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From greenhouse production to consumer choices: the role of zinc biofortification and visual cues

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ABSTRACT

Innovation in fresh vegetables increasingly combines visible differentiation, such as novel colours, with process-based improvements, such as mineral biofortification. When nutritional enhancements are not visually detectable, consumer responses depend on how visible and invisible cues are perceived and processed in the decision-making process. This study investigates the concurrent role of fruit colour (visible attribute) and zinc (Zn) biofortification (invisible credence attribute) in shaping preferences for fresh mini plum tomatoes. A greenhouse experiment was conducted to ensure the internal validity of the consumer study by testing whether foliar Zn-EDTA applications affect visually perceivable traits. The resulting products were then used to elicit consumer preferences through a lab-based real-choice discrete choice experiment ($n = 198$), involving binding purchase decisions and complemented by eye-tracking data to capture visual attention. Results indicate that colour is the primary driver of both attention and choice, with brownish and mixed assortments attracting more gaze and purchases than red-only options. A latent class model identifies three distinct consumer segments: two innovation-oriented groups willing to pay for biofortification and novel colours, and a conservative segment averse to both attributes and exhibiting signs of visual overload. Overall, the findings show that visible cues dominate decision-making when credence attributes are not salient, and that eye-tracking enhances the interpretation of preference heterogeneity.

1. Introduction

The agri-food sector is increasingly shaped by innovations, and among fresh horticultural products, mini plum tomatoes stand out for their rising popularity and market potential [1]. Mini plum tomatoes are widely appreciated for their small size, intense flavour, and versatility [2,3]. As a result, they are often preferred over traditional tomatoes for fresh consumption in many countries [4]. Recent trends in vegetable innovation increasingly involve the diversification of visual appearance through the introduction of new colours, alongside nutritional enhancement via biofortification with essential micronutrients [5,6].

Colour innovation responds to consumer demand for novelty and visual appeal, often linked to perceptions of freshness, quality, and even healthiness [7]. Introducing non-traditional colours such as brownish, orange, or yellow can differentiate tomatoes in competitive markets, potentially enhancing their attractiveness to specific consumer segments [8].

On the other hand, biofortification can be achieved through targeted agronomic practices aimed at increasing the content of essential micronutrients (e.g., zinc, selenium, or iodine) in the final product [9]. This process-oriented innovation responds to growing consumer awareness of the link between diet and health, offering added nutritional value through vegetable consumption [10].

From a nutritional perspective, Zn biofortification is motivated by evidence indicating that a significant fraction of the European population either suffers from, or is at risk of, Zn deficiency [11,12]. However, while its nutritional contribution in fresh vegetables may be relatively modest compared to staple crops, it is essential to understand whether, and to what extent, consumers are willing to accept biofortified foods [6,13], particularly when such attributes are not directly observable either prior to purchase or even after consumption.

While it is well established that agronomic mineral biofortification may affect secondary metabolite composition in fresh tomatoes [14], clear evidence of its impact on tomato appearance is still limited,

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particularly regarding consumers' ability to visually distinguish between biofortified and non-biofortified fruits. Reported effects on visual traits are often negligible or absent [15]. This lack of visual detectability is crucial, as it implies that biofortification operates as a "credence attribute" [16,17], whose evaluation depends on external information rather than direct sensory perception.

Furthermore, consumer acceptance of such innovations remains insufficiently investigated [18,19]. For mini plum tomatoes in particular, consumers' willingness to pay (WTP) for novel attributes remains underexplored, especially in real-world contexts.

Several studies have investigated acceptance of novel foods using hypothetical Discrete Choice Experiments or survey-based WTP estimates [19–21]. However, these approaches may suffer from hypothetical bias, i.e., the discrepancy between what consumers claim they would do in a hypothetical scenario and what they do when real money and real products are involved [22,23]. The literature highlights that behavioural anomalies commonly observed in hypothetical experimental settings tend to diminish when binding purchase decisions are introduced, including in laboratory experiments [24–30].

At the same time, consumer decision-making in the presence of multiple product cues can be interpreted through the lens of visual attention and signalling theories, whereby salient visible attributes may dominate choice when credence attributes are less accessible. In this context, recent advances in consumer research emphasize the importance of visual attention as a driver of choice. Eye-tracking technologies allow researchers to map how consumers visually process product information, prioritise cues, and ultimately make purchasing decisions [31,32]. For innovative foods, where unfamiliarity can trigger hesitation or selective attention, identifying the visual factors that capture attention is crucial for effective product presentation and marketing.

Finally, the focus on single-serving packaging adds an important layer: these formats meet growing consumer demands for convenience and portion control but offer limited space for communicating product attributes. In this context, understanding how consumers allocate visual attention across available cues is particularly relevant, as it helps explain how visible and non-visible attributes are processed during real purchase decisions.

Against this background, the primary contribution of this study is to advance the understanding of consumer responses to the coexistence of visible (colour) and invisible (biofortification) innovations in fresh produce. Specifically, the study investigates the relative and combined influence of fruit colour diversity and Zn biofortification on consumer preferences and visual attention in fresh mini plum tomatoes. To do so, we combined a greenhouse experiment with a lab-based real-choice Discrete Choice Experiment (DCE) on tomato single-serving packs. The agronomic component is not intended as a standalone contribution, but as a necessary step to support the internal validity of the consumer experiment, by verifying whether Zn biofortification alters visually perceivable fruit traits. Establishing that biofortification does not generate detectable visual differences is essential to treat it as a purely non-visible attribute and to disentangle its effect from that of visible cues such as colour in the subsequent choice experiment. Building on this agronomic validation, we integrate economic modelling and eye-tracking evidence to examine how consumers process and value visible and invisible product innovations, and to derive implications for product design, communication, and agri-food policy.

The study contributes to the literature in three main ways. First, it provides evidence on whether agronomic Zn biofortification alters visually perceivable tomato traits, thereby establishing the experimental condition required to isolate biofortification as an "invisible" attribute. Second, it quantifies consumers' willingness to pay for biofortification and colour assortment using a real-choice DCE, thereby reducing hypothetical bias compared to stated-preference approaches. Third, it integrates eye-tracking measures into the econometric analysis to investigate how visual attention relates to preference heterogeneity and to derive actionable implications for product design, labelling strategies, and agri-food policy.

Compared to existing DCE and eye-tracking studies, the novelty lies in the combined analysis of visible and invisible innovations within a real-choice setting, supported by agronomic validation of attribute non-visibility. Although the empirical application focuses on mini plum tomatoes, the study is designed to provide broader insights into consumer responses to "invisible" process innovations (e.g., mineral biofortification) and visible product innovations (e.g., colour diversification), combining real-choice preference elicitation with process-based attention measures.

Specifically, the study addresses the following research questions (RQs).

