Key Factors Driving Higher Purchase Intention for Blockchain-Traced Wines: Implications for responsible consumer behavior

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Abstract

Purpose – This study sought to identify homogeneous consumer segments based on their intention to purchase blockchain-traced wines and to examine the perceptions, emotional responses, and psychological, behavioural, and socio-demographic factors driving stronger willingness to buy wines with verified origin and authenticity.

Design/methodology/approach – A machine learning approach was employed to uncover complex, non-linear patterns that distinguish consumer segments with varying purchase intentions.

Findings – The results indicate that subjective norms, hedonic perceptions, trust and perceived value are key drivers of higher purchase intentions for tracked wines, with consumers who enjoy traceability, trust the technology, recognize its value and perceive social approval being more likely to exhibit stronger purchase intentions.

Originality – While prior research in the wine sector has identified psychological and behavioural drivers of purchase intentions, how these factors interact to shape distinct consumer segments with different levels of purchase propensity remains insufficiently understood.

Practical implications – Consumers who are more responsive to social influence appear to exhibit stronger intentions to purchase traceable wine. From a marketing standpoint, this suggests that emphasizing social dynamics can help to promote traceable wine while fostering perceptions of both functional and experiential value and reinforcing responsible consumption behaviours. By emphasizing transparency, authenticity and the ethical production practices enabled by blockchain technology, marketers can not only strengthen consumer trust but also actively encourage more informed, conscious and responsible consumption choices.

Keywords: Sustainable consumption, Traceability, Transparency, Origin, Authenticity, Machine learning

1. Introduction

1.1. General background

Blockchain technology (BCT) is gaining prominence in the agri-food industry as a solution to rising consumer expectations for greater transparency, data security and trust, driven by increased concern about the provenance, quality and genuineness of food products (Nguyen et al., 2025; Puthenveettil et al., 2026). BCT is a distributed and decentralized digital ledger that is structured as a sequential chain of encrypted blocks, where each block contains a set of transactions that, once verified and validated by network nodes through consensus algorithms, are sealed and permanently linked to the previous block (Puthenveettil et al., 2026). This chronological and indissoluble link ensures data immutability. It makes information tamper-proof and provides high levels of security, transparency and reliability among the actors involved in the supply chain

(Pakseresht et al., 2024; Yu et al., 2024). BCT can thus be considered a "pro-social" technology (Huang et al., 2025), as it enables consumers and other supply chain actors to access additional, verifiable information about the product's origin, production and logistics processes, as well as qualitative and sustainability aspects of agri-food supply chains (Iansiti and Lakhani, 2017). This informational capability makes BCT particularly relevant in markets characterized by information asymmetries and high levels of perceived risk.

In the agri-food sector, information on food quality and safety – encompassing environmental and ethical factors – is frequently unevenly distributed throughout the supply chain, which leads to higher transaction costs and potential market inefficiencies (Starbird and Amanor-Boadu, 2007). By offering a single, reliable source of information, BCT can facilitate better communication and cooperation among supply chain participants, enhance security, and reduce operational costs linked to fraud, disputes and information gaps. Indeed, Hina et al. (2024) have emphasized that BCT influences various aspects of consumer values, including efficiency, social perception, trust and the transparency of sustainability information, which then supports more responsible consumption decisions. BCT thus has the potential to foster a transition towards more responsible consumption in the sense of "a set of voluntary acts within the sphere of consumption performed due to awareness of the negative consequences of consumption on the external world" (Özçağlar-Toulouse, 2009, p. 5), aimed at minimizing environmental impact, reducing waste and supporting ethical choices. Ultimately, by relying on a decentralized and tamper-resistant ledger, BCT can improve transparency and responsibility across agri-food supply chains, allowing both supply chain actors and consumers to track food products, limit fraud and make better-informed decisions, while also supporting Sustainable Development Goal 12 (SDG 12). Beyond its technological dimensions, BCT-based traceability can also be framed within the broader literature on eco-innovation and circular economy. Eco-innovation encompasses innovations that contribute to environmental sustainability through changes in products, processes or organizational structures (Carrillo-Hermosilla et al., 2010). In this sense, BCT-enabled traceability systems can be interpreted as a process targeting organizational eco-innovation, as these systems improve transparency, reduce information asymmetries, and support more sustainable production and consumption patterns. Moreover, by enhancing the visibility and credibility of sustainability-related information, BCT-based traceability may also support circular-economy strategies and sustainable business model innovation in agri-food systems (Boons and Lüdeke-Freund, 2013; Triguero et al., 2022).

1.2. Research gap

Research on BCT adoption in the agri-food sector has mainly concentrated on firm-level advantages, such as enhanced operational efficiency, fraud mitigation and reduced transaction costs (Casati et al., 2024; Kramer et al., 2024; Sultan, 2026). In contrast, the consumer perspective has received comparatively limited attention; only a small number of studies have examined how BCT-based traceability systems shape consumer perceptions, as well as which socio-demographic, psychological and behavioural factors drive purchase intentions (Li et al., 2023). More recent contributions suggest that the impact of BCT-enabled traceability on purchase intention operates largely through perceived information transparency and the pivotal role of trust.

For instance, Duong et al. (2025a) focused on organic products and found that the transparency afforded by BCT positively affected consumers' willingness to buy, especially when they felt able to verify product origin and authenticity.

Traceability mechanisms are essential for improving consumers' capacity to evaluate product value. More specifically, product diagnosticity positively influences the consumer experience and product evaluation, which in turn strengthens purchase intention. For example, Bastard and Chaillet (2023) demonstrated that QR codes supported by BCT can provide consumers with detailed information on wine origin and grape varieties, thereby improving their ability to assess product quality. Similarly, in a study on sustainable food consumption, Liu et al. (2025) showed that higher levels of BCT-enabled perceived transparency are associated with a greater willingness to pay a price premium. More broadly, increased transparency appears to strengthen purchase intention while also enhancing perceived behavioural control and subjective norms. Consumers thus tend to be more receptive to adopting innovative technologies that are consistent with their personal values and social expectations, an effect further reinforced by trust (Kulviwat et al., 2009; Duong et al., 2025b). Indeed, in the absence of trust, even highly transparent information may be ineffective in shaping attitudes and purchase behaviour.

In light of this, Khan et al. (2025) have shown that consumers who trust BCT's ability to provide reliable and transparent information about the origin and authenticity of organic products are more likely to purchase those products. However, it has emerged in the literature that higher levels of trust in technology and behavioural intention largely depend on consumers' familiarity with the technology. In line with this perspective, Contini et al. (2023) have shown that BCT enhances perceived product value and purchase intention only when consumers have a clear understanding of the technology. Among the relevant factors, perceived trust exerts the strongest effect on consumers' willingness to purchase BCT-tracked products, while perceived usefulness and perceived ease of use also have a positive impact (Bandinelli et al., 2023). Indeed, consumers tend to integrate digital technologies, including QR codes, into their buying behaviour when these tools are viewed as both easy to use and beneficial (Martinelli and De Canio, 2023) and when facilitating environmental factors are favourable to the acceptance and use of new technologies (Peñarroja et al., 2019).

Although previous research has shown the central role of BCT in purchase decisions, these studies mainly focused on specific product categories such as coffee (Dionysis et al., 2022), meat (Cordero-Gutiérrez et al., 2025) or organic products (Duong et al., 2025a; Khan et al., 2025), which leaves the wine sector relatively unexplored, despite its high risk of counterfeiting and growing demand for trust, authenticity and information credibility. Most prior research has also primarily examined cognitive determinants, such as attitudes, social norms and perceived usefulness, while largely overlooking emotional and perceptual dimensions.

