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Exploring Consumers' Attitudes towards Food Products Derived by New Plant Breeding Techniques

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Abstract: New plant breeding techniques (NPBTs) are seen as promising and innovative tools to achieve food security and food safety. Biotechnological innovations have great potential to address sustainable food development, and they are expected in the near future to play a critical role in feeding a growing population without exerting added pressure on the environment. There is, however, a considerable debate as to how these new techniques should be regulated and whether some or all of them should fall within the scope of EU legislation on genetically modified organisms (GMOs), despite the product obtained being free from genes foreign to the species. In the EU, the adoption of these methods does not rely only on the scientific community but requires social acceptance and a political process that leads to an improved regulatory framework. In this paper, we present the results of an online survey carried out in Italy with 700 randomly selected participants on consumer attitudes towards food obtained by NPBTs. By applying the decision tree machine learning algorithm J48 to our dataset, we identified significant attributes to predict the main drivers of purchasing such products. A classification model accuracy assessment has also been developed to evaluate the overall performance of the classifier. The result of the model highlighted the role of consumers' self-perceived knowledge and their trust in the European approval process for NPBT, as well as the need for a detailed label. Our findings may support decision makers and underpin the development of NPBT products in the market.

Keywords: agricultural biotechnology; new plant breeding technique; NPBT; consumers' attitude; food safety; machine learning; data mining

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1. Introduction

The selection of more efficient and productive varieties is a practice that began with the birth of agriculture itself when farmers chose the best plants from the wild for domestication [1]. For a long time, conventional breeding techniques have been the only methods to improve cultivated plants [2], requiring many generations to achieve the intended results [3]. In the past, the need to increase yields and obtain quality products has usually been addressed with the use of inputs such as chemical fertilizers, pesticides, and irrigation water, in some cases raising environmental concerns [4].

Scientific advances in molecular biology over the past 50 years have contributed to significant progress in plant breeding and the establishment of genetics as a science [5] with a great potential to increase the resilience of food systems and guarantee food security and food safety. Genetic improvement may provide tools able to stabilize yields, increase resistance to biotic or abiotic stresses, increase drought tolerance, reduce adverse effects of climate change, improve nutritional quality, increase shelf life and reduce allergenicity [6]. Despite these advantages, gene editing may cause unintentional implications and genetic errors, and the effect on human health and the environment has still to be proven.

The recombinant DNA technique has been the most innovative method introduced thus far. It has made it possible to insert genes into organisms to encode desirable traits [7], reducing the time required to achieve varieties with improved agronomic and nutritional characteristics [8]. These kinds of organisms have been designated genetically modified organisms (GMOs) and are often considered transgenic cultures because of the introduction of foreign genes [9].

The new genome editing methodologies fall into a broader category of techniques defined as new plant breeding techniques or NPBTs, which have aroused great interest in the scientific community [10–14]. They have been developed to improve the accuracy and speed of breeding [15,16] and to modify existing genes rather than adding genes from other species [17], a technique used in many GMO technologies. According to some experts, this makes it difficult to determine the difference between varieties obtained from NPBT and varieties obtained from conventional breeding since identical point mutations could also occur naturally [18]. The main applications of NPBT are cisgenesis and intragenesis, direct mutagenesis by oligonucleotides, independent DNA and RNA methylation, reverse varietal selection, and agroinfiltration [19].

Notwithstanding the positive opinion of many experts in the field of molecular biology and the interest shown by stakeholders, many policymakers and lobby groups are unconvinced. The differing opinions on safety and related regulatory policies have led to substantial controversy.

Today, European legislation appears to be stringent, generating a debate regarding Directive 2001/18 EC, which categorizes NPBT products as GMOs and, therefore, are subject to a risk assessment to obtain EU authorization [12]. This discourages breeders and biotech companies, which instead pursue possibilities in other countries where plant breeding regulations are less rigorous.