- To what extent does Zn biofortification influence fruit size, shape, and visually perceivable colour traits across cultivars? (RQ1)
- How do visible (colour) and invisible (biofortification) attributes jointly influence consumer choices in a real purchase setting? (RQ2)
- To what extent does visual attention (as measured by eye-tracking) relate to consumer choice behaviour and preference heterogeneity? (RQ3)
- Does incorporating eye-tracking measures improve model fit and the interpretation of willingness to pay (WTP) in a real-choice setting? (RQ4)

2. Materials and methods

The study adopts an integrated multi-stage research framework combining agronomic, experimental, and behavioural data to address the research questions. First, a greenhouse experiment was conducted to assess whether Zn biofortification affects fruit traits, particularly those that are visually perceivable (RQ1). Second, tomatoes obtained from the agronomic trial were used as stimuli in a lab-based real-choice DCE to collect data allowing the analysis of how visible and invisible attributes influence purchase decisions (RQ2). Third, eye-tracking data were collected during the choice tasks to measure visual attention and to investigate its relationship with consumer behaviour and preference heterogeneity (RQ3). Finally, gaze-based metrics were integrated into a latent class model to assess whether attention measures improve the estimation and interpretation of WTP (RQ4).

This integrated approach allows linking product characteristics, visual processing, and economic preferences within a unified analytical framework (see Fig. 1).

2.1. Experimental crop, plant material and management practices

The fruits used to record consumers preference data were obtained from a greenhouse cultivation conducted during the 2022–2023 growing season at the experimental farm of the University of Catania (Sicily, Italy). A multi-span, East–West oriented greenhouse (30 × 27 m) was used, consisting of a steel tubular frame covered with polycarbonate panels (≥86% total visible transmittance) and equipped with adjustable side and roof vents. The microclimatic conditions inside the greenhouse were monitored every 5 min using sensors connected to a CR-10X data logger (Campbell Scientific, Inc., Logan, UT, USA). Two tomato cultivars, 'Angelle' (red fruit) and 'Dolcenera' (brownish fruit), were selected for the trial due to their commercial relevance and different fruit appearance (Supplementary Fig. S1). Five-week-old seedlings were transplanted on 19th September 2022 into an open-soilless cultivation system, with an inter-plant spacing of 0.30 m, and an inter-row spacing of 1.00 m. Fertigation was carried out using a standard nutrient solution, adopting a leaching fraction of ~25%, in order to reduce root-zone salinization [33]. The detailed description of the agronomic trial is reported in Supplementary Materials, Table S1).

The agronomic experiment followed a randomized block design with three replicates, each comprising 12 plants (excluding border plants). Two foliar treatments were applied during the cropping cycle: (i)

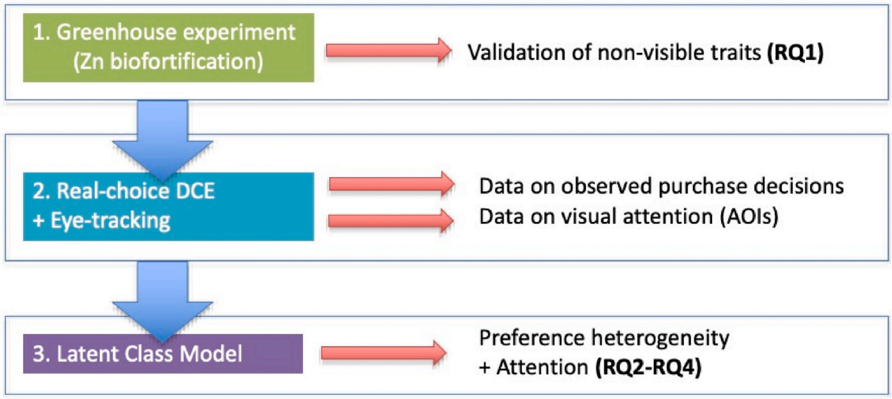

Fig. 1. Conceptual and empirical framework illustrating the alignment between research questions, experimental design, and analytical approach.

distilled water (control) and (ii) 1.7 mmol Zn L^{-1} as Zn-EDTA (Biolchim S.p.A., Medicina, BO). Treatments were applied early in the morning (8:00–9:00 a.m., local solar time) using a manual pressure sprayer, starting at full fruit set of the first cluster (32 days after transplanting, DAT), and repeated after fruit set of each subsequent cluster. A total of 10 applications were made between 20 October 2022 and 27 January 2023, thoroughly wetting the plants with ~7–30 mL of solution per plant, depending on growth stage. A non-ionic surfactant (Vector®, Chimiberg, Caravaggio, BG, Italy) was added to all solutions (i.e. 1 mL L^{-1}) to improve adhesive properties.

2.2. Fruit harvests, determination of carpometric traits and fruit Zn content

Fruit clusters were hand-harvested from 28 November 2022 to 4 March 2023. Fruits from the 5th cluster, harvested on 6 January 2023 at full maturity, were transported to the laboratory and processed within 4 h. Marketable fruits were detached from the rachis, and their fresh weight (FW) was determined gravimetrically on a subsample of 30 fruits per plot using an electronic scale (0.01 g accuracy). Fruit longitudinal (L) and transversal (D) diameters were measured with a digital calliper, and the shape index was calculated as the L/D ratio. Fruit colour was measured along the equatorial axis (2 measurements per fruit, 10 fruits per plot) using a tristimulus Chroma Meter (CR-200, Konica Minolta, Tokyo, Japan), previously calibrated with a UE-certified standard white tile. Colour parameters were expressed as L*, a*, b*, Chroma, and Hue angle [34].

For the determination of fruit Zn content, ~200 g fruit subsamples per plot were flash-frozen in liquid nitrogen and lyophilized using a freeze-dryer (Alpha 1–4 LD plus, Martin Christ, Osterode am Harz, Germany) until constant weight was reached. Dry matter content was recorded, and lyophilized samples were ground in liquid nitrogen using a laboratory mill (A11 basic, IKA, Wilmington, USA), then stored at −80 °C until analysis. For total Zn analysis, ~500 mg of tomato powder per sample were weighed into porcelain crucibles and incinerated in a muffle furnace at 550 °C until clear white ash was obtained. Ashes were digested in 20 mL of 1 M HCl in a water bath at 100 °C for 30 min. Each sample was then diluted to 50 mL with ultrapure water and filtered through Whatman No. 1 filter paper. Sample digestion and processing were performed in triplicate. Zinc content was subsequently quantified by flame atomic absorption spectrometry (PinAAcle 500, PerkinElmer, Waltham, MA, USA), equipped with a multi-element hollow cathode lamp and an air-acetylene flame. Standard solutions were freshly prepared by diluting a 10 mg L^{-1} multi-element calibration standard (TruQms, PerkinElmer) with ultrapure water. Results were then converted and expressed as μg 100 g^{-1} fresh weight (FW).

2.3. The lab-based DCE

2.3.1. Experimental design and choice attributes

Fresh mini plum tomatoes were packaged in single-serving transparent jars with lids, each containing six tomatoes. A labelled DCE was implemented, where each alternative corresponds to a specific product category (tomato colour), allowing for label-specific utility estimation. Each choice set included three labelled alternatives and an opt-out ("no purchase") option. The full experimental design consisted of 10 choice sets. The alternatives differed in terms of colour (red, brownish, or mixed), Zn biofortification (present vs absent), and price (five levels: €0.99, €1.29, €1.59, €1.89, and €2.19 per package). Price levels were selected based on a previous study on fresh tomato purchasing habits in Italy [35] (see Table 1).