These aspects are particularly important in industries such as wine, where consumers' purchase intentions are strongly shaped by experiential factors, trust, emotional responses and engagement (Calvo-Porral et al., 2020; Petroccione et al., 2025). In their examination consumer perceptions of wines traceable through QR codes and BCT, Adamashvili et al. (2024) have found that individuals with higher levels of knowledge and a stronger interest in innovation tend to display greater trust and a higher willingness to adopt these technologies.

Nevertheless, their analysis is primarily descriptive and does not rely on a robust theoretical model to account for the factors driving technology acceptance. Peiró-Signes et al. (2026) further confirm that consumers' ability to check the origin and quality of wine – referred to as diagnosticity – together with greater informational transparency, can contribute significantly to increasing perceived product value. Their findings also indicate that hedonic aspects, such as the enjoyment and pleasure associated with using the technology (e.g. scanning a QR code), play a stronger role in driving purchase intention than purely functional benefits. By contrast, perceived risk linked to concerns over potential misuse of personal data has a statistically significant but relatively limited impact on purchase intentions. Although studies in the wine sector have highlighted the psychological and behavioural factors influencing consumers' purchase intentions, it is still unclear how these factors combine to form consumer segments with varying levels of purchase propensity. Market segmentation is crucial for better understanding customers and grouping them into clusters with similar needs and characteristics, thus enabling the personalization of marketing strategies according to individual preferences. In light of this, this study addresses the following research questions:

RQ1. How do perceptions, emotional responses, and psychological, behavioural and socio-demographic factors related to BCT-based traceability shape distinct consumer segments with different purchase intentions?

RQ2. What combinations of perceptions and social/psychological conditions drive purchase intention for BCT-traceable wine?

1.3. Aim of the study and contributions

To address the identified gap and broaden the perspective of extant research, we sought to identify homogeneous segments of consumers in relation to their level of intention to purchase wine traceable with BCT and QR codes using a machine learning approach. Our objective was to understand which perceptions, emotional responses, and psychological, behavioural and socio-demographic factors characterize a greater intention to purchase a traced wine, which allows information to be acquired about its origin and authenticity. The theoretical framework of the study is based on the Stimulus–Organism–Response (SOR) theory (Mehrabian and Russell, 1974) and the theory of perceived risk (Bauer, 1960). In the SOR model, external factors such as product diagnosticity, social influences, facilitating conditions, information transparency and traceability act as stimuli. These stimuli shape consumers' internal psychological reactions (organism), including perceived product quality, usefulness, enjoyment, and trust in BCT and QR-code traceability. Together, these reactions influence responses, increasing consumers' willingness to purchase traceable products.

Perceived risk also significantly affects consumers' intention to purchase traceable agricultural products. Perceived risk is a key driver of consumer behaviour and creates anxiety that influences decisions, especially in technology adoption contexts. This investigation was conducted in Italy, given the country's importance on the world stage as the leading producer of wine, accounting for 19.5% of global wine production, and third largest consumer (10.4%) (OIV, 2025). Italian wine is also one of the agri-food products most susceptible to

fraudulent activity. In 1986, Italy experienced the most serious scandal in its wine history due to the addition of methanol to increase the alcohol content of wine; this adulteration resulted in 23 deaths and numerous cases of severe injuries. However, fraud is not confined to the past. According to the 2024 report by the Central Inspectorate for the Protection of Quality and Prevention of Fraud in the Agri-Food Sector of the Italian Ministry of Agriculture, Food Sovereignty and Forestry, the value of seizures in the wine sector, primarily due to labelling issues, totalled €9.9 million, equivalent to 43.7% of the total value of agri-food product seizures.

A machine learning approach has been used in this study to move beyond traditional linear modelling and to identify complex, non-linear patterns that characterize distinct consumer segments with different purchase intentions. Unlike traditional regression-based approaches, which assume linear and symmetric relationships among predictors, a machine learning approach is particularly appropriate because it allows identification of complex structures in the data without imposing restrictive functional assumptions. Consumer responses can be characterized by non-linear effects, threshold dynamics, and interaction patterns among the psychological, behavioural and socio-demographic variables. In this context, a machine learning approach can identify distinct consumer profiles based on combinations of conditions rather than isolated net effects. This approach complements the theoretical framework by identifying non-linear combinations of stimuli, organism states and perceived risk conditions that shape different levels of purchase intention.

The originality of this study lies in applying a holistic, multi-dimensional framework that encompasses psychological, behavioural and socio-demographic factors to the examination of how these factors interact to form distinct consumer segments in the wine sector, specifically regarding BCT-based traceability, a field that is both highly susceptible to fraud and largely unexplored. The study thus offers relevant theoretical and practical implications. From a theoretical perspective, it contributes to the literature by shifting the focus of BCT adoption in agri-food systems from firm-centred benefits to consumer-centred mechanisms. By applying a machine learning–based segmentation approach, we reveal distinct consumer profiles characterized by different levels of trust, technological familiarity, emotional engagement and purchase propensity towards BCT-traceable wine. Building on gaps in previous research, we incorporate emotional responses, experiential enjoyment, perceived value and trust alongside perceptions, psychological and behavioural factors, and socio-demographic characteristics to examine how these elements interact in shaping the intention to purchase BCT-traceable wine. This integrative perspective addresses a gap in the understanding of the complex combinations of factors driving technology adoption and provides deeper insights into consumer decision-making. We also highlight the potential role of BCT in guiding increasingly responsible consumption choices, showing how transparent and traceable information can encourage more conscious and ethical purchase decisions. The results offer practical insights for producers and technology providers. For wine producers in particular, the findings emphasize the need for targeted communication strategies, user-friendly and engaging traceability tools, and credibility-building initiatives to enhance consumer trust and adoption. Overall, the study underscores BCT's potential not only as a technological solution for traceability and anti-counterfeiting but also as a strategic marketing and trust-building instrument in the wine industry.

2. Methodology

2.1 Data collection and sample

This study is based on a nationwide survey of Italian wine consumers and uses a quantitative, prediction-oriented design to classify consumers by level of intention to purchase traceable wine using a machine learning approach. Data were gathered with a structured online questionnaire administered in February 2025 through a CAWI (Computer-Assisted Web Interviewing) platform with an estimated completion time of 10 minutes. The target population comprised Italian residents aged 18–80 years who reported having consumed wine at least once in the previous 15 days. To approximate the socio-demographic structure of the Italian population, we applied stratified sampling by gender, age group and macro-region (North, Centre, South and Islands) using the main population breakdowns adopted by ISTAT in national surveys. Within each stratum, individuals were randomly invited to participate, which reduced selection bias and ensured that all major socio-demographic segments were represented. In total, 1,061 questionnaires were returned. After screening for missing data and inconsistencies, 60 responses were removed, leaving 1,001 valid cases with complete information, which corresponds to a final response rate of about 94%. Overall, the sample closely mirrors the Italian population in terms of gender and geographic distribution, supporting its representativeness (see annex). Although individuals aged 61 and above, particularly those over 70, are somewhat overrepresented compared with the most recent census data (Istat, 2025), the sample remains a reliable reflection of the Italian population. Common method bias (CMB) was previously assessed and ruled out in the same dataset by Peiro et al. (2026), where multiple procedural and statistical diagnostics confirmed that CMB did not threaten the validity of the findings.

