photograph recognition: Do you recognise this wild edible plant?
*Portulaca oleracea* L. (Common purslane, Duckweed, Little hogweed)
*Allium ursinum* L. (Wild garlic, Wild cowleek, Bear's garlic)
*Foeniculum vulgare* Mill. (Wild fennel)
*Crithmum maritimum* Mill. (Sea fennel)
*Asparagus acutifolius* L. (Wild asparagus)

Plant distribution
Wild asparagus is found in forests, meadows, and among maquis shrubland and dry stone walls in the coastal area of the Republic of Croatia. (**T**)
Wild garlic is found in forests, meadows, and among maquis shrubland and dry stone walls in the coastal area of the Republic of Croatia. (**N**)
Purslane is resistant to high temperatures and drought. (**T**)
Sea fennel is found in deciduous forests. (**N**)
Wild fennel can be harvested throughout the Republic of Croatia. (**N**)

Nutritional properties and healing effects
Wild asparagus boosts immunity. (**T**)
Wild garlic enhances bile secretion. (**T**)
Purslane has no special nutritional value. (**N**)
Sea fennel is beneficial for body detoxing. (**T**)
Wild fennel is a flavouring herb and, as such, has no special nutritional value. (**N**)

Morphology
Wild asparagus is a perennial plant. (**T**)
Wild garlic resembles other plants that are poisonous (Lily of the valley, Autumn crocus, Hellebore). (**T**)
Purslane resembles other plants that are poisonous. (**N**)
Sea fennel is a perennial plant. (**T**)
Wild fennel is a perennial plant. (**T**)

Usage
Wild asparagus is often used as an ingredient in scrambled eggs. (**T**)
Wild garlic pesto is a common processed product. (**T**)
Purslane is often used in salads. (**T**)
Dishes containing sea fennel should not be salted. (**T**)
Wild fennel is expressly used as a herb for cooking. (**N**)
**T – true; N – not true**

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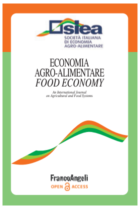


# Uncovering the Determinants of the Transition to Digital Agriculture: A Survey-Based Tobit Analysis

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*Abstract*

This study examines the state of digital agriculture in the Republic of Armenia, a sector characterized by small farm sizes, extensive production models, and limited financial capacity. Using a stratified sample of 400 farms, the research assesses the extent of digital technology adoption, key obstacles, and the determinants of digital penetration. Descriptive findings reveal low adoption rates across most digital tools, driven by high costs, limited awareness, insufficient digital literacy, and skepticism toward digital practices. To provide a more rigorous empirical assessment, a Tobit regression model was applied. The results show that all included variables significantly influence digital adoption, with farm size exerting the strongest positive effect, underscoring the importance of economies of scale. Education, income, production orientation, production model, and age also significantly shape adoption likelihood. The combined descriptive and econometric evidence indicates that the discussed digital gap is largely rooted in structural limitations, particularly the prevalence of very small farms. The study concludes by recommending targeted policies (land consolidation, financial assistance, and farmer training) to support a more modern, efficient, and digitally integrated agricultural sector.

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## Introduction

Agriculture is undergoing a significant transformation driven by digital technologies. As the global population grows, the demand for efficient and sustainable food production intensifies. Digitalization presents an opportunity to address these challenges by improving farming practices and resource management.

These issues are highly relevant for the Republic of Armenia (RA). Agriculture is one of the indisputably important sectors of the Armenian economy, which provides the food security of the country and provides employment for the rural population (Asatryan *et al.*, 2022). According to official data for 2022, agriculture provides 10.4% of the GDP, the share of food products in the export volume is 23.9%, and 68.7% of the total area of Armenia is agricultural land. In the conditions of the 4$^{th}$ industrial revolution, the digital transformation of Armenian agriculture can mitigate the issues of productivity, efficiency, and sustainability of agriculture collectively bringing to the provision of Food security (Manucharyan, 2021). Despite ongoing government efforts (particularly the adoption of the "2023-2026 Food Security Development Strategy") Armenia continues to face significant challenges in achieving self-sufficiency in essential food products (Asatryan *et al.*, 2025), underscoring the need for further agricultural development to strengthen national food security. Taking into account all these issues this paper examines the digitalization of agriculture in RA by addressing the following research questions:

- What is the current state and level of digitalization in the agricultural sector?
- To what extent has digital penetration progressed within Armenian agriculture?
- What are the principal obstacles and opportunities shaping the transition toward digital agriculture?
- Which farm-level determinants influence the digital transformation of farms?

The aim of this paper is the provide a comprehensive study of the digitalization of Armenian agriculture and directions of future development.

## 1. Literature Review

### 1.1. *Defining Digital Agriculture*

As the 4$^{th}$ industrial revolution is in full swing digitalization is transforming the traditional landscape of national economics by penetrating various digital achievements of digital technologies into all the economic sectors. In this regard, agriculture is no exception. Digital agriculture, also referred to as smart farming or precision agriculture, integrates advanced digital technologies into agricultural practices to enhance productivity and efficiency of production. Digital agriculture encompasses a broad range of technologies, including the Internet of Things (IoT), big data, artificial intelligence (AI), drones, robotics, etc. As Wolfert *et al.* (2017) state in their study, digital agriculture involves the integration of advanced technologies in agricultural practices, enabling farmers to gather and analyze vast amounts of data to improve crop yields and resource management. Zhang *et al.* (2019) emphasize that digital agriculture relies on data analytics to inform farming decisions, which can lead to improved efficiency and reduced environmental impact. The Food and Agriculture Organization (FAO, 2021) highlights that digital agriculture not only enhances productivity but also promotes sustainable farming practices by minimizing waste and optimizing resource use. Precision agriculture, a critical component of digital agriculture, uses GPS technologies to manage field variability in crops, leading to targeted interventions that enhance yield at the same time reducing inputs, which leads to an increase in productivity and efficiency (Gebbers and Adamchuk, 2010). So, adopting digital technologies in agriculture can lead to increased profitability and efficiency for farmers through better crop management and reduced operational costs.