To generate the choice sets, a multi-stage experimental design procedure was adopted [36,37]. In the first stage, an initial orthogonal design was created using Ngene [38], assuming non-informative priors for most parameters and a preliminary negative coefficient for price based on prior estimates. In the second stage, these priors were updated using parameter estimates obtained from preliminary analyses, allowing for an iterative refinement of the design. In the final stage, the design was further optimised to enhance the allocation of attribute levels across alternatives and choice sets, ensuring both statistical efficiency and realism.

The choice sets were organised into blocks to reduce respondent burden. Blocks were generated directly within the experimental design procedure in Ngene, and each participant was randomly assigned to one block and completed two choice tasks, corresponding to two consecutive purchase occasions.

While the colour of the tomatoes was directly visible to participants, information on biofortification and price was provided through a label placed at the base of each jar (Fig. 2). Specifically, the label reported the presence/absence of Zn biofortification and the product price, while

Table 1
Attributes and levels.

Attributes	Levels
Tomato colour (label)	Red
	Brownish
	Mixed
Zn biofortification	Absent (0)
	Present (1)
Price (€/pack)	0.99
	1.29
	1.59
	1.89
	2.19

Note: Colour is a labelled attribute, while biofortification and price are communicated through product labels.

Fig. 2. Example of the purchase scenario used in the labelled DCE.

colour was not explicitly labelled. Zn biofortification was communicated in neutral and informative terms (e.g., "zinc-enriched tomatoes"), without explicit health claims, in order to avoid framing effects and isolate the effect of the attribute itself. Pre-tests were conducted to identify the most effective label format.

2.3.2. Experimental procedure and incentive compatibility

To minimise potential position bias, jar placement was periodically varied by randomly changing the left–right order of alternatives. Jar positions were recorded for each session and included in the dataset to test for position-based heuristics (e.g., systematic selection of the leftmost or rightmost option). The purchasing task took place in a standardised laboratory booth with white interior surfaces to minimise visual distractions. Lighting conditions were controlled to ensure constant luminance. During the experiment, participants wore a mobile eye-tracking device (Tobii Pro Glasses 2; 50 Hz).

To enhance realism, participants received a €5.00 voucher, which could be used to purchase zero, one, or two single-serving packages across two consecutive purchase occasions. This incentive-compatible design ensured that choices had real economic consequences, thereby reducing hypothetical bias. This design allowed us to observe both initial choice behaviour and subsequent decisions under reduced choice sets. At the end of the experiment, participants received a printed receipt showing any remaining credit, which could be used in future sessions.

Before each choice task, the product display was concealed using a cardboard cover featuring the calibration target. After calibration, the cover was removed and participants were given 10 s to visually adjust before being invited to choose at their own pace. After the first choice, the selected jar was removed. If a purchase occurred, a second purchase round was conducted using the remaining two alternatives; otherwise, the session proceeded to the post-experiment questionnaire. The presence of a second purchase occasion with a reduced choice set allowed us to capture sequential decision behaviour and potential changes in attention and preferences across choice rounds. All sessions were administered by the same trained experimenter to ensure procedural consistency.

2.3.3. Participants and eye-tracking data processing

The study involved non-invasive procedures and collected anonymous data. Participation was voluntary and all participants provided informed consent prior to the experiment. No sensitive personal data were collected, and data were processed in accordance with applicable data protection regulations.

Participants were recruited among faculty staff, research fellows, PhD students, undergraduate students, and technical-administrative staff from the Department of Agriculture, Food and Environment (Di3A), University of Catania (Italy).

Experiments were conducted between January and March 2023 in three waves (corresponding to three harvested clusters). A total of 201 individuals participated; three were excluded due to incomplete questionnaires. The final sample included 198 participants (59% male), aged 21–71 years (mean = 42.39; SD = 14.5) (see Fig. 3).

Eye-tracking data were pre-processed in Tobii Pro Lab (version 1.123). Rectangular Areas of Interest (AOIs) were defined around each jar and its label for both recorded purchase occasions. Fixation-based metrics were extracted at the AOI level [39,40].

To analyse visual attention during the choice process, several standard eye-tracking metrics were initially considered, including total fixation duration, fixation count, and time to first fixation. These metrics capture different dimensions of visual processing, such as attention intensity, frequency of visual engagement, and early orientation towards stimuli.

Among these, total fixation duration was selected as the primary attention measure. This choice was guided by both theoretical and empirical considerations. From a theoretical perspective, fixation duration is widely interpreted as a proxy for sustained visual attention and depth of information processing. From an empirical perspective, preliminary analyses conducted on the dataset indicated that fixation duration provided a more consistent and interpretable relationship with observed choice behaviour compared to alternative metrics. Alternative metrics, such as fixation count and time to first fixation, were also explored but not retained in the final specification, as they showed lower explanatory power and less stable patterns across choice tasks.

Fixation duration was computed at the level of AOIs corresponding to each product (jar) and its associated label. For each choice task, fixation times were aggregated at the alternative level, resulting in a measure of total visual attention allocated to each option during the decision process. These variables were included in the econometric model in their original scale (seconds), as fixation duration directly reflects the intensity of visual attention and does not require

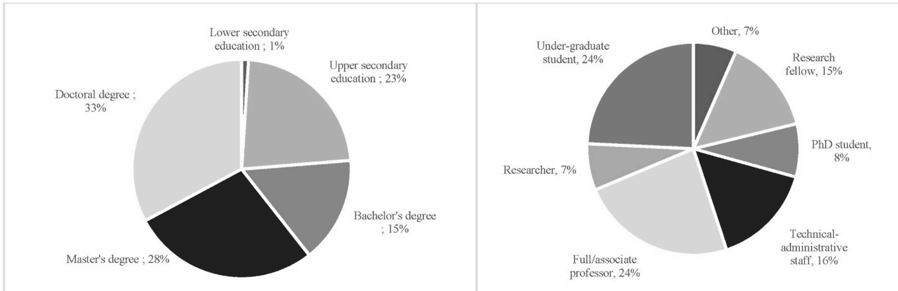

Fig. 3. Socio-demographic characteristics of the sample (n = 198).

transformation for interpretative purposes. No standardisation or normalisation was applied, as maintaining the original scale preserves the behavioural meaning of the metric and allows for a more direct interpretation of the relationship between attention and choice behaviour.

3. Data analysis

The study involved two main stages of data analysis, directly corresponding to the research questions: (i) the evaluation of the physical traits of the biofortified tomatoes (RQ1), and (ii) the investigation of consumer preferences through gaze and DCE data (RQ2–RQ4). This two-step approach reflects the integrated framework of the study, whereby agronomic evidence is first used to validate the non-visibility of biofortification and then informs the interpretation of consumer behaviour.

In the first stage, carpometric data were checked for normality and homogeneity of variance using the Shapiro–Wilk and Levene's tests, respectively. A two-way factorial analysis of variance (ANOVA; treatment × genotype) was then performed, consistent with the randomized block design adopted in the greenhouse experiment. Means were compared using Tukey's honestly significant difference (HSD) test ($P \leq 0.05$). All statistical analyses were conducted using Excel® 2016 (Microsoft Corporation, Redmond, WA, USA) and Minitab® 16.1.1 (Minitab Inc., State College, PA, USA).