2.2 Questionnaire design and variable construction

The survey instrument was designed to capture multiple psychological and behavioural dimensions relevant to the consumer decision-making process. The questionnaire consisted of six sections and was structured as a closed-ended survey; it employed items from prior established and validated measurement scales. The first section focused on external stimuli influencing consumer perceptions, including BCT-related attributes (e.g. traceability and transparency), subjective norms, facilitating conditions related to technological support and the diagnostic value of information in evaluating product credibility. The constructs included in this section were measured using items adapted from measurement scales previously validated in the literature (Alam et al., 2024; Choe et al., 2009; Huynh et al., 2024; Shahzad et al., 2024). The second section measured internal evaluations (organism) in terms of perceived value, perceived usefulness, perceived trust, and hedonic perception. Items were adopted from prior scales validated by Irimia-Diéguez et al. (2023) and Alam et al. (2024). The third section collected data to assess purchase intention towards traceable wine (Huo et al., 2023; Yuan et al. 2020), BCT and QR-code knowledge and awareness (Duong et al., 2024), and perceived risk regarding new technology adoption (Galib et al., 2018). Socio-demographic characteristics were collected in the final part of the questionnaire.

Items representing each construct were phrased as closed statements assessed on a 7-point Likert scale ranging from 1 = "strongly disagree" to 7 = "strongly agree". Construct scores were computed as the arithmetic mean of their respective items. Before feeding the constructs into the machine learning framework, the reliability and validity of the measurement model were assessed (see tables in the annex). Internal consistency was evaluated using Cronbach's α and composite reliability (ρA), while convergent validity was assessed via the average variance extracted (AVE). Finally, discriminant validity was examined using the heterotrait-monotrait ratio (HTMT). The target variable, Purchase Intention, was operationalized into three categories, low (1–3), medium (3–5) and high (5–7). This categorization reflects the conceptual structure of the Likert scale, where 4 represents a neutral position, thus enabling the identification of behaviourally meaningful consumer segments (reluctant, ambivalent and strongly inclined). The resulting class distribution was 204, 440 and 357 respectively, which is sufficiently balanced to support stable multi-class learning. Socio-demographic variables, originally coded during data collection, were used in their numeric form, as the chosen algorithm was able to handle such inputs and no additional transformations were required.

2.3 Machine-learning framework

2.3.1 Algorithm choice

A supervised multi-class classification approach has been adopted to explain and predict consumers' purchase-intention category from a large set of behavioural constructs and socio-demographic variables. XGBoost was selected as the modelling technique. XGBoost incrementally builds an ensemble of trees by fitting new trees to the residuals of previous ones, thus capturing complex non-linear relationships and interaction effects among predictors (Chen and Guestrin, 2016).

2.3.2 Evaluation metrics, validation and tuning

Because the outcome is a three-class variable and the class frequencies are moderately unbalanced, the F1-macro score was used as the main performance metric. F1-macro is computed as the unweighted mean of the class-specific F1 scores; it therefore gives the same importance to low, medium and high purchase intention, regardless of their sample sizes. This property prevents the creation of a model that performs well only on the majority class while ignoring minority groups.

Data were split into training (80%) and test (20%) sets using a stratified sampling scheme to preserve the class proportions in each subset. For the training set, a grid search over key XGBoost hyperparameters (number of trees, maximum tree depth, learning rate, subsample fraction, column subsampling and regularization term) combined with stratified 5-fold cross-validation was carried out. The mean F1-macro across folds was computed and the combination that maximized this value was selected for each hyperparameter configuration. An early stopping rule based on cross-validated F1-macro controlled for overfitting by stopping the addition of new trees once performance ceased to improve. The final tuned model was then refitted on the full training data and evaluated on the test set.

2.3.3 Model interpretation

SHAP (SHapley Additive exPlanations) was applied to interpret the fitted XGBoost model. This provided a decomposition of each prediction into a sum of feature contributions grounded in cooperative game theory (Lundberg and Lee, 2017). For every respondent, SHAP values indicate how much each predictor (i.e. perceived value) pushes the prediction towards or away from a given purchase-intention category relative to the model's baseline output. Aggregating SHAP values across individuals yields a global importance ranking of the features.

While SHAP clarifies the impact, direction and nature (i.e. symmetric or asymmetric) of individual variables, the model decision logic remains difficult to understand. To obtain a more transparent representation of the model logic, we trained a decision-tree surrogate model that mimics the predictions of the XGBoost model (Breiman et al., 1984). Using the same predictors, we performed a grid search over tree depth and minimum leaf size; this allowed us to balance fidelity (how closely the surrogate reproduces the model's predictions) with simplicity (depth of the tree) and predictive accuracy on the true labels to select the best surrogate tree. The resulting tree summarizes the main decision paths – that is, the combinations of variables and socio-demographic characteristics that lead to low, medium or high purchase intention – in a form that is close to the logic of configurational approaches based on necessary and sufficient conditions (Ragin, 2000).

This methodological combination (XGBoost + SHAP + surrogate tree) moves beyond estimating average marginal effects and instead reveals how combinations of cognitive and affective evaluations jointly shape consumers' purchase intentions, which is theoretically meaningful within the SOR paradigm, where outcomes emerge from the interaction of evaluative perceptions and trust-based judgements rather than from the isolated influence of single perceptual constructs.

3. Results

3.1. Model performance

The first step in evaluating the classification model is to assess its predictive performance. In this study, the outcome variable was the level of purchase intention for traceable wine (low, medium or high), as shown in Table 1. The classification performance on the test set of the optimized model trained with the selected hyperparameters in the grid search was evaluated (max_depth = 3, n_estimators = 100, learning_rate = 0.1, s colsample_bytree = 0.7, subsample = 0.6, reg_alpha = 0). The model achieved an overall accuracy of 77% and a macro-averaged F1-score of 0.77 on the test set (n = 201). Following the multivariate classification literature (Hair et al., 1998), a model can be considered satisfactory when its accuracy exceeds the maximum chance criteria (43.9%) and the proportional chance criteria by at least 25% (45.24%). In this case, model's accuracy is substantially higher than the level suggested for multivariate classification tasks, which indicates that the selected machine learning specification provides a robust basis for explaining and predicting discrete levels of purchase intention for traceable wine. Class-specific performance was also satisfactory. For the low purchase-intention segment, the values for precision, recall and F1-score were all 0.78. For the medium segment, the corresponding values were 0.74, 0.77 and 0.76; for the high-intention segment they were 0.81, 0.76 and 0.79.

The model thus provides balanced performance across the three categories, without favouring the majority class. These results are reflected in the confusion matrix, where most cases appear on the main diagonal, which indicates correct classification of consumers into their observed category of purchase intention, whereas off-diagonal cells contain comparatively fewer misclassifications.

[Table 1]

3.2. Feature importance

SHAP values for all predictors were computed to clarify how the model uses the available information. SHAP values decompose each prediction into the additive contribution of each input variable relative to a baseline model output, which allows us to assess their importance. Importance is summarized by the mean absolute SHAP value of each feature across all observations, which we used to rank the predictors in Figure 1.

Figure 1 shows a clear hierarchy among the constructs. The variable subjective norms (SN) is the most influential, followed by hedonic perception (HP), perceived trust (PT) and perceived value (PV). Perceived usefulness and perceived risk occupy an intermediate position, whereas BCT knowledge (BK), traceability and transparency form a second tier of technological perceptions with smaller but still visible contributions. Socio-demographic and behavioural controls, such as age or consumption habits, appear at the bottom of the ranking, with comparatively low mean SHAP values. The constructs that capture social influence and evaluative reactions to the product and its digital traceability environment thus account for most of the predictive power, while background characteristics adjust the predictions only marginally.

Figure 2 shows the direction and distribution of SHAP values per class. These patterns align with expectations from the underlying theoretical framework. Higher levels of perceived value, trust, usefulness, hedonic perception and subjective norms tend to push the SHAP values towards the high-intention class and away from the low-intention class. In practical terms, when a respondent reports strong enjoyment of the traceable wine experience, trusts the information provided by the technology, perceives clear benefits and feels that others approve of such purchases, there is an increased probability that the model assigns that individual to the high purchase-intention category. However, contrary to our expectations, high perceived risk contributes positively to the SHAP values for the high-intention class and negatively for the low-intention class, reflecting the role of risk perceptions in the adoption of new technology. The relatively smaller contributions of consumer familiarity with BCT and QR technology, as well as perceptions of traceability and transparency, suggest that these factors are enabling conditions rather than main drivers. In other words, they help convert favourable attitudes and social pressures into concrete intention but are less likely to drive purchase intention on their own.