The agricultural biotech industry and connected groups encourage the use of new genetic modification techniques, claiming that they are precise, safe, and controlled and provide us the tools to meet the challenges of environmental overexploitation and climate change.

However, these claims are used to assert that these techniques should be exempted from the EU's GMO regulations and not subject to safety and traceability rules or GMO labeling since they are essentially traditionally bred varieties. On the other side, environmental groups, food retailers, small farmers, and the organic industry criticize this position, insisting that these techniques are fundamentally different from natural processes and that there may be unintentional negative effects. The issue has, therefore, wide implications for investments in plant breeding and trade in agricultural products [20].

In light of this debate, this research aimed to explore consumers' opinions and attitudes toward food derived from NPBTs. It reports the results of a survey conducted in Italy in which respondents had the possibility to express their potential intentions to purchase products derived from NPBTs. To this purpose, we have applied a data mining methodology to discover the relation among attributes, applying a classification algorithm (J48) to predict consumers' behavior.

2. EU Regulation of NPBTs and the Ongoing Debate

The varieties obtained from NPBTs are regulated as GMOs, according to Directive 2001/18 EC [12]. Article 2 defines GMOs as "an organism, except humans, in which the genetic material has been altered in a way that does not occur naturally by mating and/or natural recombination". The Directive aims to protect human health and the environment [12]. The Directive does not apply directly to approvals for the import and processing of genetically modified food and feed, which are governed by Regulation 1829/2003 (EC 2003a) and are defined as "containing, consisting of or produced from GMOs" [21]. It is worth noting that all food and feed covered by Regulation 1829/2003 are also subject to labeling and traceability requirements (EC 2003b) [22].

European Union decides whether to authorize the release of new varieties based on the scientific opinion of the European Food Safety Authority (EFSA), which assesses plant varieties resulting from genetic techniques based on compositional analysis, molecular characteristics, mode of action of the protein expressed by the newly introduced gene, changes in metabolic pathways, and environmental exposure [23]. The process of obtaining the authorization demands high costs and long waiting times for breeders who instead find more possibilities for growth in other countries. In the European Union, approval of a GM crop costs between 11 and 17 million euros and takes, on average, 6 years [24].

On 25 July 2018, the Court of Justice of the European Union (CJEU), upon the request of the French Council of State, has further confirmed that organisms obtained by mutagenesis are GMOs, therefore subject to the requirements of the EU GMO legislation and the obligations of EU-wide authorization processes, traceability, and labeling rules [25,26]. This judgment discouraged European breeders, scientists, and stakeholders, stirring up debate on how the new techniques should be regulated. The focal point is whether the regulation of NPBTs should be product-based or process-based [2].

There are two main points of view: The first is that of advocates for unregulated use and approval of these techniques, which call for an evidence-based approach to proving an organism's harm to human health and the environment [27]. On the opposite side are proponents of a regulatory approach, favoring a comprehensive risk evaluation of GMOs. Advocates of this point of view believe that in the absence of scientific data regarding the probability that an organism will cause harm, products should be removed from the market until they are proven safe [28].

On 29 April 2021, the European Commission published a new study on NPBTs based on the opinions of EFSA and main stakeholders in the member countries of the EU. The study reaffirmed that organisms obtained through NPBTs are considered GMOs, but it also expressed concerns about the current legislation, whose lack of definitions or clarity on the meanings of the key terms causes ambiguity. As NPBTs constitute a heterogeneous group of techniques, EFSA has identified some techniques that have no new hazards compared to conventional techniques [13].

The report stressed the need to develop specific risk assessment procedures for NPBTs. Moreover, the study highlighted the possibility that the EU could encounter problems in international trade relations with countries that approve and use the new genetic engineering techniques. It is extremely complex to distinguish varieties of genetic techniques derived from natural or induced mutants, with consequent implications on world trade, such as a substantial decrease in the number of raw materials imported from third countries, on which the European Union and Italy, in particular, rely.