Digitalization in agriculture is reshaping farming practices, making them more efficient, sustainable, and responsive to global challenges. The significance and relevance of digitalization in contemporary agriculture is manifested in the following benefits:

1. Digital technologies enhance agricultural productivity. For example, precision agriculture practices, such as the implementation of sensors and satellite imagery, allow farmers to monitor crop health, soil conditions, and weather patterns in real-time. It brings an increase in yields by optimizing inputs like irrigation water, fertilizers, and pesticides, leading to better resource management (Jansson *et al.* 2019).
2. Digital agriculture includes data collection and analysis, allowing farmers to make informed decisions. Zhang *et al.* (2019) discuss how big data analytics in agriculture allows for better forecasting and management of crops, helping farmers respond quickly to challenges.
3. The use of digital technologies can lead to cost reduction and increased profitability in agriculture. By optimizing operations and minimizing inputs, digital agriculture can enhance the economic performance of farms (Geng *et al.*, 2024).
4. Agriculture digitalization promotes sustainable agricultural practices by enabling farmers to use resources more efficiently. Data-driven decision-

making helps to minimize waste and reduce the environmental impact of farming. Digital tools can enhance sustainable practices by facilitating better resource allocation and reducing emissions. (Hrustek, 2020).

## 1.2. *Key Technologies in Digital Agriculture*

Digital technologies are transforming agriculture, enhancing productivity, sustainability, and efficiency. This review explores several key technologies, including precision agriculture, the Internet of Things (IoT), drones, big data analytics, and blockchain.

1. Precision Agriculture: Precision agriculture utilizes e.g. GPS, sensors, and data analytics to optimize field-level management. Farmers can make informed decisions regarding planting, watering, and harvesting, leading to increased yields and reduced waste. Research shows that precision agriculture can boost crop productivity by 10-30% while decreasing inputs like fertilizers and water (Schmidt *et al.*, 2018).
2. Internet of Things (IoT): IoT devices, such as soil moisture sensors and weather stations, collect real-time data that helps farmers monitor and manage their crops more effectively. By connecting equipment and devices, farmers can make data-driven decisions. A study by Khosrow-Pour (2019) highlights that IoT can improve irrigation efficiency by up to 50%.
3. Drones: Drones are increasingly used in agriculture for tasks such as crop monitoring, soil analysis, and aerial spraying. They provide high-resolution images and data that help farmers assess crop health and identify issues early. According to a report by Dandois and Ellis (2010), drones can significantly reduce the time required for crop surveillance, enabling timely interventions. Drones that employ remote sensing technology can help in gathering data about crop health and land use.
4. Big Data Analytics: Big data analytics allows farmers to process vast amounts of information from various sources, including weather patterns, market trends, and soil health. By analyzing this data, farmers can forecast yields and optimize resource allocation. A study by Zhang *et al.* (2017) found that integrating big data into farming practices can lead to a 20% increase in productivity.
5. Blockchain: Blockchain technology offers secure and transparent supply chain management, enhancing traceability in agricultural products. This technology can help reduce fraud and improve food safety. According to a study by Kamble *et al.* (2019), blockchain can increase consumer trust and enhance the overall efficiency of agricultural supply chains. Discussed innovations not only enhance the productivity of agricultural activities

but also promote sustainable practices which in turn will contribute to the sustainable development of the sector.

6. Enterprise Resource Planning (ERP) and Customer Relationship Management (CRM): ERP in digital agriculture refers to an integrated software platform that manages and coordinates all key farm or agribusiness processes, such as production planning, input procurement, inventory control, financial accounting, sales, logistics, and human resources, within a unified digital system (Habeeb *et al.*, 2025). CRM in digital agriculture refers to an integrated system designed to manage interactions between agricultural enterprises (such as farms, cooperatives, or agribusinesses) and their customers, suppliers, and partners (Binoy *et al.*, 2023).

### 1.3. *Challenges and Barriers on The Path to Digital Agriculture*

Digital agriculture holds great potential, but several challenges hinder its widespread adoption. First and foremost, the challenge is technological access and literacy. Many rural areas lack the necessary infrastructure, such as high-speed internet and electricity, to support digital tools, which raises the issue of technological accessibility. Another manifestation of this challenge is the high cost of technology: the cost of purchasing and implementing digital technologies can be prohibitively high for smallholder farmers (Choruma *et al.*, 2024). Another challenge is the lack of digital literacy, as, many farmers don't have the necessary skills to utilize digital tools effectively, leading to underutilization of available technologies (Cheng *et al.*, 2024).

As in the case of any type of innovation digital technologies face resistance stemming from skepticism toward new technologies. Extensive farming practices may lead to resistance against adopting new digital methods, especially if the farmers are old and are used to old-fashioned practices (Klerkx *et al.*, 2019). So behavioral factors must be addressed in policymaking for the successful transition into digital agriculture. Behavioral aspects of digital penetration in agriculture also touch on the issue of data privacy and security concerns from farmers. Farmers may be hesitant to share data due to concerns over privacy and the potential misuse of their information (especially if it includes personal data, income level, etc.) (Pino *et al.*, 2020).

A huge challenge on the path of digital penetration in agriculture is the limited access of farmers to financial resources. Farmers, especially smallholders, often lack access to credit and financial resources necessary for adopting digital technologies (Albrecht *et al.*, 2020).

There is also the problem of difficulties in integrating new technologies with existing, extensive production systems, which can lead to inefficiencies and increased costs (van der Wal *et al.*, 2021).