Figure 1 – Feature importance

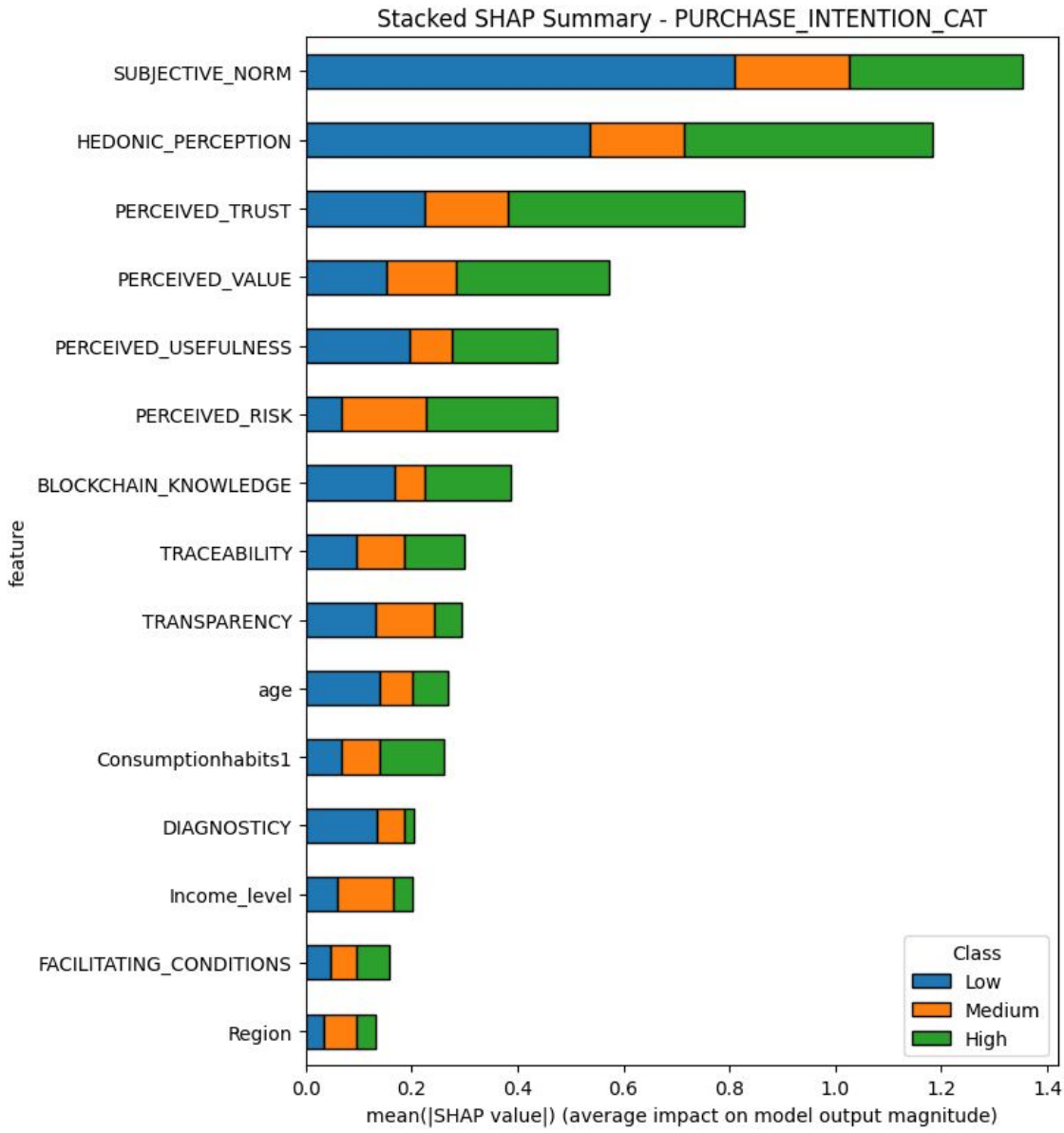
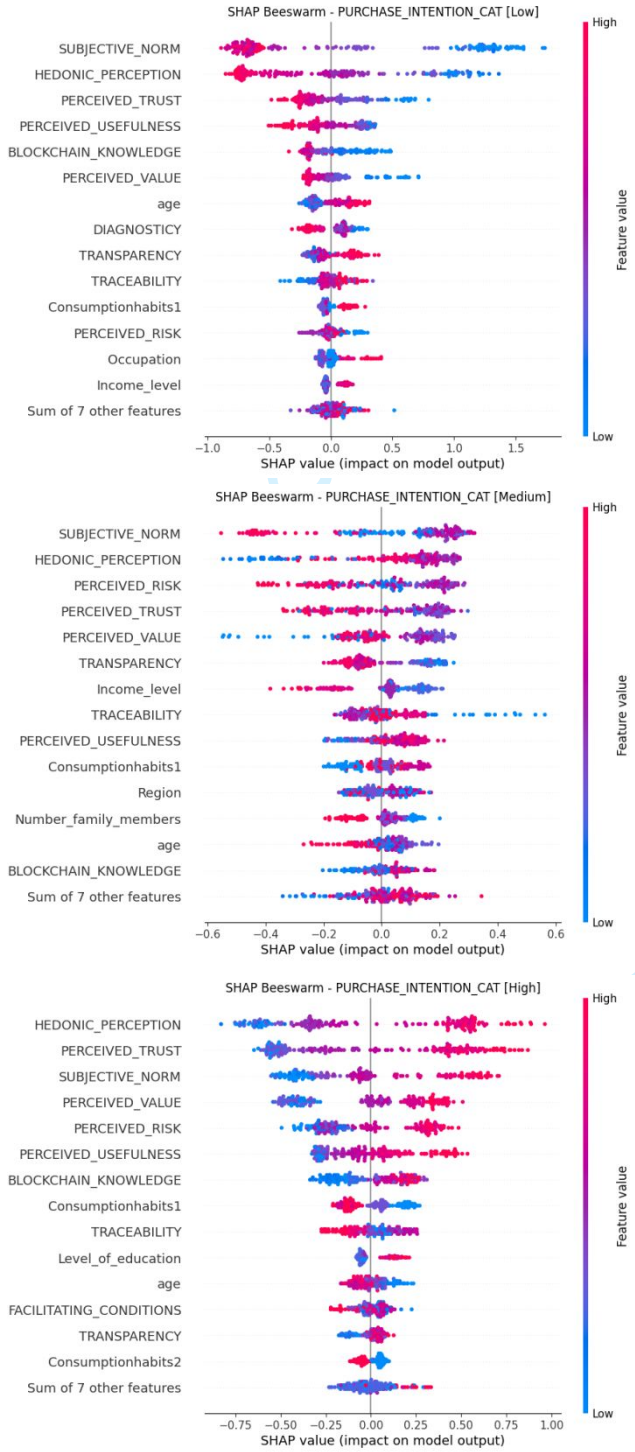


Figure 2 – Distribution of SHAP values by level of the output



3.3. Decision rules from the surrogate tree

To understand the decision rules of the model, we tested different tree classifiers and selected a tree surrogate with a tree depth of 4 with 20 minimum samples per leaf. The selected tree showed a fidelity of 84.1% and predicted the purchase intention with an accuracy of 74.6%. The resulting tree can be viewed as a set of paths from the root to the leaves, each path representing a specific combination of cut-off points in the main

constructs leading to a predicted class. As in qualitative comparative analysis, these paths can be interpreted as configurations of conditions associated with different outcomes (Ragin, 2000). Table 2 summarizes the paths of the tree surrogate. Consistent paths (consistency higher than 80%) to low, medium and high purchase intention are highlighted in bold.