Therefore, in light of the different regulatory frameworks for NPBTs in other countries, such as the United States and Brazil, which do not specifically regulate genome edited crops, the EU could run into commercial limitations and confusion and thus put European stakeholders at a competitive disadvantage [29]. As a consequence, plant breeding companies have stronger motivations to relocate their research to other countries.

The GMO regulatory process is seen as time consuming and very costly, especially for small–medium enterprises (SMEs) that may lack the know-how and the financial power to face this challenge [30].

Furthermore, EFSA confirms that many of the plant products obtained from NPBTs have the potential to contribute to the Sustainable Development Goals through the EU's Green Deal goals and "Farm to Fork" strategy. The study highlights "the need to make legislation more resilient, future-proof and uniformly applied". The current European regulatory system on NPBTs still remains unclear in its scope and implementation, ill-suited to the advances of the scientific community regarding rapid developments in genetics and genome editing, and poorly harmonized with equivalent systems.

During the development of the study, the issue of consumer perspective remains the key point to consider, as they remain the most important players in influencing the trajectories of agricultural biotechnology innovation.

3. Research Design and Data Analysis

3.1. Data Collection

An online survey was carried out in Italy from March 2021 to June 2021 and disseminated via social media channels. A snowball sampling technique was used to gather responses to our survey [31]. It was adopted to generate a pool of participants for our study through referrals made by individuals to recruit people who have heard of genetic improvement techniques, although they were not well informed. The final sample size was made up of 700 respondents.

The study was grounded in literature concerning consumers' attitudes towards food purchasing habits with the aim to further validate previous research and address the research questions. The questionnaire included only closed questions. It consisted of three parts: the first part focused on the socio-demographic profile of the respondents; the second part explored consumers' food purchasing behavior; the third part addressed the respondents' acceptance and intention to purchase products derived from new breeding techniques. The surveys provided fundamental information, starting with the definition of new plant breeding techniques. The difference between NPBTs and GMOs was highlighted since, in common perception, the two terms often overlap. Participants were also informed that to date, the cultivation of plants and the marketing of products derived from NPBTs is not allowed in Italy, as well as in most European countries, and as such, the products fall under the regulation of GMOs.

3.2. Socio-demographic Characteristics of the Respondents

The socio-demographic profile of the participants is presented in Table 1. Most of the respondents were women (65%), with 39% of all respondents aged under 25, 38% between 26 and 49, and 23% over 50. The respondents' average level of education is high: most have a high school degree (42.6%) or a university degree (43%). The respondents' level of income corresponds to the average distribution of the Italian population: 46.1% have an income between 20,000 € and 50,000 € and 42.3% less than 20,000 €. Considering the country in terms of Northern, Central, and Southern Italy, as conventionally used in official Italian statistics, most of the responses were from southern Italy (77.6%) and a smaller percentage from northern Italy (17%) and central Italy (5.4%).

Table 1. Demographic distribution of survey participants (number and percentage of responses).

Gender	Male	241	34.4
	Female	459	65.6
Age	<25	275	39.3
	26–49	263	37.6
	>50	162	23.1
Residence area	South Italy	534	77.6
	North Italy	119	17.0
	Center Italy	38	5.4
Education	Middle school	62	8.9
	High school	298	42.6
	University degree	301	43.0
	Doctorate/maste	39	5.6

Table 1. *Cont.*

Occupation	Student	287	41.0
	Employment	331	47.3
	Unemployment	82	11.7
Income	<20,000€	296	42.3
	20,000€–50,000€	323	46.1
	>50,000€	81	11.6

3.3. Consumers' Food Purchasing Behaviour

We adopted a 5-point Likert scale (1 = Strongly Disagree, 2 = Disagree, 3 = Uncertain, 4 = Agree, 5 = Strongly Agree) to analyze consumers' food purchasing behavior and to measure the intensity of respondents' opinions [32], thereby collecting more detailed information than a dichotomous survey [33]. We proposed some topics of interest to respondent consumers to evaluate to what extent these issues guide consumers' purchasing choices.