### 1.4. *Case Studies*

Several case studies and evidence-based reports highlight the success stories of digital agriculture. In the US John Deere's adoption of precision agriculture technologies significantly improved productivity in corn and soybean production. Farmers using their technology reported an average yield increase of 10-15% (Wolf & Dyer, 2018). Another example is FarmLogs: this platform helps farmers in the U.S. manage their operations by providing data-driven insights on crop health and soil conditions[1]. A similar platform is employed in Kenya called M-pesa. This mobile platform revolutionized access to financial services for farmers, enabling them to receive payments and access credit (Aker & Mbiti, 2010). Another example is "The Kisan Suvidha" app (developed in India), which provides farmers with real-time information on weather, market prices, and agricultural best practices, resulting in increased income for over 1 million farmers (Kumar & Singh, 2020). In Denmark, the practices of smart farming are rapidly developing. Farmers implemented IoT devices in greenhouse management, leading to a 20% reduction in water usage while maintaining crop yields (van der Wal *et al.*, 2021).

In pest and disease control practices digital technologies provide huge assistance. For example, in Brazil farmers utilized drone technology for monitoring large soybean fields, leading to early detection of pests and diseases. This resulted in an estimated 15% increase in yield (Silva & Costa, 2022). Or in China AI-driven systems have been developed for pest identification and management. This technology has reduced pesticide usage by 30% while maintaining crop productivity (Li & Zhao, 2021).

Digital agriculture represents a transformative approach to farming, leveraging technology to enhance productivity, sustainability, and economic viability. As the agricultural sector continues to evolve, understanding the definition and implications of digital agriculture becomes crucial for stakeholders at all levels. The challenges hindering digital penetration in agriculture are multifaceted, ranging from technological and economic barriers to cultural and regulatory issues. Addressing these challenges requires a coordinated effort among stakeholders, including policymakers, technology providers, and farmers. By tackling these issues, the agricultural sector can unlock the full potential of digital transformation.

While there are challenges to overcome, the potential benefits for productivity, sustainability, and economic growth are substantial. The

1. FarmLogs (2022). Farm Management Software. Retrieved from https://www.farmlogs.com.

journey to digital agriculture is multifaceted, involving education, technology adoption, data management, and collaboration among various stakeholders. By following these steps and leveraging the provided references, farmers and agricultural professionals can navigate this transformative path effectively.

## 2. Materials and methods

In the scope of the research, the state of agriculture digitalization in Armenia was assessed. The studying of the level of digitalization, regardless of the field, the purpose of the research, and the scope of inclusion, has specific difficulties. The problem lies in the fact that in RA, in terms of official statistics, there are no statistical publications that will specifically address or provide data about the state of the digital economy and digitalization in general in various spheres of life, which means the availability of official statistical data on the state of digitalization of rural areas is out of the question. Taking into account the research objectives and absence of official statistical data on agriculture digitalization, this article adopted a methodology framework, which was utilized in a similar study by Arion *et al.* (2024) "Determining Digitalization Issues (ICT Adoption, Digital Literacy, and the Digital Divide) in Rural Areas by Using Sample Surveys: The Case of Armenia".

The methodological basis for collecting the primary information about the state of digital agriculture in RA was the method of sample survey. The strata of the survey were the Armenian farms operating in all 10 regions of Armenia. A stratified sampling approach was applied, under which the target survey population (comprising farms) was partitioned into homogeneous strata, and respondents were then selected from each stratum through random sampling to ensure representativeness and reduce sampling bias (Arion *et al.*, 2024).

To determine the sample size the number of all kinds of organizations operating in agriculture must be considered. According to the RA Statistical Committee, the number of economic units engaged in agricultural production (farms) was 360 611[2], which would be the size of the main population of the surveys. To calculate the required representative sample size with a 95% confidence level and 5% margin of error, the following formula was used, developed by Arkin H. and Colton R.:

2. The data was obtained from official statistics of The RA Statistical Committee, source: https://armstat.am/file/doc/99501108.pdf, page 3, last accessed 11.11.2024.

$$Sample\ size = \frac{\frac{(z^2p(1-p)}{e^2}}{1+\frac{(z^2p(1-p)}{e^2N}}$$ , where:

$N$ - population size,
$p$ - expected rate of occurrence (50%),
$e$ - margin of error (percentage as a decimal) (0.05),
$z$ - this is a value that indicates how much deviation occurs from the mean value. At the confidence level of 95% z = 1.96.

The required sample size for the research was at least 384 units, that is, at least 384 households from rural areas of the RA must participate in the survey to provide a representative sample with a 95% confidence level and 5% margin of error. Considering the obtained number 400 surveys were conducted among Armenian farms in the first half of 2024. All the farms had an equal opportunity to be selected and included in the sample, and the selection of farms was carried out using a random address generator.

To ensure the highest accuracy of the survey results, prevent the inclusion of incomplete questionnaires, and minimize potential response bias, the data collection process was conducted exclusively through structured face-to-face interviews.

Even though low cost-effective and time-consuming compared to online or telephone surveys, this way provided reliable, complete data and the response bias was minimized (all the questionnaires were completed, there was no missing data, and the respondents fully understood the meaning of the questions, so the results were as reliable as possible). The questionnaires consisted of 13 questions, which explore the basic information about farms specifics (average incomes from agriculture activities, specialization, size, etc.) as well as questions specifically related to agriculture digitalization: the use of digital technologies, their accessibility, the attitude towards digitalization, the internet use directions, etc. The results of the survey allowed for forming a comprehensive knowledge about the state of digital agriculture in RA. In the questionaries, the list of digital technologies that are implemented in agriculture was included (see Table 1).