In the second stage, we used a Latent Class (LC) model [41]. This model is widely used in consumer research to capture unobserved heterogeneity in preferences by segmenting the sample into distinct groups ("classes") that share similar choice patterns. Unlike the standard Multinomial Logit (MNL) model, which assumes homogeneous preferences across respondents, the LC model allows for the identification of segments, each characterised by its own set of parameter estimates [42]. According to the Random Utility Model (RUM) framework, the utility of the n-*th* individual for the j-*th* alternative in the t-*th* repeated choice occasion is the sum of a systematic or indirect utility (V_{njt}) and of a random idiosyncratic error term (ε_{njt}):

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

The model was estimated within a WTP-space framework, where the parameters directly represent marginal willingness to pay (WTP) for each attribute. This specification avoids the need to estimate preference-space coefficients and subsequently compute WTP ratios [43]. The deterministic utility component was specified as a function of price, biofortification, and alternative-specific constants (capturing colour effects), without including interaction terms, in line with the focus on capturing the relative and combined influence of visible and invisible attributes on consumer choice:

$$U_{n,red,t} = -\alpha_n {*} PRICE_{n,red,t} + WTP_n {*} Biofort_{n,red,t} + \varepsilon_n$$

$$U_{n,brownish,t} = ASC_{brownish} - \alpha_n {*} PRICE_{n,brownish,t} + WTP_n {*} Biofort_{n,brownish,t} + \varepsilon_n \tag{2}$$

$$U_{n,mixed,t} = ASC_{mixed} - \alpha_n {*} PRICE_{n,mixed,t} + WTP_n {*} Biofort_{n,mixed,t} + \varepsilon_n$$

$$U_{n,none,t} = ASC_{none} + \varepsilon_n$$

where U_n. is the utility of individual *n-th* for each option in the *t-th shopping occasion (with t = 1,2),* α_n is the individual scale parameter that converts WTP into monetary utility, WTP_n is the marginal WTP for the attribute "biofortified" for the n-*th* respondent, ε_n is the error term, capturing the unobserved component of utility, and *ASC* is the Alternative Specific Constant for each option. It represents the average WTP associated with a given alternative that is not explained by the observed attributes.

As specified in equation (2), interaction effects between colour and biofortification are not explicitly modelled. This modelling choice reflects the aim of disentangling the role of visible and invisible attributes and capturing their relative importance in shaping consumer decision-making, rather than estimating formal interaction terms.

The LC model, also called Panel Logit Model with Finite Mixing [44–46], assumes that respondents' behaviour depends on observable attributes and on latent heterogeneity varying with unobserved factors. Preferences vary among classes but are strongly homogeneous within each class. Everyone is sorted in a specific q-*th* class, but the researcher does not know the class to which the individual belongs. Therefore, the probability that alternative j-*th* is chosen by the individual n-*th* on choice occasion t-*th* equals to:

$$P_{njt}(j|q) = \frac{e^{ASC_j + x'_{njt}\beta_q}}{\sum_{i=1}^{4} e^{ASC_i + x'_{nit}\beta_q}} \tag{3}$$

The probability of the sequence of choices of individual n-*th* is:

$$P_n(j|q) = \prod_1^2 P_{njt}(j|q) = \prod_1^2 \left(\frac{e^{ASC_j - \alpha_{nq} {*} PRICE_{njt} + WTP_{nq} {*} Biofort_{njt}}}{\sum_{i=1}^{4} e^{ASC_i - \alpha_{nq} {*} PRICE_{nit} + WTP_{nq} {*} Biofort_{nit}}} \right) \tag{4}$$

The probability Ψ_{nq} of individual *n*-th belonging to class *q*-th is usually modelled in the literature as a logit probability:

$$\Psi_{nq} = \frac{exp\left(\gamma_{0q} + \sum_i^I \gamma_{iq} {*} z_{in}\right)}{\sum_{q=1}^{Q} exp\left(\gamma_{0q} + \sum_i^I \gamma_{iq} {*} z_{in}\right)} \tag{5}$$

where z_{in} represents exogenous observable variables related to n-*th* respondent, γ_{iq} is the vector of corresponding parameters for the q-*th* class, and γ_{0q} are constant terms.

To investigate the role of visual attention (RQ3 and RQ4), eye-tracking metrics were included as covariates in the class membership function. These variables are interpreted as behavioural correlates of attention during the choice process, rather than as causal determinants of preferences. Their inclusion is therefore intended to capture associations between visual attention patterns and preference heterogeneity, without implying a unidirectional causal relationship.

As it concerns z_{in} variables, we tested whether eye-tracking metrics related to each visual component of the shopping scenario (i.e., each jar and corresponding label) contribute to explaining consumer segmentation. To this end, two model specifications were estimated and compared: a baseline LC model without eye-tracking variables, and an extended model including fixation-based metrics as covariates in the class membership function. Model comparison was based on goodness-of-fit indicators, including log-likelihood, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC), in order to assess whether the inclusion of attention measures improves model fit and the interpretation of preference heterogeneity (RQ4). LC models were estimated using Apollo 0.3.0 in R 4.3.1 for Darwin [47].

4. Results

4.1. Fruit Zn content and main carpometric traits

To address RQ1, we first assess whether Zn biofortification affects visually perceivable fruit traits across cultivars. As shown in Table 2, the Zn-EDTA application increased the fruit Zn content compared to control (186 vs. 113 μg 100 g^{-1} FW, +65%), without affecting morphometric traits nor the color characteristics of the fruits. Regarding the genotypic effects, 'Dolcenera' showed lower fruit Zn content than 'Angelle' (132 vs. 167 μg 100 g^{-1} FW), but higher fruit weight (23.5 g), D (31.3 mm), and L/D ratio (1.48). Regarding the fruit chromatic traits, the Zn application per se had no significant effect. Differently, compared to 'Dolcenera', 'Angelle' showed higher values of L* (38.0), a* (18.6), and Chroma (26.8), and lower values of b* (19.3) and Hue angle (46.1) (Table 2). Moreover, the significant 'treatment × genotype' interaction revealed that the Zn-EDTA application reduced genotypic differences in b* (from 2.8 to 1.5), while increased those in Chroma (from 4.7 to 5.5) (Table 3).

Since Zn application did not affect visually perceivable fruit traits, choice results reflect consumers' responses to colour assortment and to the biofortification label as distinct sources of information.

4.2. Behavioural and gaze analysis

To address RQ2, we examine how visible (colour) and invisible (biofortification) attributes influence consumer choices in a real purchase setting. Fig. 4 illustrates the distribution of purchasing choices across colour options during the first and second shopping occasions. Descriptive evidence indicates a strong attraction towards brownish-coloured tomatoes, particularly when combined with traditional red varieties, suggesting an openness to visually novel products. In contrast, single-colour red options appear less preferred, pointing to a potential shift in consumer expectations toward more differentiated visual attributes. The no-purchase option was selected infrequently in the first round but became more relevant in the second, suggesting a tendency toward variation-seeking and avoidance of repetition.

Overall, 78% of participants selected packages containing brownish tomatoes at least once, primarily driven by curiosity and perceived novelty (see Supplementary Materials, Table S2). Similarly, 82% of participants chose biofortified products in at least one choice task. While these descriptive results suggest a general openness to both visual and nutritional innovations, they should be interpreted with caution, as they reflect context-dependent choices rather than underlying preferences.