The software Tableau was used to create a graph of the survey results. Tableau provides multiple tools such as analytics, data mining, data visualization, and data infrastructure, allowing the user to visualize a large amount of information [34].

From Figure 1, it is possible to observe the aspects which drive consumer purchasing choices.

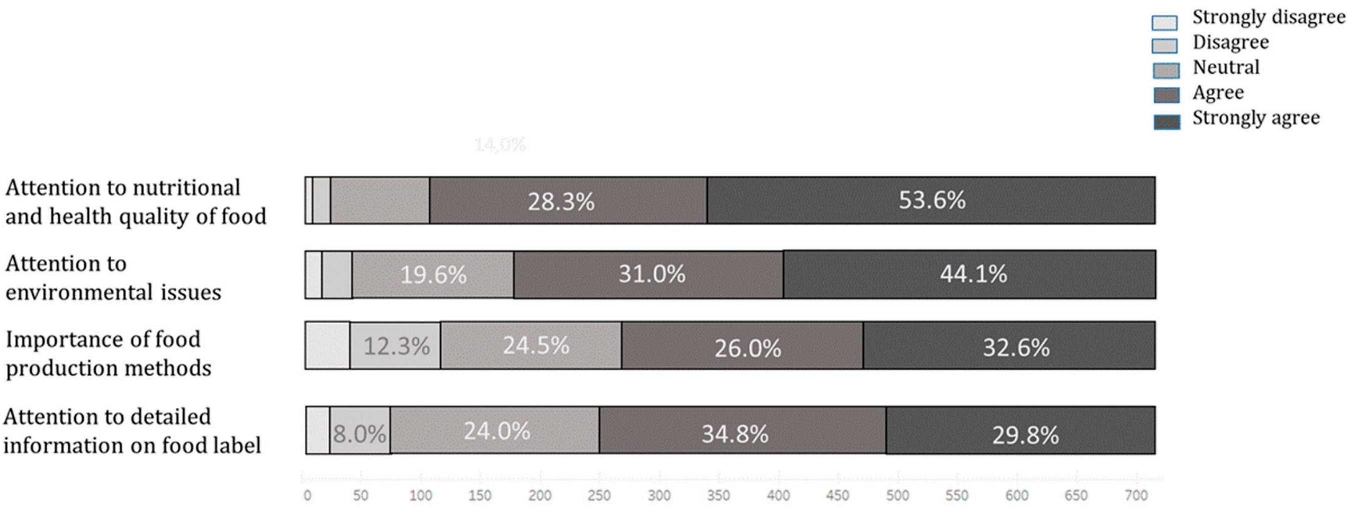

Figure 1. Survey results on factors driving consumers' choice of food. Source: our elaboration with Tableau Software.

The most important aspect for respondents is health qualities of the product (53.6%). Moreover, consumers pay attention to environmental issues. Hence they may be likely to purchase "green" products (44.1%).

The consideration of the process used to obtain the product is more diversified among the respondents. The highest percentage (32.6%) consider this aspect very important or somewhat important (26%), but a relatively high percentage is indifferent to the topic (24.5%).

The importance of the product label is also, in this case, diverse: the respondents seem split between those who pay a lot of attention to the label (29.8%) and those who do not pay particular attention to its content (24%).

3.4. Prediction of Acceptance and Intention to buy NPBTs: A Decision Tree Classification

In recent years there has been a growing interest in the application of artificial intelligence (AI) tools for the identification of regularity phenomena in a set of complex data. Data extraction using specific AI algorithms allow the user to obtain higher levels of information synthesis and to study the possible cause-effect relationships among the available data [35,36]. This highlights the strategic role of some information and the irrelevance of others. This process is known as data mining, which is only one of the phases of a larger interactive process called knowledge discovery in database (Kdd).