[Table 2]

The most prominent path to high purchase intention (path 9, consistency = 0.96 and 57% coverage) includes high hedonic perception (HP > 5.13) and high subjective norms (SN > 5.3). When hedonic perception is high (HP > 5.13) but subjective norms are not high (SN ≤ 5.3), if there is high perceived value (PV > 4.83) and perceived trust (PT > 5.3), customers also tend to show high purchase intention (path 8, consistency = 0.86 and 13% coverage). For the medium-intention category, the surrogate tree reveals one consistent path (path 4, consistency = 0.94 and 49% coverage), which corresponds to customers with a medium hedonic perception (2.88 < HP ≤ 5.3), as well as a medium-high level of subjective norms (SN > 2.63) and perceived value (PV ≤ 4.83). These configurations capture consumers who are open to purchasing traceable wine but not yet strongly committed to doing so. In the low-intention category, the unique consistent path (path 1, consistency = 0.92 and 53% coverage) in the tree combines low hedonic perception (HP ≤ 2.88) and subjective norms (SN ≤ 2.13). A further result concerns necessity and sufficiency understood in configurational terms. Each consistent path in the surrogate tree represents a sufficient combination of conditions to obtain a given level of purchase intention, because a substantial number of cases following that path reach the outcome. A condition (or set of conditions) can be treated as necessary when it appears in all high-consistency paths leading to the same outcome and its own consistency is 0.90 or higher (Ragin, 2000). The unique and high consistency paths to low and medium purchase intention (paths 1 and 4) indicate that their combination of conditions can also be interpreted as necessary conditions for belonging to these categories. For high purchase intention, because high hedonic perception (HP > 5.13) is present in all high-consistency paths leading to the high-intention category and its combined consistency reaches 0.94, it operates as a necessary condition for high purchase intention, while subjective norms, perceived value and trust act as complementary, but not individually necessary, ingredients of the different sufficient configurations.

4. Discussion

Numerous studies have highlighted the growing consumer interest in agri-food products traced through BCT (Bastard and Chaillet, 2023; Duong et al., 2025a, 2025b). This trend is also evident in the wine sector, thus reflecting consumers' increasing attention to product quality, origin and authenticity (Adamashvili et al., 2024; Contini et al., 2023; Peiro-Signes et al., 2026). Existing research indicates that consumers' willingness to buy traceable wines is largely driven by their capacity to confirm the product's origin and quality, together with increased transparency throughout the supply chain. Overall, these factors contribute to a higher level of perceived value among consumers (Peiro-Signes et al., 2026). Consumers' understanding of the technology

and the comfort interacting with it also play a significant role (Contini et al., 2023), as they strengthen consumer trust and intention to use BCT (Adamashvili et al., 2024). In contrast to the current literature, the present study focused on identifying the psychological and behavioural mechanisms, together with socio-demographic determinants, shaping consumers' intention to purchase wine traceable via BCT.

The preliminary estimation of SHAP values for all predictors considered in the study revealed that subjective norms, hedonic perception, perceived trust and perceived value are the most influential factors in shaping consumers' intention to purchase tracked wines. A smaller, yet still significant, contribution is made by perceived usefulness, perceived risk, knowledge of the technology, and traceability and transparency. In other words, individuals who derive strong enjoyment from the experience of traceable wine, have confidence in the information provided through the technology, recognize its tangible benefits and perceive social approval for such behaviour are more likely to be classified within the high purchase-intention segment.

This result is further supported by the machine learning analysis, which classified consumers into three segments with different levels of purchase intention and identified the main psychological and behavioural conditions associated with each level. Consumers with high purchase intention are mainly characterized by strong hedonic perception, high social endorsement, and, in some configurations, high perceived value and trust. Consumers with medium purchase intention appear more open to BCT-traceable wine, but are not yet fully convinced, as their profiles combine moderate hedonic perception with intermediate levels of subjective norms and perceived value. By contrast, consumers with low purchase intention are characterized by weak hedonic perception and low social endorsement. From a theoretical perspective, these findings are consistent with the SOR framework. Subjective norms operate as the external stimulus shaping consumers' internal evaluations, while hedonic perception, perceived value and trust function as organism states that reinforce purchase intention.

The results thus confirm that the intention to purchase BCT-traceable wines is not only driven by functional considerations, but also by social and experiential mechanisms. This is in line with previous studies showing that social influence affects the adoption of traceability-related technologies and that enjoyable and engaging interactions strengthen consumer responses to digital tools in the wine sector and beyond (Alam et al., 2024; Higgins et al., 2014; Peiró-Signes et al., 2026). The results further highlight the importance of trust and perceived value in shaping consumer behaviour. Specifically, purchase intention tends to increase when consumers trust the information delivered through BCT systems and view the traced product as authentic, dependable and valuable. These findings are consistent with earlier studies indicating that BCT-enabled transparency improves confidence in product information while also reinforcing perceptions of quality and authenticity (Duong et al., 2025a; Khan et al., 2025; Li et al., 2023; Treiblmaier and Garaus, 2023). Overall, the results suggest that trust and perceived value are key mechanisms through which BCT traceability can encourage more informed and responsible wine choices.

Contrary to previous findings (Duong et al., 2025a, 2025b), the results suggest that consumers' familiarity with BCT and QR technologies, along with their perceptions of traceability, transparency and perceived risk, may play a marginal role in shaping purchase intentions. The relatively limited magnitude of their effects

suggests that these factors are primarily enabling conditions rather than core motivational determinants. They facilitate the translation of favourable attitudes and social pressures into concrete purchase intentions, but they are unlikely to exert a significant influence when considered in isolation.

Surprisingly, the results indicate that perceived risk does not have a significant influence on purchase intention. Risk theory is thus only partially supported in this context, suggesting that consumers' concerns about potential risks do not play a decisive role in shaping their intention to purchase BCT-traceable wine. It is likely that strong positive organism states – such as perceived trust, perceived value, perceived usefulness and hedonic perceptions – outweigh negative evaluations such as perceived risk. In other words, consumers tend to focus more on the benefits than on potential drawbacks when assessing traceable wine. Finally, the results show that the adoption of innovations such as BCT for wine traceability is driven primarily by cognitive and attitudinal factors rather than by socio-demographic characteristics such as age, income or consumption habits. Indeed, BCT addresses broad and widely shared needs (e.g. safety, transparency and authenticity) that are not tied to specific demographic segments but rather reflect individual values and sensitivities that are similarly present across people of different ages, genders and levels of education.

5. Conclusions, implications and future research directions

This study examined the psychological, behavioural and socio-demographic factors that influence differences in consumers' intentions to purchase BCT-traceable wine. The results highlight that subjective norms, hedonic perception, perceived trust and perceived value are the most influential consumer factors in shaping a higher intention to purchase tracked wines. More specifically, consumers who take greater pleasure in traceable wine experiences, trust the accuracy and reliability of technology-enabled information, clearly perceive its practical value, and feel social endorsement for such choices are more likely to belong to the segment with higher purchase intentions.