These descriptive patterns are complemented and further clarified by model-based evidence presented in the following section, which allows for a more rigorous, ceteris paribus assessment of the relative importance of product attributes.

Fig. 5 shows the distribution of biofortified product choices across shopping occasions and colour combinations. Results suggest that biofortified products perform best when combined with visually appealing colour assortments, reinforcing the importance of embedding non-visible innovations within attractive visual contexts.

In terms of expenditure, participants spent on average €2.92, corresponding to 58.6% of their available budget (see Supplementary Materials, Table S5), indicating a willingness to allocate resources to products perceived as novel or of higher quality.

Self-reported data indicate that 60% of respondents considered all attributes during the choice tasks, consistent with a compensatory decision-making framework in which individuals trade off multiple product characteristics [42]. The remaining participants reported focusing on a subset of attributes, with colour being the most salient (34%), followed by biofortification (18%) and price (10%). This pattern reflects the phenomenon of Attribute Non-Attendance (ANA), whereby individuals disregard certain attributes either deliberately or due to cognitive constraints [48,49]. While ANA may affect the interpretation of stated preferences, eye-tracking data provide an additional

Table 2
Zinc content and carpometric traits of mini plum tomatoes as affected by the main factors and their interaction (mean ± standard deviation).

Source of variation	Zn content (μg 100 g^{-1} FW)	Fruit FW (g)	L (mm)	D (mm)	L/D (adimensional)
Treatment					
Control	113 ± 18	20.7 ± 3.0	45.9 ± 1.2	29.7 ± 2.2	1.55 ± 0.10
Treated	186 ± 20	21.2 ± 2.7	45.5 ± 1.0	29.3 ± 2.0	1.56 ± 0.08
HSD treatment$_{(P < 0.05)}$	17	NS	NS	NS	NS
Genotype					
Angelle	167 ± 41	18.4 ± 0.6	45.0 ± 1.0	27.7 ± 0.7	1.63 ± 0.05
Dolcenera	132 ± 39	23.5 ± 0.8	46.3 ± 0.7	31.3 ± 0.9	1.48 ± 0.03
HSD genotype$_{(P < 0.05)}$	17	1.1	NS	1.4	0.07
Treatment × Genotype					
Control Angelle	129 ± 3	18.1 ± 0.7	45.4 ± 1.3	27.9 ± 0.8	1.63 ± 0.07
Control Dolcenera	97 ± 4	23.4 ± 1.2	46.4 ± 0.9	31.5 ± 1.5	1.48 ± 0.04
Treated Angelle	204 ± 4	18.8 ± 0.3	44.7 ± 0.3	27.5 ± 0.6	1.63 ± 0.03
Treated Dolcenera	168 ± 6	23.7 ± 0.4	46.3 ± 0.6	31.1 ± 0.1	1.49 ± 0.02
HSD interaction$_{(P < 0.05)}$	NS	NS	NS	NS	NS
Overall mean	149 ± 42	21.0 ± 2.8	45.7 ± 1.1	29.5 ± 2	1.56 ± 0.09

FW: fresh weight; L: fruit longitudinal diameter; D: transversal diameter. NS: not significant.

Table 3
Chromatic traits of mini plum tomatoes as affected by the main factors and their interaction (mean ± standard deviation).

Source of variation	L*	a* (relative units)	b*	Chroma	Hue angle (sexagesimal degrees)
Treatment					
Control	34.9 ± 3.4	7.4 ± 12.4	20.3 ± 1.5	24.3 ± 2.6	72.7 ± 30.1
Treated	35.0 ± 3.4	7.4 ± 12.1	20.4 ± 0.9	24.3 ± 3.1	73.3 ± 29.0
HSD treatment$_{(P < 0.05)}$	NS	NS	NS	NS	NS
Genotype					
Angelle	38.0 ± 0.3	18.6 ± 0.5	19.3 ± 0.5	26.8 ± 0.3	46.1 ± 1.4
Dolcenera	31.9 ± 0.4	−3.8 ± 0.2	21.4 ± 0.6	21.8 ± 0.6	100.0 ± 1.6
HSD genotype$_{(P < 0.05)}$	1.0	0.8	0.8	0.7	2.44
Treatment × Genotype					
Control Angelle	38.0 ± 0.1	18.8 ± 0.7	18.9 ± 0.3	26.7 ± 0.4	45.3 ± 1.3
Control Dolcenera	31.8 ± 0.3	−3.9 ± 0.3	21.7 ± 0.4	22.0 ± 0.4	100.2 ± 2.7
Treated Angelle	38.1 ± 0.4	18.5 ± 0.4	19.7 ± 0.3	27.0 ± 0.1	46.9 ± 1.1
Treated Dolcenera	32 ± 0.4	−3.6 ± 0.1	21.2 ± 0.6	21.5 ± 0.6	99.8 ± 2.4
HSD interaction$_{(P < 0.05)}$	NS	NS	1.1	1.0	NS
Overall mean	35.0 ± 3.2	7.4 ± 11.7	20.4 ± 1.2	24.3 ± 2.7	73.0 ± 28.2

NS: not significant.

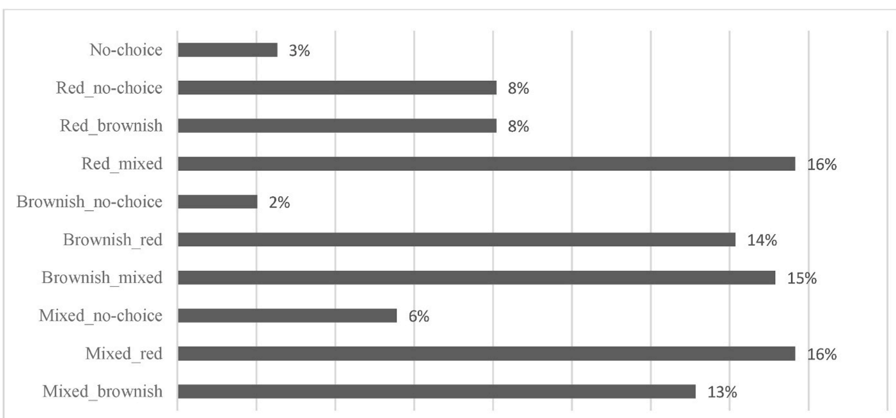

Fig. 4. Percentages of tomato purchases across colour options recorded during the first and second shopping events*
* The first term indicates the product chosen in the first shopping occasion, while the second term refers to the subsequent choice (or the opt-out option). For example, "Red_brownish" indicates a switch from red to brownish tomatoes between the first and second purchase occasions. Percentages represent the share of observed choice sequences.

behavioural measure to assess whether declared attention aligns with actual visual processing during the choice task [50–52].

To address RQ3, we analyse how visual attention, as measured through eye-tracking metrics, relates to observed choice behaviour. The total recording duration averaged 21.18 s (S.D.: 14.25), with longer durations observed in the first shopping occasion compared to the second (29.17 vs. 12.98 s; see Supplementary Materials, Table S6), suggesting a learning or familiarisation effect.