Data mining techniques are mainly used to build predictive models for determining the future behavior of some relevant attributes. Classification, one of the major aims of data mining, is used to discover the relationship between the class attribute and other attributes. This knowledge can be utilized to predict the class label, which is not known in advance. The decision tree, a supervised machine learning algorithm, is a multidimensional classification method that is widely adopted for classification purposes [37]. This method predicts class membership by recursively splitting the dataset into smaller subsets for each branch [38] based on the "divide and conquer strategy" often applied in data analysis [39]. This process is then repeated at each node on the branch until a leaf node is reached. The output is a hierarchical decision tree structure where instances are ordered down the tree from the root node to a leaf node, which provides the classification of the instances. Basically, a decision tree defines a set of paths from the root node to the leaf nodes by running a series of tests. Based on information theory approach, the algorithm employs entropy in relation to the information contained in a probability distribution. The goal is to select the attribute that is most useful for classifying instances according to the so-called information gain, a measure that reveals how much information a feature provides about a class. Information gain helps to determine the order of attributes in the nodes of a decision tree [40].

In our study, we adopted decision tree J48, one of the best machine learning algorithms for classification of data [41]. It is an improved version of C4.5 algorithms developed by Quinlan and implemented in Weka, an open-source machine learning software. Weka contains a collection of visualization tools and algorithms for data analysis and predictive modeling, together with graphical user interfaces for easy access to these functions. The software supports several standard data mining tasks, more specifically, data preprocessing, clustering, classification, regression, visualization, and feature selection. In this research, the J48 decision tree has proved to be a suitable method to explore consumers' attitudes towards NPBT products since it is an exploratory analysis process in which we gather to predict a future outcome. Decision tree is a data mining technique for solving classification and prediction problems. Data mining consists of different methods and algorithms used for discovering knowledge from large datasets.

For this purpose, the classification attribute considered was intention to purchase.

Based on literature analysis [42–46], we have identified a set of attributes that have been included in the database: conditions of purchasing, concerns, barriers, degree of self-perceived knowledge, detailed label, and trust in EU food safety. All the information included in the model is shown in Table 2. For each attribute, the respective items, response count, and response percentage are shown.

Based on our set of attributes, a decision tree was induced to predict the relationship of each attribute to consumers' intention to purchase. Table 3 shows the main branches of the tree for predicting consumers' attitudes toward NPBT products. The table reports the decision rules that can be read as a simple IF-THEN statement, consisting of a condition and a prediction. For example: IF the knowledge is high AND the products are perceived as environmentally friendly (condition), THEN the consumer is willing to buy it (prediction).

Table 2. Model information.

Attributes	Number of Items	Items	Count	%
Conditions of purchasing	3	Useful for human health (enhanced with nutrient attributes)	487	69.6
		Lower price compared to the conventional breeding product	183	21.1
		Beneficial for environmental sustainability (reduced pesticides, water use and food waste, resistence to pests and diseases)	30	4.3
Consumers' concerns on NPBT food products	4	No concerns	129	18.4
		Potential risks for human health	219	31.3
		Ethical concerns (over exploitation of these techniques)	93	13.3
		Potential negative impact on made in Italy conventional food products	31	4.4
Barriers to the diffusion of NPBT products in EU market	3	Costs of the regulatory adoption	286	40.9
		Costs to develop new varieties	164	23.4
		Lack of consumers trust in engineering genetic techniques	209	29.9
Level of self-perceived knowledge	3	High knowledge	128	18.3
		Low knowledge	499	71.3
		No knowledge	69	9.9
Detailed label for risk mitigation	3	Important	579	82.7
		Not important	24	3.4
		Maybe important	89	12.7
Trust in EU food safety authorities	3	High trust	365	52.1
		Medium trust	231	33.0
		No trust	101	14.4

Table 3. J48 Decision tree model for consumers' attitude towards NPBT products.