These findings provide relevant insights for researchers and practitioners seeking to better understand consumer decision-making in technology-enabled wine markets. First, the findings have important theoretical implications. The evidence that purchases intention is higher among consumers who are more sensitive to social norms enriches social influence–based models, such as the Theory of Planned Behaviour and the SOR framework, by suggesting that BCT is perceived not only as a functional technological tool but also as a socially relevant signal that legitimizes consumption choices. Consistent with this perspective, social influence operates as an external stimulus triggering internal emotional and cognitive states in the individuals (organism), which subsequently shapes consumers' behavioural responses. This social pressure significantly shapes consumer evaluations of new technologies, especially in terms of perceived usefulness and practicality. Judgements expressed by family, friends and other reference groups tend to enhance positive perceptions of tools such as BCT, reinforcing both their ease of use and their functional value in information search and purchasing decisions.

The study also highlights the central role of perceived value, showing that BCT contributes to the construction of a multidimensional perceived value by reinforcing product quality, authenticity and reliability, beyond

reducing information asymmetry. The consumer's ability to verify the transparency of the BCT-based traceability system – and thus to access and check product information – increases the perceived value of the product, which is consequently regarded as premium, more reliable and more desirable. This effect is further reinforced by familiarity with BCT, as traceability is interpreted as a guarantee of quality and safety. Perceived value thus acts as an internal mechanism, or organism in the SOR model, linking external stimuli to behavioural responses. It captures consumers' cognitive and emotional evaluation of benefits versus costs, translating marketing inputs into outcomes such as purchase intention, loyalty and engagement. The positive effect of hedonic perception on purchase intention extends the technology adoption literature, which has traditionally focused on utilitarian dimensions, by highlighting the relevance of experiential and affective factors in shaping consumer behaviour. This result suggests an integrated perspective that bridges the technology acceptance models (e.g. TAM and UTAUT) with experiential consumption theories, in which enjoyment, pleasure and emotional engagement play a central role.

Finally, the importance of trust in information provided through BCT strengthens the theoretical debate on trust in digital technologies. Trust is not merely an outcome of technological transparency, but rather a central cognitive mechanism that mediates the relationship between technological innovation and purchase intentions. This is particularly true in contexts where there is high information uncertainty and the origin and authenticity of products are highly relevant, as in the wine market. These considerations demonstrate that the study's results corroborate and extend existing consumer behaviour theories by showing that technology adoption in the wine market is driven by an integrated set of social, cognitive and experiential factors.

From a managerial perspective, the findings suggest several practical implications for wineries seeking to promote BCT-traceable wine. The findings show that purchase intention for traceable wine is higher among consumers who are more susceptible to social influence. From a marketing strategy perspective, this implies that leveraging social dynamics is essential to encourage the purchase of traceable wine and to shape both utilitarian and hedonic perceptions. Wineries may therefore benefit from using social media content, storytelling and visually appealing digital interfaces that make traceability easy to access and enjoyable to explore. However, in line with the study's results, digital tools should aim to create user experiences driven by pleasure, entertainment and emotional satisfaction rather than relying solely on functional utility. This can be achieved through interfaces featuring aesthetically pleasing elements that foster emotional engagement. In other words, marketing strategies, beyond emphasizing the technological benefits of traceability (e.g. access to information about origin, process quality and products along the entire supply chain) should highlight the symbolic and experiential aspects of consumption to stimulate consumers' psychological involvement. In particular, developing interactive features such as narrative storytelling or visual mapping of production processes can make traceability a pleasant and engaging activity, thereby increasing emotional resonance and consumer interest. Wineries could thus share the stories of winemakers, vineyards and the different stages of production to showcase the journey of the wine in an engaging way.

Overall, the study results demonstrate consumers' interest in purchasing wine tracked with BCT, which allows them to make more informed and responsible choices in line with SDG 12, aimed at ensuring responsible

consumption and production. BCT is especially well-suited to support emerging trends in the wine market, where consumers are increasingly seeking wines with reduced or no alcohol content, as well as organic and sustainably produced products. By providing transparent and traceable information on production practices, ingredient sourcing and sustainability credentials, BCT not only allows consumers to make more informed and responsible choices but also fosters trust and confidence in the products' ethical and environmental claims. This information may include not only origin and authenticity, but also environmental indicators and circular practices that are increasingly relevant for sustainability-oriented consumers. In practice, wineries can combine emotionally engaging experiences with BCT-enabled transparency to both strengthen consumer interest and foster responsible consumption, ultimately creating competitive advantage while contributing to broader societal goals.

Beyond communication strategies, our findings allow us to derive concrete actions for different supply chain actors to promote responsible consumption through BCT-enabled traceability. For producers (wineries), BCT can be leveraged to provide verifiable information on origin, production practices and sustainability attributes (e.g. environmental impact, certifications). Embedding QR codes linked to immutable records allows wineries to strengthen credibility and reduce information asymmetry, thereby fostering trust and encouraging more responsible purchasing decisions. For distributors, BCT systems can enhance coordination and data sharing across the supply chain, ensuring that product information remains consistent and tamper-proof throughout logistics processes. By maintaining data integrity and traceability, distributors can help reduce fraud and reinforce accountability, which are essential for building consumer confidence. For retailers, BCT-based traceability can be translated into in-store and online decision-support tools; retailers can highlight verified origin, certification, or sustainability indicators directly at the point of sale, making responsible choices more visible and accessible. Integrating BCT information into digital interfaces (e.g. apps or smart labels) can also enhance transparency and empower consumers to make informed decisions.

Beyond its role in traceability and anti-counterfeiting, BCT can also be understood as an enabling mechanism for sustainable innovation in the wine sector. By making verifiable information on origin, production practices, certifications and sustainability attributes more accessible to consumers, BCT traceability may support process and organizational eco-innovation and reinforce more circular forms of value creation based on transparency, accountability and informed consumption. From a managerial perspective, this means that wineries can use BCT not only to strengthen trust and authenticity claims, but also to communicate sustainability-related information more effectively (e.g. environmental practices, carbon footprint, packaging choices, bottle reuse or recycling initiatives, and other responsible production attributes). BCT traceability can thus contribute not only to marketing effectiveness, but also to firms' competitive positioning through sustainable innovation. More broadly, these implications are consistent with SDG 12 and, to a lesser extent, SDG 9 (Industry, Innovation and Infrastructure), as BCT supports the digital and sustainable transformation of agri-food systems.

Although this study makes several contributions, certain limitations should be acknowledged. First, the data were gathered through an online survey using the CAWI method, which may not fully reflect actual purchasing behaviour, given the well-known discrepancy between stated intentions and real actions. Consumer perceptions and intentions were also measured at a single time point, which restricts the possibility of establishing causal relationships. Future studies could address these limitations by adopting longitudinal or experimental approaches to track how purchasing behaviour and decision-making evolve over time. While this research focused on consumers' intention to purchase wines with BCT-based traceability, examining consumers' willingness to pay a price premium for such products would also provide valuable insights into their economic commitment to transparency. Given that BCT adoption for wine traceability is still emerging, willingness-to-pay should ideally be measured using direct approaches, such as experiments or auctions, to reduce hypothetical bias. Another limitation is the study's focus on consumers as the final link in the supply chain. Because implementing BCT requires coordination among multiple supply chain actors – and considering the extensive research on BCT adoption at the firm level – future studies should explore how BCT can facilitate collaboration across the entire supply chain.

From a methodological perspective, some limitations related to the machine learning approach should be acknowledged. While models such as XGBoost make it possible to capture complex, non-linear relationships and interactions among variables, they are primarily prediction-oriented and do not establish causal relationships between constructs. Although interpretability techniques such as SHAP values and surrogate trees have been employed to improve transparency, the results are inherently dependent on the data provided, which means that the identified patterns and feature importance rankings may vary across different samples or contexts. Future research could address these limitations by combining machine learning approaches with complementary methodologies. For instance, experimental designs could help establish causal relationships between key variables, while qualitative case studies could provide deeper insights into how consumers interpret and respond to BCT-based traceability in real-world contexts.