To strengthen the quantitative analysis of the study and identify the key determinants of digital technology adoption at the farm level, a Tobit regression model was employed. The use of the Tobit model is justified by the nature of the dependent variable, which is censored, taking the value 1 when the farm uses at least one digital technology and 0 otherwise (Asatryan *et al.*, 2024). Ordinary Least Squares (OLS) would be inappropriate due to the limited range of the dependent variable, whereas the Tobit specification

*Table 1 - The list of digital technologies implemented in agriculture*

| | |
|---|---|
| 1 | Digital devices (drones, robots, etc.) |
| 2 | Automated systems (irrigation systems, “smart farms”, etc.) |
| 3 | Sensor devices (hygrometers, soil analysis devices, etc.) |
| 4 | Weather forecasting devices, programs, applications, etc. |
| 5 | 3D printing, modeling |
| 6 | Internet of things |
| 7 | Cloud computing |
| 8 | Big Data |
| 9 | Artificial Intelligence (AI) |
| 10 | Enterprise Resource Planning (ERP) |
| 11 | Customer Relationship Management (CRM) |

accounts for censoring at the lower bound and provides consistent parameter estimates. The mathematical expression of the Tobit model is as follows:

$$Y_j = \alpha + X_j \beta + \varepsilon_j, j = 1, 2\ldots, N$$

Where $Y_j$ is the Digital adoption dummy (1 = farm uses at least one digital technology from Table 1; 0 = otherwise).

$\alpha$ is the coefficient of intercept.

$X_j$ is a matrix of explanatory, independent variables. Based on theoretical considerations and data availability, the following explanatory variables were incorporated:

- Farm size (ha) – continuous,
- Farmer age (years) – continuous,
- Education level – categorical (primary / secondary / higher),
- Farm income (AMD) – continuous,
- Production orientation – dummy (1 = animal husbandry; 0 = horticulture),
- Production model – dummy (1 = intensive; 0 = extensive).

These variables capture the structural, socioeconomic, and organizational characteristics of farms that the literature identifies as essential for explaining digital adoption behavior.

$\varepsilon_j$ is the stochastic error.

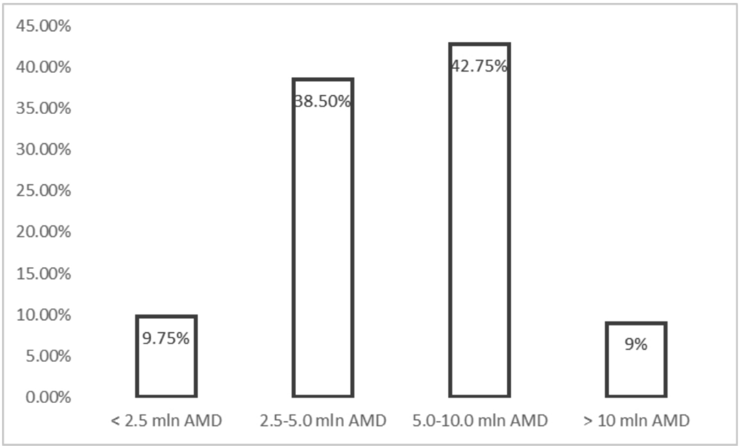
The model was estimated using maximum likelihood estimation. Marginal effects were computed to interpret the influence of each variable on the probability of adopting digital technologies. This approach complements the descriptive findings and provides robust statistical evidence on the factors shaping the digital transition of Armenian farms.

## 3. Results and discussion

- The descriptive statistics of the surveyed farms are presented below. Of the respondent farms, 55% are specialized only in horticulture, 45% are specialized in animal husbandry, and 18% are specialized in both horticulture and animal husbandry. It must be noted that these two main branches of agriculture have specific requirements for digital penetrations and their cases must be studied separately, Studies show that the prerequisites for digital adoption are different for horticulture and animal husbandry and are strongly conditioned by their production characteristics.
- Since the implementation of digital technologies in agriculture is usually coupled with the transformation of the production model (extensive, intensive, etc.) during the survey the farms were sorted according to those criteria, and results show that the vast majority of farms lead the extensive farming (specifically 83.75%), and only 16.25% use intensive. It must be noted that those with the intensive model have an average farm size of 13.4 ha (in horticulture-specialized farms), and the average farm size for the extensive model was only 2.5 ha, which provides food for thought for further discussions.

Since digital penetration is undoubtedly related to the financial potential of farms, during the surveys the farm's agriculture average income was taken into consideration. The results are presented in Chart 1.

*Chart 1 - The composition of surveyed farms according to the income level*




The majority of farms fall into the group of 5.0-10.0 million Armenian drams (AMD) income, with the mean value of income of all surveyed farms being 5.4 million AMD, for comparison the average wage level in RA is 230*12 = 2760 thousand AMD yearly. Farm income is a crucial determinant on the path to digitalization because it is the main source of funding for digital penetration in agriculture. The income and digital agriculture relationship is more in-depth discussed in the later part of the paper.

One of the cornerstone pieces of data obtained through the surveys is the assessment of the state of digital technology use in RA farms. The list of the technologies is presented in Table 1 and Charts 2 and 3 represent the usage of those technologies.