<table>
<tr><td>Knowledge = LOW</td></tr>
<tr><td>| Detailed label = Maybe important: Maybe (27.04/0.04)</td></tr>
<tr><td>| Detailed label = Important</td></tr>
<tr><td>| Factors affecting purchase = cheaper: Maybe (117.0/6.0)</td></tr>
<tr><td>| Factors affecting purchase = environmental_friendly</td></tr>
<tr><td>| Trust in EU Food safety = low: Yes (0.0)</td></tr>
<tr><td>| Trust in EU Food safety = high: Yes (8.14/2.0)</td></tr>
<tr><td>| Trust in EU Food safety = medium: Maybe (5.09/1.09)</td></tr>
<tr><td>| Factors affecting purchase = healthier: Maybe (33.0/5.0)</td></tr>
<tr><td>| Detailed label = Not important: No (19.03/0.03)</td></tr>
<tr><td>Knowledge = HIGH</td></tr>
<tr><td>| Factors affecting purchase = cheaper: Maybe (33.0/15.0)</td></tr>
<tr><td>| Factors affecting purchase = environmental_friendly: Yes (164.66/1.0)</td></tr>
</table>

Table 3. *Cont.*

∣ Factors affecting purchase = healthier: Yes (268.0/2.0)
∣ Detailed label = Maybe important: Maybe (3.0/0.0)
∣ Detailed label = Important: Maybe (21.03/0.03)
∣ Detailed label = Not important: No (2.0/0.0)
Knowledge = NO
∣ Detailed label = Maybe important: Maybe (3.0/0.0)
∣ Detailed label = Important: Maybe (21.03/0.03)
∣ Detailed label = Not important: No (2.0/0.0)

Data visualization (Figure 2) provides clear information efficiently and in an understandable way.