Another limitation concerns the geographical focus of the study, which is based on Italian consumers. While Italy represents a highly relevant context due to its strong wine culture, consumer perceptions of BCT-based traceability may differ across countries. Cultural factors, levels of technological familiarity, trust in institutions and attitudes towards sustainability may influence how consumers perceive and value BCT-enabled transparency. Future research should therefore test the generalizability of these findings in different cultural and market contexts, including countries with lower wine consumption or different levels of digital adoption, to assess the external validity of the proposed relationships. Cross-cultural comparative studies would also help identify whether the relative importance of factors such as subjective norms, trust and hedonic perception remains stable or varies across socio-cultural environments.

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FIGURES

Figure 1 - Features importance

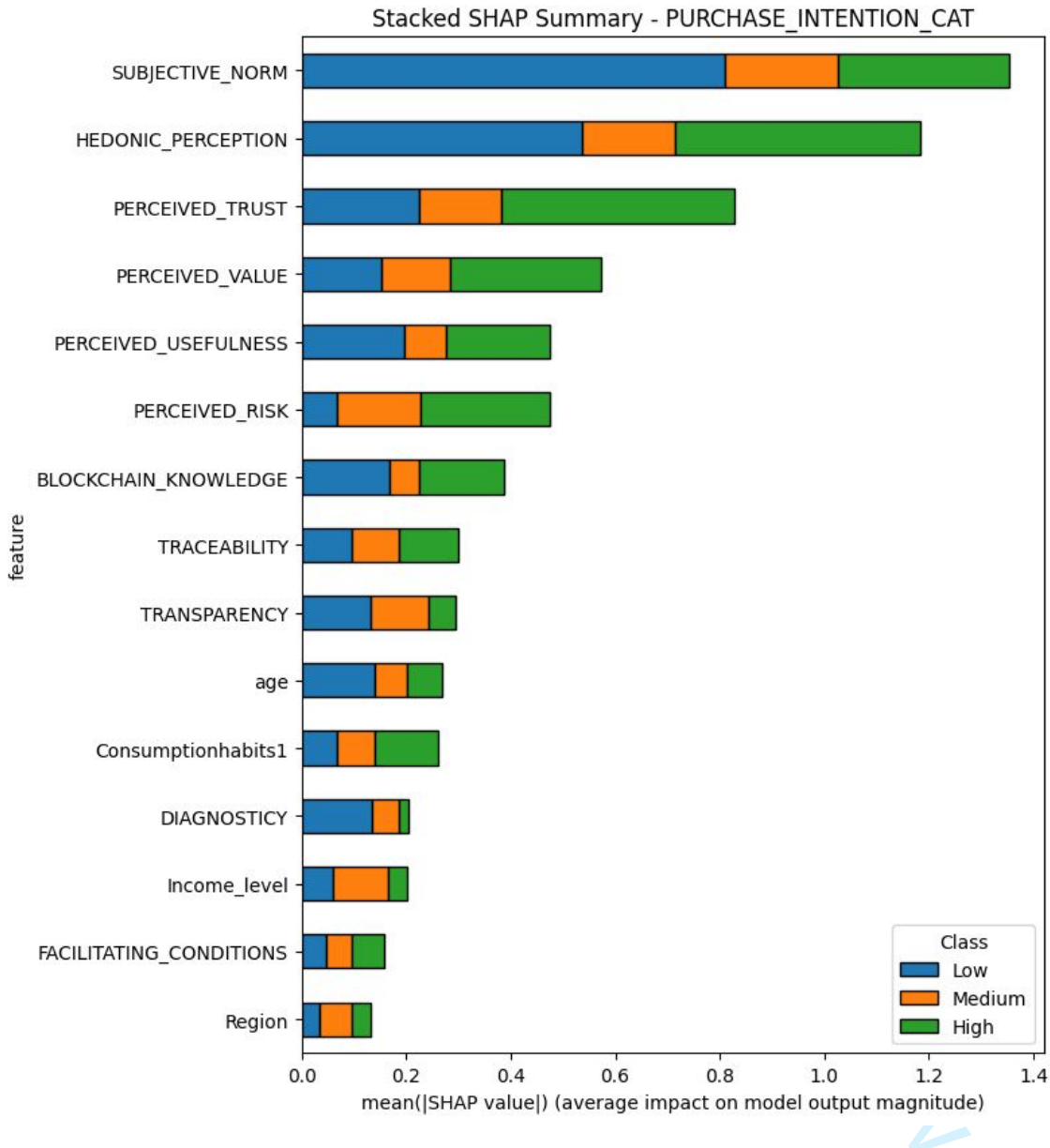
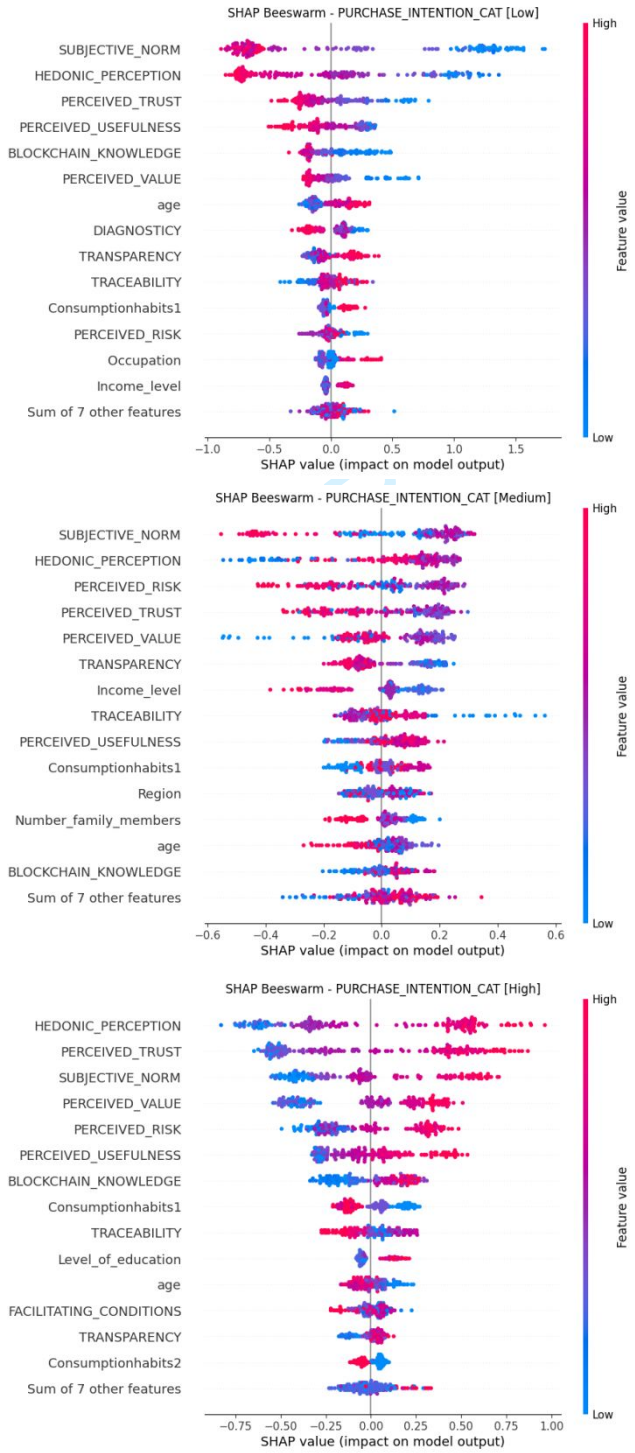