Fig. 6 reports the relationship between visual attention and purchase decisions across the two choice occasions. Results indicate that only a limited share of participants selected the option that received the highest level of visual attention, suggesting that attention alone does not fully explain choice behaviour. However, fixation duration appears to provide a more consistent proxy for attention compared to fixation count, as discrepancies between attention and choice are less pronounced when using this metric.

Further analysis explores the relationship between visual attention and self-reported attribute relevance. By comparing gaze allocation across products and labels, we assess whether participants visually focused on the attributes they declared as most important (see Fig. 7). Results partially support this relationship: participants reporting a focus on colour or biofortification generally exhibited higher fixation durations on the corresponding visual elements, particularly in the first shopping occasion. This pattern becomes more consistent in the second round, suggesting that experience with the task improves alignment between attention and stated preferences.

Finally, some evidence of position bias emerges, with a subset of participants systematically choosing options located on the left or right side of the display. Gaze data indicate that visual attention was predominantly directed toward the product (tomatoes) rather than the labels, regardless of the metric used (see Supplementary Materials, Fig. S7), confirming the dominant role of visual cues in shaping initial attention.

While descriptive patterns provide useful initial insights into consumer behaviour, the econometric analysis allows for a more rigorous assessment of the relative importance of product attributes. In particular, the latent class model isolates preferences ceteris paribus and captures heterogeneity in responses to colour and biofortification,

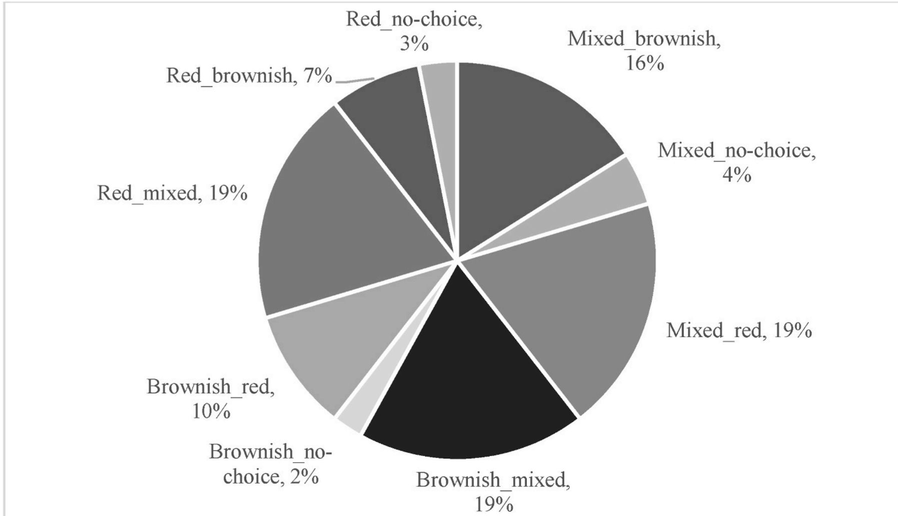

Fig. 5. Share of biofortified tomato purchases across colour options and purchase occasions*
* The first term indicates the product chosen in the first shopping occasion, while the second term refers to the subsequent choice (or the opt-out option). For example, "Red_brownish" indicates a switch from red to brownish tomatoes between the first and second purchase occasions. Percentages refer to the proportion of selected alternatives that were biofortified.

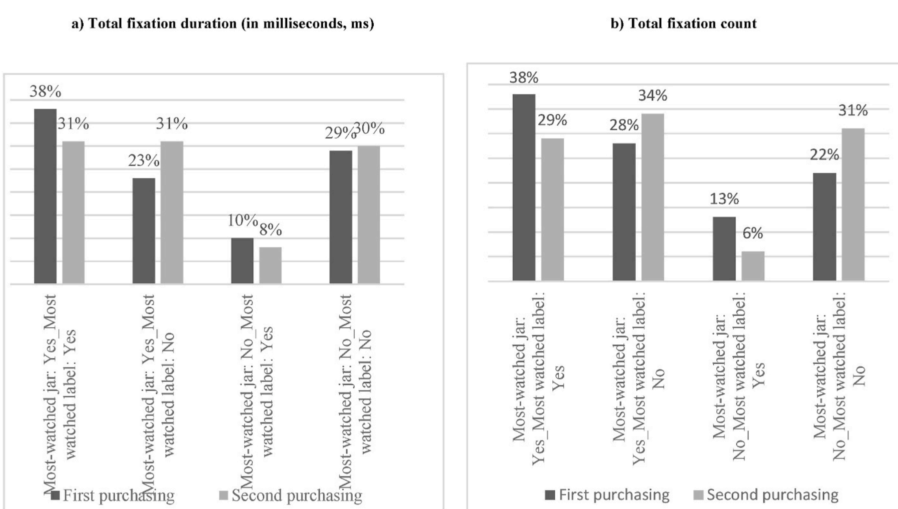

Fig. 6. Distribution of purchases conditional on visual attention patterns, measured through eye-tracking metrics, where visual attention patterns refer to the allocation of gaze across product and label areas during the choice task*
* Categories indicate whether the chosen alternative corresponds to the most visually attended option, based on gaze metrics measured on the product (jar) and its label, thereby distinguishing between choices driven by product attention and those influenced by label information. Percentages represent the share of choices in each category.

offering a more robust basis for interpretation compared to raw purchase frequencies.

As fixation duration is expressed in seconds, coefficient magnitudes should be interpreted relative to the scale of the variable, rather than in absolute terms.

4.3. LC estimations

To address RQ4, we estimate latent class models and assess whether the inclusion of eye-tracking metrics improves model fit and the interpretation of willingness to pay. The optimal number of latent classes was identified by estimating models with two to six classes and evaluating model fit based on the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). While AIC favours models with better fit, it applies a relatively mild penalty for model complexity. In contrast, BIC applies a stricter penalty for additional parameters, thus favouring more parsimonious models [53,54]. Our results show that the lowest AIC was achieved by the five-class model (AIC = 887), whereas the three-class model yielded the lowest BIC (BIC = 961) (see Table 4). Given that BIC is generally preferred in latent class modelling due to its stronger protection against overfitting, we selected the three-class solution as the most appropriate for our data.

After determining the optimal number of latent classes, we estimated two model specifications: a baseline LC model without eye-tracking metrics, and an extended model incorporating these metrics as covariates. Integrating eye-tracking metrics into the LC model improved model fit, as reflected in a reduced AIC value (864 compared to 909), highlighting the added value of visual attention measures in explaining unobserved heterogeneity in consumer preferences.

Table 5 reports coefficient estimates. The latent class model reveals three distinct consumer segments characterised by different preference structures.