*Chart 2 - The usage of digital technologies in RA farms (part 1)*

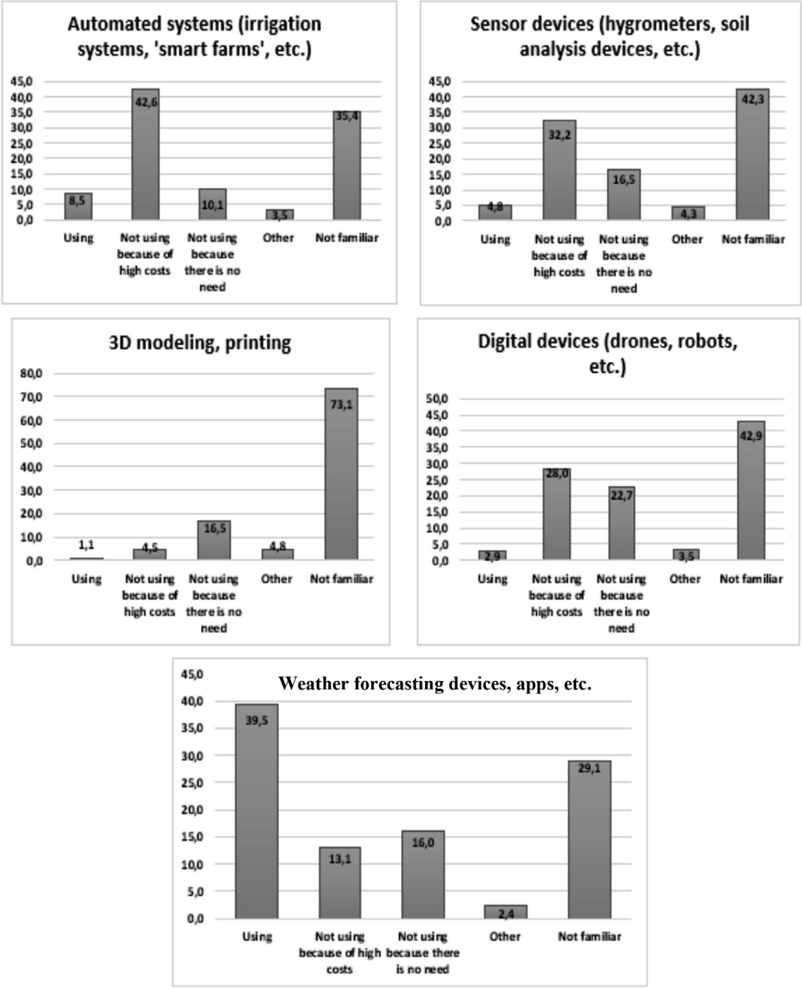
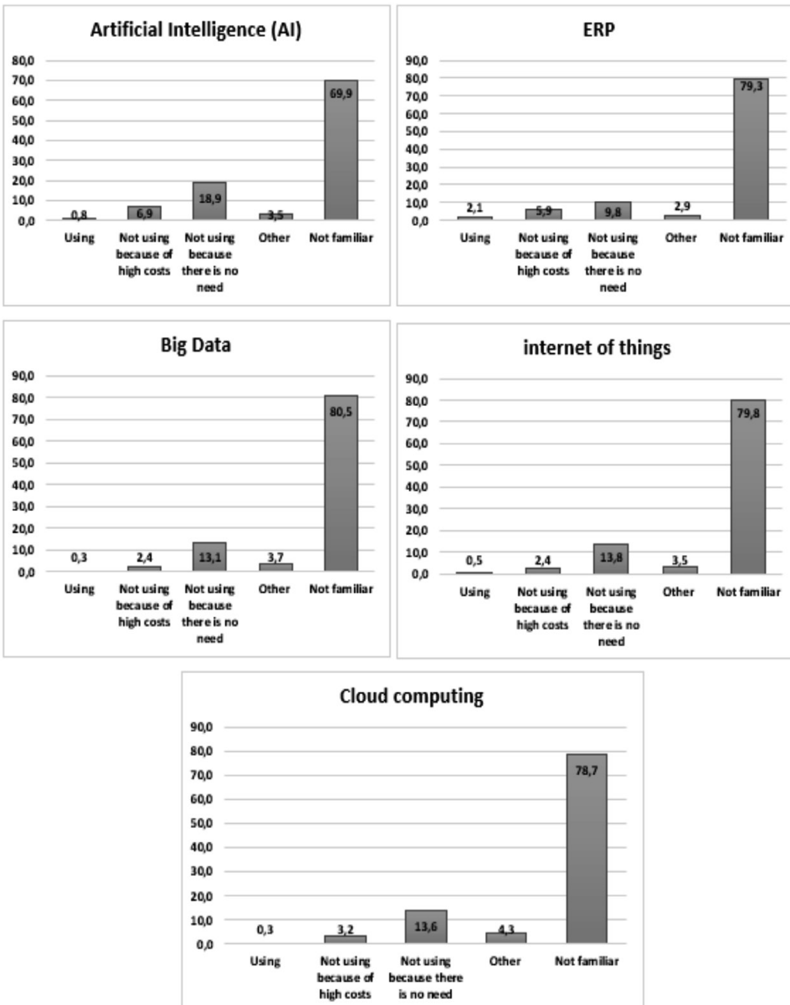


*Chart 3 - The usage of digital technologies in RA farms (part 2)*




Only 4.8% of surveyed farmers use digital devices such as drones, robots, etc., indicating low adoption. The main barriers include high costs (32.2%) and perceived lack of necessity (16.5%). Notably, 42.3% of farmers are unfamiliar with these devices, suggesting a significant knowledge gap. This lack of familiarity and high-cost perception highlights the need for awareness-raising and possibly financial support to encourage the adoption of digital technologies in agriculture. With automated systems, only 8.5% of respondents use these systems, while a significant portion (42.6%) do not

use them due to high costs. Additionally, 35.4% are unfamiliar with these technologies, indicating a substantial knowledge gap. About 10.1% of farmers do not perceive a need for these systems. The chart suggests that the main obstacles to adopting automated systems are financial constraints and limited awareness, which could be targeted through education and financial support initiatives. There is low engagement and familiarity with 3D modeling and printing among farms, with lack of awareness being the primary reason for non-use. The majority of surveyed farmers (73.1%) are "Not familiar" with 3D modeling and printing. A smaller portion (16.5%) indicated they are "Not using because there is no need." Only 1.1% are currently "Using" this technology. The farms reporting the use of 3D modeling and printing are those engaged not only in primary production but also in processing and beverage manufacturing. In these cases, 3D modeling is primarily applied within the processing stage (such as in packaging design or equipment optimization) although respondents appear to have generalized its use to the entire scope of farm activities.