Figure 2 - Shap values distribution by level of the output



TABLES

Table 1. Classification Report

Predicted True	Low	Med	High	precision	recall	f1-score	support
Low	32 (15.9%)	8 (4%)	1 (0.5%)	0.78	0.78	0.78	41
Medium	8 (4%)	68 (33.8%)	12 (6%)	0.74	0.77	0.76	88
High	1 (0.5%)	16 (8%)	55 (27.4%)	0.81	0.76	0.79	72
			accuracy			0.77	201
			macro avg	0.78	0.77	0.77	201
			weighted avg	0.77	0.77	0.77	201

Table 2 - Tree surrogate paths

Sol	*HP≤ 5.13*	*HP≤ 2.88*	*SN ≤ 2.13*	*SN ≤ 2.63*	*PV ≤ 4.83*	*SN ≤ 5.13*	*PT ≤ 5.3*	0	1	2	Pred	Cons.	Cov.
1	***T***	***T***	***T***					***87***	***8***	***0***	***0***	***0,92***	***0,56***
2	T	T	F					17	11	0	0	0,61	0,11
3	T	F		T				37	54	3	1	0,57	0,15
4	***T***	***F***		***F***	***T***			***4***	***178***	***8***	***1***	***0,94***	***0,49***
5	T	F		F	F			5	35	22	1	0,56	0,10
6	F					T	T	3	25	6	1	0,74	0,07
7	F				T	T	F	2	42	46	2	0,51	0,16
8	***F***				***F***	***T***	***F***	***0***	***6***	***36***	***2***	***0,86***	***0,13***
9	***F***					***F***		***0***	***6***	***159***	***2***	***0,96***	***0,57***

Annex

Table A1. Socio-demographic distribution of the sample

Socio-demographic data/group	Variable	Frequency	Percentage
Gender			
1	Male	492	49.2
2	Female	509	50.8
Age			
1	18-30	119	11.89
2	31-40	181	18.08
3	41-50	226	22.58
4	51-60	183	18.28
5	61-70	200	19.98
6	Above 70	92	9.19
Marital status			
1	Single	305	30.5
2	Married	565	56.4
3	Divorced	62	6.2
4	Separated	31	3.1
5	Widowed	22	2.2
6	Prefer not to answer	16	1.6
Household			
1	1 Person	137	13.69
2	2 People	340	33.97
3	3 People	251	25.07
4	4 People or more	273	27.27

Occupation			
1	Employee	476	47.6
2	Self-employed	130	13.0
3	Retired	204	20.4
4	Student	37	3.7
5	Unemployed	60	6.0
6	Housewife	75	7.5
7	Other	19	1.9
Income level			
1	With my family's income, we have a lot of difficulty making it to the end of the month	92	9.2
2	With my family's income, we have some difficulty making it to the end of the month	294	29.4
3	With my family's income, we have no difficulty making it to the end of the month	373	37.3
4	With my family's income, we are able to put some savings aside	176	17.6
5	Prefer not to answer	66	6.6
Education level			
1	Elementary school diploma	1	0.1
2	Secondary school diploma	94	9.4
3	High school diploma	554	55.3
4	Bachelor's degree	107	10.7
5	Master's degree	118	11.8
6	Single-cycle degree	79	7.9
7	PhD / master's program	48	4.8
Region of residence			
1	North (Piedmont, Aosta Valley, Liguria, Lombardy, Veneto, Friuli-Venezia Giulia, and Trentino-Alto Adige)	462	46.15
2	Center (Emilia-Romagna, Tuscany, Umbria, Marche, Lazio, and Abruzzo)	201	20.08

3	South and Islands (Campania, Apulia, Molise, Basilicata, Calabria, and the islands of Sicily and Sardinia)	338	33.77
Wine consumption frequency			
1	Every day	239	23.88
2	Two-three times in a week	261	26.07
3	Once a week	219	21.88
4	Once in every 15 days	282	28.17
Wine consumption habit			
1	At home	553	55.24
2	On social events	448	44.76

Table A2. Measurement model results

Construct/ Item	**Cronbach's alpha**	**Composite Reliability**	**AVE**
Blockchain knowledge	0,913	0,917	0,795
What is your familiarity with blockchain?			
How much do you know about blockchain?			
How clear is your understanding of the characteristics of tracking systems?			
How would you rate your knowledge about blockchain relative to your colleagues, friends, family members?			
Traceability & Transparency	0,955	0,956	0,761
BT-enabled wines are traceable			
BT-enabled wine traceability system provides rich and detailed product information.			
BT-enabled wine traceability system provides accurate and real-time information about the product.			
BT-enabled wine traceability system provides complete information about supply chain actors			
BT-enabled traceable wine production and delivery procedures is transparent			

BC-enabled traceable wine system ensures wineries are accountable to consumers for their actions			
BT-enabled traceable wine system provides detailed information about each stage of wine production, from vineyard to bottle, via QR code			
BT-enabled traceable wine system makes it easy for consumers to access the information they need by scanning the QR code			
Diagnoscity	0,885	0,887	0,813
The traceability system can help me carefully evaluate the wine			
Careful evaluation of the product will make it easier for me to purchase wine			
The traceability system can help me get the real feeling of the wine			
Subjective norms	0,956	0,957	0,883
The people who matter to me think I should use QR codes when purchasing wine.			
People who influence my life believe that I should use QR codes to access information about the wine I purchase.			
People whose opinions are important to me think that I should use QR codes to check the wine I buy.			
People around me who use QR codes to buy wine seem to have more prestige than those who do not.			
Facilitating conditions	0,732	0,730	0,652
I have the necessary resources to use QR codes (ex. smartphone)			
When I have trouble using QR codes, I can get help from others			
I can get technical support for using QR codes			
Perceived Value	0,883	0,884	0,811
The quality of wine with traceable information is very good.			
The wine purchased from brands that disclose traceable information can meet my expectations.			
The wine purchased from brands that disclose traceable information make me feel very happy			
Hedonic Perception	0,930	0,930	0,877
The fun derived from using QR code will be / is a significant factor that influences my usage.			
The experience of using QR code will be / is enjoyable.			
The process of tracing wine using QR code will be / is pleasurable and entertaining			
Perceived Usefulness	0,902	0,910	0,836

BC-enabled wine traceability systems are useful			
Using BC-enabled wine traceability systems makes it easier to purchase product			
BC-enabled wine traceability systems allow quick access to the information through QR codes			
Perceived Risk			
I am worried that my personal information could be stolen	0,900	0,944	0,830
I am worried that my personal information collected could be misused			
The security systems built into the BC and QR code-enabled wine traceability system would not be strong enough to protect my personal data			
Purchase intention	0,934	0,937	0,751
Traceable wine can arouse my interest in purchasing			
I will buy wine that uses traceable systems			
I will give priority to the use of traceable system of wine			
I am willing to spend more money on traceable wine than regular wine			
For me, it's worth buying traceable wine despite high price			
I am willing to pay a premium price for traceable wine			

Table A3. Discriminant validity (HTMT)

	Diagnosticity	Facilitating conditions	Hedonic Perception	IT/BC Knowledge	Perceived Usefulness	Perceived risk	Perceived value	Purchase intention	Subjective norms
Facilitating conditions	0.625								
Hedonic Perception	0.663	0.584							
BCT Knowledge	0.119	0.222	0.304						
Perceived Usefulness	0.812	0.685	0.804	0.213					
Perceived risk	0.052	0.106	0.098	0.181	0.038				
Perceived value	0.800	0.631	0.811	0.252	0.855	0.138			
Purchase intention	0.614	0.532	0.839	0.368	0.735	0.166	0.774		

Subjective norms	0.422	0.470	0.665	0.391	0.485	0.252	0.590	0.739	
Traceability & Transparency	0.878	0.623	0.515	0.106	0.755	0.030	0.702	0.442	0.269

Figure A1. Methodology