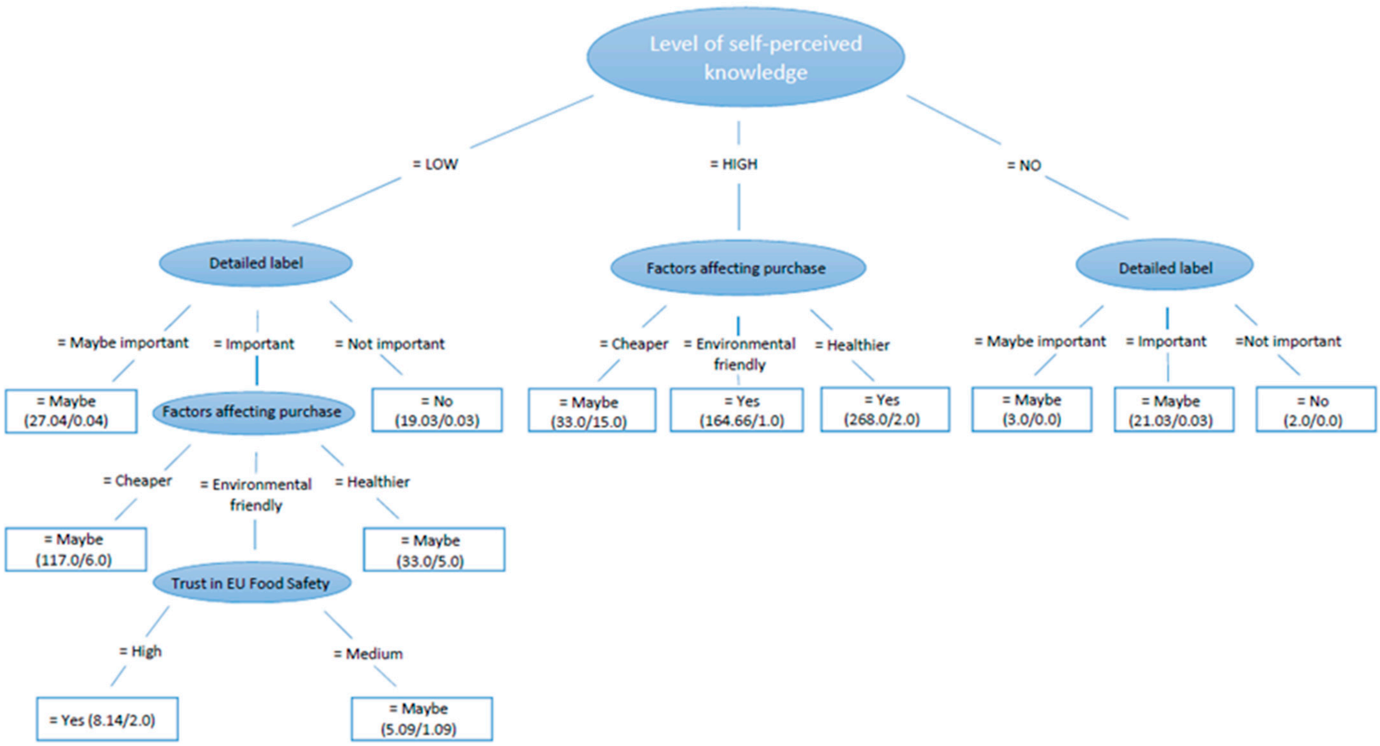

Figure 2. J48 Graphical representation of decision tree model.

Weka software applies the conventional 10-fold cross-validation to estimate the skill of a machine learning model to uncover hidden patterns. Often the procedure has a single parameter k that refers to the number of groups into which a provided data sample is to be split. Therefore, it is called k-fold cross-validation. In our case study, we have chosen a specific value for k, i.e., k = 10, becoming 10-fold cross-validation. Cross-validation is a resampling procedure used to evaluate machine learning models on a limited data sample. During this process, the software trains and evaluates 10 subsets to estimate how useful the learned model is for prediction. In Table 3 and in Figure 2, the statistic in brackets summarizes the performance of the classification. The first value is the total number of instances in each leaf. The second value shows the number of instances incorrectly classified in that leaf. When a value of the attribute in a tree is not known, the system splits the case and sends a fraction down each branch. The three important attributes according to the model are: level of self-perceived knowledge, factors affecting purchasing, and detailed label. The "level of self-perceived knowledge" appears as the first splitting attribute in the decision tree, i.e., the attribute that can best discriminate among the others. These are reasonable results, considering the well-established axiom that lack of information can generate skepticism and mistrust towards specific scientific and technological innovations.

The model shows that if the degree of self-perceived knowledge is high, respondents who have an adequate or very good understanding of the issue are willing to buy these products when there is a strong association with specific benefits for human health and for the environment, whereas the price does not seem to be such a relevant driver of motivation to purchase. If the degree of knowledge is low, the model predicts that a detailed label is crucial if it is associated with a collective benefit. This occurs in the presence of a high level of trust in European food safety authorities. Even if there is a lack of knowledge, a detailed label plays an important role, although consumers still seem to be undecided.

3.5. Assessing Classifier Performance

We have used the classification accuracy and confusion matrix in order to analyze how predictive our model is. In the present work, the accuracy is estimated as 94.3%. Classification accuracy by class (Table 4) summarizes the performance of a classification model as the number of correct predictions divided by the total number of predictions. However, using accuracy as a performance measure assumes that the class distribution is known and, more importantly, that the errors of incorrectly classified instances are equal. Accuracy may be particularly problematic as a performance measure when the dataset studied is biased in favor of a majority class [47]. In addition, we have used the statistical metrics Precision (P), Recall (R), and F-Measure (the harmonic mean of precision and recall values, it allows us to evaluate P and R together). Specifically, recall is the ability of a model to find all the relevant cases within a dataset. It is defined as the number of true positives divided by the number of true positives plus the number of false negatives. Precision quantifies the number of positive class predictions that rightfully belong to the positive class. As precision increases, recall decreases and vice-versa. Matthews correlation coefficient (MCC) is a robust metric that summarizes the classifier performance in a single value if positive and negative cases are of equal importance.