Regarding the weather forecasting tools, including devices, programs, and applications: a significant portion (around 40%) of respondents are actively "Using" these tools. However, a notable group (about 25%) is "Not familiar" with them. Some respondents are "Not using because of high costs" (around 10%) or "Not using because there is no need" (about 15%). A small percentage chose "Other" reasons.

A large portion of surveyed farms (42.9%) is "Not familiar" with digital devices. Of those who are familiar, many are "Not using because of high costs" (28.0%) or "Not using because there is no need" (22.7%). Only a small fraction (2.9%) is currently "Using" such devices. So, there is limited usage and high unfamiliarity with digital devices like drones and robots, with cost and lack of need being major barriers for those who are aware of them.

A significant majority of respondents (around 80%) indicated that they are not familiar with Big Data, showing a potential gap in awareness or understanding. A smaller portion (around 10-15%) stated that they are not using Big Data as they don't see a need for it, which may indicate that they either don't see its relevance or lack use cases applicable to their needs. Similarly, a large percentage (approximately 70%) of respondents are not familiar with AI, suggesting that awareness and knowledge of AI might also be low among the participants. Around 15-20% indicated they are not using AI due to a lack of need, hinting that AI applications may not align with their current objectives or industries. Both charts indicate low usage and high unfamiliarity with these technologies, primarily due to a lack of knowledge and perceived necessity. Cost is a smaller but notable barrier. These findings could suggest a need for educational initiatives to increase awareness and demonstrate the potential benefits of Big Data and AI in various fields.

The majority of respondents (close to 80%) are unfamiliar with ERP and CRM systems, indicating a low awareness of these tools, which suggests an opportunity for increasing education and potentially lowering barriers, such as cost, to encourage usage. The chart also highlights that both cloud computing and IoT have low usage rates among the respondents, with a high percentage of respondents not familiar with these technologies, especially Cloud Computing.

A very important aspect of the path to digital agriculture is the incorporation of the Internet in the agricultural production value chain. Besides production processes, supply and sales must rely on the use of the Internet too. To assess the situation the direction of Internet use for agricultural purposes was revealed, the results of which are summed in Table 2.

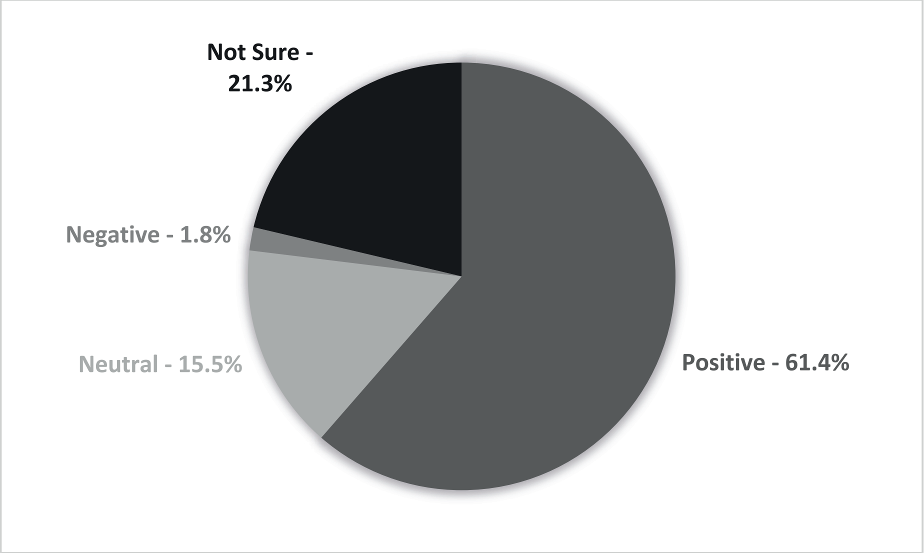
*Table 2 - The Internet's use for agricultural purpose*

| **Internet's use** | **Farms (%)** |
|---|---|
| To obtain information on land cultivation or livestock management | 52.3 |
| For extension services | 39.5 |
| To obtain/purchase production means (equipment, machinery, pesticides, fertilizer, etc.) | 40.1 |
| To sell their products | 30.0 |
| Other | 0.8 |

Results show that internet usage by Armenian farmers for different purposes averages 50%. So nearly half of surveyed farms do not use the Internet for agricultural purposes. Farmers mainly use the internet and its tools for gaining information on land cultivation or livestock management. Yet it must be noted that the bulk of digital technologies simply require the internet to operate. Various apps and platforms that are employed for extension services, pest and disease control, and trade of agricultural goods, just need the use of the internet to be functioned. Studies by Arion *et al.*, (2024) and Harutyunyan *et al.* (2024) show that Internet availability and accessibility in rural areas of Armenia are high, so average and low usage of the Internet for agricultural purposes is not conditioned by the issues of Internet availability in rural, remote areas (Granado-Díaz *et al.*, 2024).

One of the determinants of digital adoption and penetration in agriculture is the behavioral aspect (Granado-Díaz *et al.*, 2024), which encompasses the farmers' attitudes toward digital technologies. The survey results of the attitude of farmers towards digital technologies are presented in Chart 4.

*Chart 4 - Farmers' perception of digital technologies' impact on their activities*




Survey results indicate that a good portion of Armenian farmers has a positive attitude toward digital technologies, however, the decree of scepticism is rather high. Nearly 40% of the surveyed farmers either found digital technologies' impact neutral or negative or were not even sure about the possible consequences of digital adoption, This raises the question of awareness of farmers, and the issue was apparent regarding the analysis of technologies use. Behavioral analyses again raise the issue of lack of awareness, support, and guidance. These were the main findings of farm surveys.