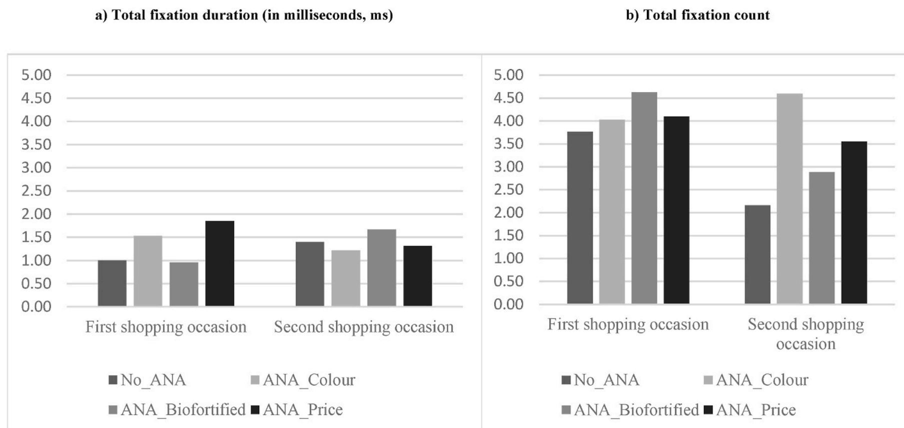

Fig. 7. Differences in fixation duration between product (glass) and label areas across observed attention pattern, across observed attention patterns, defined as the distribution of gaze between product (glass) and label areas.
* Categories indicate the attribute receiving the highest level of visual attention during the choice task, based on gaze metrics. "ANA_Colour", "ANA_Biofortified", and "ANA_Price" identify cases where colour, biofortification, or price, respectively, attracted the highest fixation measure, while "No_ANA" denotes the absence of a dominant attention focus. This classification allows identifying which attribute primarily guided visual attention during the decision process.

Table 4
Fitting statistics.

	2-Classes	3-Classes	4-Classes	5-Classes	6-Classes
AIC	926	905	898	**887**	896
BIC	962	**961**	973	982	1011

AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion.

- "innovation-oriented consumers" (Class 1), comprising 28% of the sample, display a strong and statistically significant positive WTP for both Zn biofortified (+1.00, $p < 0.01$) and brownish tomatoes (+2.20, $p < 0.001$), while remaining neutral toward mixed-colour tomatoes (+0.20, n.s.). This segment also shows a significant negative preference for the no-purchase option (−2.40, $p < 0.001$), indicating a strong inclination to make a purchase;
- "visual-driven innovators" (Class 2), representing 23% of consumers, exhibit significant positive preferences for biofortified (+0.92, $p < 0.05$), brownish (+0.93, $p < 0.05$), and especially mixed-colour tomatoes (+2.50, $p < 0.001$), combined with a strong aversion to the no-purchase option (−2.30, $p < 0.001$). This segment appears particularly responsive to visual stimuli and product differentiation;
- "traditional consumers" (Class 3), the largest segment at 48%, show no significant preference for biofortification (0.00, n.s.), but express significant negative preferences for brownish (−1.90, $p < 0.001$) and mixed-colour tomatoes (−1.00, $p < 0.01$), alongside a strong aversion to the no-purchase option (−3.50, $p < 0.001$), reflecting a more conservative preference structure.

Importantly, the inclusion of eye-tracking variables provides additional insights into the visual drivers of choice. The γ coefficients measure the influence of fixation duration on each jar and label within the choice scenario on the probability that an individual belongs to a given class. Since the covariates are expressed in seconds, coefficient magnitudes should be interpreted relative to the scale of the variable rather than in absolute terms.

Visual-driven innovators (Class 2) and traditional consumers (Class 3) exhibit distinct, often opposite reactions to visual attention measures. For example, Class 2 shows positive and significant responses to fixation duration on red and mixed label options (γ label red = +40, $p < 0.001$; γ label mixed = +44, $p < 0.001$), while Class 3 displays large negative reactions (γ label red = −130, $p < 0.05$; γ label brownish = −180, marginally significant). Similarly, gaze time on jar containers elicits positive effects in Class 2 (e.g., γ jar mixed = +150, $p < 0.001$), but mixed or negative effects in Class 3 (e.g., γ jar brownish = −55, $p < 0.001$). In contrast, innovation-oriented consumers (Class 1) show less pronounced or non-significant visual effects, suggesting that their

Table 5
Coefficient estimates from the Latent Class Model.

	Colour-driven innovators			Variety-oriented innovators			Conservative consumers		
	Estimate		Std. error	Estimate		Std. error	Estimate		Std. error
WTP bio	1.00	**	0.37	0.92	*	0.46	0.00		0.32
ASC brownish	2.20	***	0.46	0.93	*	0.40	−1.90	***	0.33
ASC mixed	0.20		0.44	2.50	***	0.44	−1.00	**	0.35
ASC none	−2.40	***	0.66	−2.30	***	0.67	−3.50	***	0.29
Class constant allocation function				−46.00	***	12.00	48.00	***	9.80
γ label red				40.00	***	0.38	−130.00	*	81.00
γ label brownish				−61.00	***	1.30	−180.00	.	110.00
γ label mixed				44.00	***	0.20	5.70		17.00
γ glass red				−100.00	***	0.85	35.00	**	14.00
γ glass brownish				−66.00	***	2.90	−55.00	***	5.60
γ glass mixed				150.00	***	0.78	49.00	***	3.20
Class_size	28%			23%			48%		

$p < 0.10$; $*p < 0.05$; $**p < 0.01$; $***p < 0.001$. WTP values are expressed in euros.

decisions are less driven by visual attention and more by underlying preferences for product attributes.

Overall, these results demonstrate that integrating behavioural eye-tracking measures into latent class modelling enhances the ability to explain preference heterogeneity, revealing not only attitudinal differences but also distinct visual processing patterns across consumer segments.

5. Discussion

Agronomic results about carpometric traits suggest that the foliar application of Zn-EDTA led to a significant increase (+65% on average across both genotypes) in fruits' Zn content, thus confirming the feasibility of Zn biofortification in mini plum tomatoes [9]. As a consequence of this increase, the coverage of the average requirement for adults (equal to 6.2 mg day^{-1}) [55] based on a 100 g serving of mini plum tomatoes, rose from 1.8% (control fruits) to 3.0% (biofortified fruits). Although this contribution alone is not sufficient, it should be viewed as part of a diversified dietary strategy in which multiple biofortified vegetables contribute to increase the Zn intake, while providing a wide range of phytochemicals and supporting the overall nutrient adequacy [56,57].

On the other hand, this biofortification treatment did not significantly affect fruit size or morphological traits in either cultivar, inducing only minor colour variations that were instrumentally detectable only in 'Angelle' fruits. Specifically, the mean total colour difference (ΔE) between control and treated fruits was 0.8 for 'Angelle' and 0.7 for 'Dolcenera' (data not reported), both well below the commonly accepted minimum threshold (1) for visually perceivable colour differences [58].

This result is pivotal for the entire analysis, as it strongly supports the design of a DCE based on two distinct attributes: Zn biofortification and colour. Since Zn biofortification can be achieved without altering the tomatoes' visual traits, and thus without creating perceptible differences between biofortified and non-biofortified fruits, treating these attributes as independent in the experimental design is justified. This ensures that any consumer preference for a particular tomato colour cannot be attributed to unintended visual cues related to biofortification, and vice versa. Such separation strengthens the internal validity of the lab-based DCE and enhances the reliability of preference estimates. As the Zn-EDTA treatment significantly increased fruit Zn concentration without affecting visually perceivable traits, the biofortification attribute was conveyed to consumers exclusively through the label. Given that consumers are unable to visually distinguish biofortified from non-biofortified tomatoes, the market success of such products is likely to depend on effective communication strategies. Labelling, certifications, and credible information become essential tools to convey the added nutritional value and support consumer uptake.