The Tobit regression results provide robust empirical evidence on the factors shaping digital adoption among Armenian farms. All explanatory variables included in the model are statistically significant, confirming that digital adoption is influenced simultaneously by structural, socioeconomic, and organizational characteristics of farms (Table 3).

Among all determinants, farm size exhibits the largest and most influential coefficient, underscoring its decisive role in the digital transition. Larger farms demonstrate a substantially higher propensity to adopt digital technologies, consistent with the economies of scale argument widely supported in the literature (McBride & Key, 2018; Fountas *et al.*, 2020). This result also aligns with the descriptive statistics, which showed that intensive farms with larger landholdings display greater digital engagement.

*Table 3 - The results of Tobit regression*

| Variables | Coefficient | Std. Error | z-Statistic | p-value |
|---|---|---|---|---|
| **Farm size (ha)** | 0.188969 | 0.036534 | 4.091881 | *** |
| **Farmer age (years)** | –0.07169 | 0.003967 | –3.96878 | ** |
| **Education level** (1 = higher) | 0.070192 | 0.039827 | 2.013722 | ** |
| **Farm income (AMD)** | 0.089263 | 0.045698 | 2.96354 | ** |
| **Production orientation** (1 = livestock) | 0.06180 | 0.004563 | 3.15476 | ** |
| **Production model** (1 = intensive) | 0.12365 | 0.006978 | 4.23659 | ** |
| **Constant** | 0.423885 | 0 | 5.143894 | *** |

*Note*: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Farmer age shows a negative association with digital adoption, indicating that younger farmers are more inclined toward technological integration. This pattern reflects generational differences in familiarity, openness, and perceived ease of use of digital tools.

Education level positively affects adoption, suggesting that more educated farmers are better equipped to understand, evaluate, and implement digital solutions. This finding reinforces the importance of human capital and digital literacy in driving digital transformation.

Farm income also demonstrates a positive and significant effect, implying that financial capacity remains a key enabling factor for digitalization. Higher-income farms have greater ability to invest in digital tools, absorb risks, and cover operational costs associated with technology use.

Production orientation is significant as well: animal husbandry farms exhibit a higher likelihood of adopting digital tools compared to horticultural farms. This difference is consistent with the technological specificity and monitoring needs typically associated with animal husbandry.

The production model (intensive vs. extensive) has a strong positive effect, indicating that farms operating under intensive models are significantly more likely to adopt digital technologies. This reflects both structural readiness and the higher expected returns from digital investments.

Overall, the econometric results highlight that farm size is the most powerful single predictor of digital adoption, while age, education, income, production orientation, and production model all contribute meaningfully to shaping the technological trajectory of Armenian farms. These findings reinforce the conclusion that digital agriculture in Armenia is constrained primarily by structural factors, especially small farm sizes, and that targeted policies addressing scale, education, and financial access are essential to accelerate digital transformation. By summing up the previous literature review results and survey results the main challenges on the path of digital adoption were listed and presented in Table 4.

*Table 4 - Main challenges on the digital adoption in agriculture*

| Challenges most mentioned and discussed in scientific literature | Challenges that were mentioned by Armenian farmers (according to their intensity) |
|---|---|
| Technological access | The small size of farms (81.6% of respondents) |
| Digital literacy | Lack of financial resources (80.2% of respondents) |
| High costs of technology | Skills and literacy issues related to digital technology use (78.3% of respondents) |
| Skepticism and resistance toward new technologies | Physical unavailability issues or high costs of digital technologies (75.1% of respondents) |
| Data privacy | Skepticism (25.4% of respondents) |
| Limited financial resources | Lack of awareness (24.7% of respondents) |
| Integration issues with extensive farming | Lack of state support and guidance (21.5% of respondents) |

In contrast to global trends, where limited technological access and low digital literacy are typically identified as the primary barriers to digital penetration, in Armenia the challenges largely stem from the small size of farms, which underlies many of the obstacles reported by respondents. The land plots in Armenia are very small, as are animal breeding farms (with few animals). These small farms have neither the scale nor the capacity to adapt to various digital technologies. In some cases, not adopting the digital technologies by farms is justified, as it does not provide necessary cost efficiency. The adoption of digital technologies in agriculture is influenced by various determinants that can be broadly categorized into individual, organizational, and contextual factors. Cost-benefit effectiveness is one of those determinants.

Several studies discuss farm size and digital adoption relations. McBride and Key state that larger farms can spread the costs of technology over a greater output, making the investment in digital tools more feasible (McBride & Key, 2018). Logically this leads to higher rates of digital adoption among large farms. Larger farms typically have greater access to financial resources, skilled labor, and management expertise, facilitating the acquisition and implementation of digital technologies (Fountas *et al.*, 2020). Larger farms may have a more robust ability to absorb risks associated with technology adoption, such as implementation costs and potential failures. This willingness to take risks can lead to faster adoption of digital solutions (Deichmann *et al.*, 2020). Larger farms often have more diverse production systems, making it easier to justify investments in tailored digital technologies that optimize various aspects of their operations (Ward & Sweeney, 2021). Larger farms are more likely to engage in networks that facilitate knowledge sharing and access to innovation, enhancing their capacity to adopt digital technologies (Klerkx *et al.*, 2019).

The findings of foreign authors complement the results obtained in this study. In summary, it can be stated that farm size does matter on the path of agricultural digitalization, as larger farms are generally more equipped to adopt digital technologies due to their ability to leverage economies of scale, access resources, manage risks, and navigate operational complexities. So, on the path of agricultural digitalization in Armenia, the issue of farm size must be addressed during policymaking because it will indirectly promote digital adoption.

By summarizing the main challenges that hinder digital adoption the following conditions can be singled out that promote digitalization in agriculture:

- Infrastructure Availability (access to reliable internet, mobile networks, and necessary hardware, and devices).
- Digital Literacy of Farmers.
- Perceived Usefulness (farmers are more likely to adopt technologies they perceive as beneficial) and easy to use.
- Supportive Regulatory Environment from State.
- Availability of Financial Resources (access to loans and financial assistance can promote the ability of farmers to invest in digital technologies).

Since digital penetration in agriculture is provided through farms operating at the macro level of the economy, then understanding and discussing various farm-specific variables that can affect farmers' decisions to integrate technology into their practices becomes essential. Farm size is already discussed, so let's just mention it as a prominent farm-level variable for digital adoption. Next is farm specialization, particularly crop type, or animal type depending on which agriculture subsector it is. Different crops may require different technological applications. For example, high-value crops often see higher rates of digital adoption due to greater potential returns on investment (Ward & Sweeney, 2021; Manucharyan, 2025). Related to farm specialization the geographical location of the farm is an important variable too. Location impacts access to technology, infrastructure, and knowledge networks (Khachatryan *et al.*, 2025). Regions with better infrastructure tend to see higher adoption rates (Reddy *et al.*, 2021). Availability of financial resources is another variable, as access to capital and credit significantly influences the ability of farmers to invest in digital technologies. Farmers with better financial resources are more likely to adopt new technologies (Albrecht *et al.*, 2020). In line with the necessary infrastructure and financial resources, the availability of skilled labor also affects digital penetration, as farms with a workforce that has higher digital literacy are more likely to integrate technology effectively (Klerkx & Rose, 2020). However, money and labor are not the only factors that must be accessible to farmers: Access to Extension Services is important, because support from agricultural extension services can facilitate technology adoption. Knowledge transfer through extension services enhances farmers' confidence in using digital tools (Lobo *et al.*, 2020). Other inter-farm variables are the production goals and management practices. Farmers' management styles and openness to innovation play a critical role. Those who prioritize modern management practices are more likely to adopt digital tools (Klerkx *et al.*, 2019). Farmers' objectives regarding productivity, sustainability, and efficiency can drive adoption. Farms focused on high productivity often invest more in digital solutions (Bock, 2019).

Understanding these farm variables is crucial for developing targeted strategies to enhance digital adoption in agriculture. By addressing the specific needs and contexts of different farms, stakeholders can facilitate the transition to more technologically advanced agricultural practices.

## Conclusion

The digitalization of Armenian agriculture remains constrained by a combination of structural, economic, and behavioral factors, the most prominent of which is the small scale of farms. While descriptive survey results already suggested a clear divide between extensive and intensive farming models, the Tobit regression analysis provides strong empirical confirmation of the determinants shaping digital adoption. All variables included in the model were statistically significant, with farm size emerging as the most influential predictor of digital adoption. This reinforces the international consensus that larger farms, benefiting from economies of scale, stronger financial capacity, and a higher ability to absorb technological risks, are substantially more likely to adopt digital tools. In contrast, the predominance of small, extensive farms in Armenia severely limits the feasibility and perceived usefulness of digital solutions. Other determinants (including age, education, income, production orientation, and production model) also play essential roles in shaping adoption. Younger and more educated farmers are more open to integrating digital tools, while farms with higher income and intensive production structures show greater readiness for digital transformation. These findings confirm that digital adoption is a multidimensional process shaped simultaneously by human capital, financial capacity, and organizational features of farms. Behavioral and informational factors further compound these structural challenges. Low digital literacy, limited awareness of technological benefits, and skepticism toward digital tools collectively restrict the willingness of farmers to engage with emerging technologies. Despite high availability of internet infrastructure in rural Armenia, its limited use for agricultural purposes reveals a disconnect between infrastructural access and actual digital engagement.

To unlock the full potential of digital agriculture in Armenia, several strategic actions are recommended:

1. Education and Training: Providing farmers with targeted training on digital tools and their benefits is essential for effective adoption.
2. Policy Support: Policymakers should create frameworks to promote digital penetration. Given the current lack of awareness and skepticism, support programs should focus on building awareness and fostering positive attitudes toward digital technologies. Additionally, financial support for farms investing in digital practices is crucial.

In summary, for Armenia's agriculture sector to successfully digitalize, the following are key:

- robust policy support from the government;
- farmer education and increased awareness;
- policies promoting land consolidation.

The role of state support is especially critical in fostering digital agriculture in Armenia. However, as of October 2025, the Armenian Government has not implemented a state support program specifically promoting digital agriculture. Of the 15 support programs administered by the RA Ministry of Economy[3], only a few indirectly address digital adoption. The issue of small farm sizes has been addressed through two currently operating programs (the Pilot Program of Land Reform and the Program for Consolidation of Agricultural Land in Armenia, 2023-2025) which aim to create larger, more viable farming units.

3. The Official website of the RA Ministry of Economy, source: https://mineconomy.am/en/page/1338, last accessed 11.11.2024.

In conclusion, digitalizing Armenian agriculture requires a nuanced, multi-faceted approach that considers both macro-level and farm-specific variables. Policymakers and stakeholders must recognize the diverse needs and capabilities of farms across various agricultural sectors. By doing so, they can create a more inclusive digital landscape that bridges gaps in financial resources, technical knowledge, and access to technology. With targeted support and strategic interventions, Armenia can progressively overcome current barriers, paving the way for a digitally enabled agricultural sector that enhances productivity, sustainability, and resilience.

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## Declarations

### Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

### Conflicts of Interest

The authors declare no competing interest.

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