In terms of consumer behaviour, descriptive evidence highlights a strong appeal for brownish-coloured tomatoes, suggesting a growing openness toward less conventional food appearances. This pattern is consistent with broader trends associated with premiumisation and product differentiation. Curiosity emerges as a key driver of these choices, reinforcing the role of visual novelty in shaping initial purchase decisions. At the same time, the increased selection of the no-purchase option in the second shopping round suggests a tendency toward variety-seeking and avoidance of repetition.

Biofortified products were also frequently selected, indicating a general openness to nutritional innovations. However, more cautious attitudes expressed in stated intentions suggest that repeated adoption may depend on effective communication and consumer trust. Importantly, the combination of biofortification with visually appealing colour assortments appears to enhance product attractiveness, highlighting the complementary role of visible and non-visible attributes.

Spending behaviour further supports this interpretation, as participants allocated a substantial share of their budget to the products, reflecting a willingness to invest in perceived quality or innovation. At the same time, eye-tracking results reveal that visual attention is predominantly directed toward colour, with secondary attention to biofortification and price, suggesting that visible cues play a primary role in guiding initial information processing.

The latent class model provides a more structured interpretation of these patterns, revealing substantial heterogeneity in consumer preferences. Innovation-oriented consumers (Class 1) and visual-driven innovators (Class 2) display positive valuations for both biofortification and non-traditional colours, although with different underlying mechanisms. Innovation-oriented consumers appear generally open to product innovation, while visual-driven innovators are more strongly influenced by visual salience and product differentiation. In contrast, traditional consumers (Class 3) exhibit a more conservative preference structure, with negative valuations for non-conventional colours and no significant preference for biofortification.

These findings highlight how visual and attitudinal factors jointly shape purchasing behaviour across segments. While interaction effects are not formally estimated, the results indicate that the relative importance of colour and biofortification varies across consumer groups, providing insights into their combined role in shaping preferences.

Importantly, the apparent discrepancy between descriptive purchase frequencies and model-based estimates reflects the distinction between observed choices and underlying preferences. While a large share of participants selected brownish tomatoes at least once, these choices were made within specific choice contexts, where trade-offs across attributes, product combinations, and budget constraints influence decisions. In contrast, the latent class model isolates preferences ceteris paribus, revealing that a substantial segment exhibits a negative valuation of brownish tomatoes when controlling for these contextual factors.

6. Conclusions

This study offers a comprehensive understanding of consumer preferences and behaviours in relation to key mini plum tomato attributes by addressing four research questions on the role of visible and invisible attributes, visual attention, and preference heterogeneity in consumer decision-making. In particular, it focuses on Zn biofortification and fruit colour as the core dimensions shaping consumer choice. A major strength of the study lies in the integration of agronomic data with behavioural insights. The confirmation that Zn biofortification can be achieved without perceptible changes in fruit appearance is especially important, as it justifies the independent treatment of biofortification and colour attributes in the DCE, thereby enhancing its internal validity.

The experimental findings, supported by real monetary incentives and enriched by eye-tracking data, reveal that visual cues strongly influence consumer decisions. Brownish-coloured tomatoes attracted notable levels of attention and curiosity, particularly when combined with traditional red varieties. At the same time, consumers showed a generally positive, albeit cautious, attitude toward Zn biofortified products, with novelty and perceived uniqueness emerging as key drivers of choice. The inclusion of eye-tracking data in the choice model enabled a more nuanced understanding of consumer heterogeneity and decision-making processes, and the identification of three distinct consumer segments —Innovation-oriented consumers, visual-driven innovators, and traditional consumers—provides actionable insights for tailoring marketing strategies and guiding future product development.

Overall, the findings provide clear answers to the research questions guiding this study. First, Zn biofortification does not alter visually perceivable fruit traits, confirming its role as a non-visible attribute (RQ1). Second, consumer choices are primarily driven by visible attributes, particularly colour, while biofortification plays a secondary but still relevant role (RQ2). Third, visual attention is associated with choice behaviour, although not fully deterministic, highlighting the importance of gaze patterns in understanding decision processes (RQ3). Finally, the inclusion of eye-tracking metrics improves the interpretation of preference heterogeneity and enhances model fit, supporting their value in discrete choice modelling (RQ4).

However, the study presents some limitations. First, the observed marginal WTP values are relatively high and may partly reflect behavioural economic biases, which do not necessarily align with real-world spending behaviours. In lab experiments involving real monetary incentives, there is a risk that participants treat the experimental budget as windfall or restricted-use money. In line with mental accounting theory, the perceived need to “use it or lose it” may have inflated WTP estimates, even though a residual credit receipt useable for future experiments conducted in the same lab was returned to participants [59]. Moreover, the use of the scientific term “biofortified” may have triggered food neophobia in certain participants. Future research could validate these results using alternative terminology, such as “nutrient-enhanced” or simply “enriched” [60]. Finally, while eye-tracking offered valuable insights into patterns of visual attention, it does not fully capture deeper cognitive evaluations or emotional responses [61]. Future studies would benefit from combining behavioural data with additional physiological or neurological measures, such as EEG or galvanic skin response, to gain more accurate insights into the subconscious processes underlying consumer decision-making.

Nevertheless, despite these limitations, the study provides useful empirical insights that can inform the actions of policymakers, producers, and other stakeholders aiming to develop and promote innovative consumer-oriented food products. From a practical perspective, the findings support the promotion of Zn biofortification programs, as Zn applications can substantially increase fruit Zn content without compromising visually perceivable quality traits, thereby preserving the product's marketability. At the same time, results indicate that product diversification through mixed-colour assortments represents a promising strategy, as colour emerges as a primary driver of visual attention and purchasing behaviour, often outweighing the role of nutritional enhancement during the choice process. In particular, visually distinctive product designs may be especially effective for Visual-driven innovators, while clearer and more informative labelling strategies may be needed to engage more Traditional consumers. Overall, the findings highlight that visible and invisible attributes jointly shape consumer choices through their relative importance rather than through formal interaction effects.

In conclusion, our findings offer actionable insights for policymakers, producers, and stakeholders to foster the adoption of innovative, consumer-oriented food products through effective product design and communication strategies.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT (OpenAI) to improve readability and language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication. ChatGPT was also used to assist in the design of the pictograms included in the graphical abstract and in the preparation of Fig. 2 by providing text-based instructions. The final figures were assembled by the authors.

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CRediT authorship contribution statement

Maria De Salvo: Conceptualization, Formal analysis, Investigation, Methodology, Software, Supervision, Validation, Writing – original draft, Writing – review & editing. **Laura Giuffrida:** Data curation, Investigation, Software, Validation, Visualization. **Marika Cerro:** Data curation, Investigation, Software, Validation, Visualization. **Claudio Cannata:** Data curation, Investigation, Validation, Visualization. **Giovanni Signorello:** Investigation, Methodology, Resources, Writing – original draft, Writing – review & editing. **Giuseppe Cucuzza:** Investigation, Project administration. **Rosario Paolo Mauro:** Formal analysis, Methodology, Validation, Writing – original draft, Writing – review & editing. **Cherubino Leonardi:** Conceptualization, Funding acquisition, Investigation, Methodology, Resources, Supervision, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jafr.2026.103010.

Data availability

Data will be made available on request.

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