Table 4. Detailed accuracy by class.

TP Rate	Fp Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
0.977	0.728	0.858	0.977	0.914	0.875	0.959	0.924	Maybe
0.945	0.020	0.989	0.945	0.966	0.909	0.971	0.963	Yes
0.655	0.000	1000	0.655	0.792	0.803	0.803	0.716	No
0.943	0.036	0.949	0.943	0.943	0.895	0.966	0.941	Weighted Avg.

In machine learning, performance can also be calculated using the AUC (Area Under the Curve) and ROC (Receiver Operating Characteristics) area to summarize the overall accuracy of the classifier. It takes values from 0, which indicates a perfectly inaccurate classification, to 1, which reflects a perfectly accurate test. The precision–recall curve (PRC) can be interpreted as the relationship between precision and recall (sensitivity) and is considered to be an appropriate measure for unbalanced datasets.

An alternative method to gain better insight into the classification and misclassification distribution is the confusion matrix (Table 5). It contains information about actual and predicted classifications made by a classification system [47]. It shows the correct classification against the predicted classification for each class. The number of correct predictions can be found on the diagonal of the matrix. All other numbers represent the numbers of misclassification errors. Misclassifications occur when the row and column classes of a cell do not match. If the intersection across predicted and actual classes of different levels is empty (or zero), then no misclassification has occurred. In our case, the matrix can be interpreted as 212 instances correctly classified in class "a" (Maybe), 5 instances incorrectly classified in class "b" (Yes), and 0 incorrectly classified in class "c" (No).

Table 5. Confusion Matrix.

a	b	c	
212	5	0	a = Maybe
25	430	0	b = Yes
10	0	19	c = No

4. Results and Discussion

Data analysis has shown how the degree of self-perceived knowledge affects the consumers' intention to purchase food obtained by NPBTs. Results of the study demonstrate that perceived knowledge is the most relevant driver of people's risk, benefit, and value perception.

Evidence from previous studies confirms that higher levels of knowledge promote positive acceptance to purchase [48,49], especially when consumers perceive benefits for human health and for the environment, which are issues considered by consumers during their purchasing decisions. This is confirmed by the increasing attention to sustainable food consumption and by people's awareness of their role and responsibilities towards the environment, individual and public health, habitat and biodiversity, social cohesion, and economy [50]. This consciousness leads to a change in consumer attitudes towards a "green" lifestyle, starting with everyday consumption choices [51].

Our results show that consumers who are familiar with NPBTs are more positive toward and more willing to buy such products, especially in relation to their impact on reducing inputs such as chemical fertilizers and pesticides to mitigate greenhouse gas emissions and improve water use efficiency [52]. Health considerations are also crucial drivers in food purchasing decisions. Respondents who consider themselves informed about genetic techniques would be willing to buy NPBT products if they enhance the food's nutritional and health benefits. Despite that, in economic literature, price is usually considered one of the main drivers of food consumer behavior [53], in the case of NPBT products, it appears to be not so relevant. Our findings show that consumers do not pay as much attention to economic convenience as they are interested in products with specific characteristics such as health and environmental aspects [54].

However, several studies underline the differences between stated and revealed preferences, finding that consumers tend to overestimate their valuation of a particular good, service, or outcome, which can lead to misleading estimates of relative value [55]. Therefore, in our study, individuals' stated preferences may not correspond closely to their actual preferences, and this can be considered a drawback of the results obtained.

The model has also revealed that consumers' concerns about NPBT food products are not seen as a threat to the type made in Italy's agri-food system, which is strongly linked in local production with certification labels [56].

When consumers' self-perceived knowledge is low, our model highlights the importance of a detailed label. Hence, a poor self-perceived knowledge does not result in the intention to purchase if not supported by clear and understandable information on the product characteristics [57]. Literature about consumption stresses the key role that the label plays in communicating information about the improved characteristics of novel food and how the food was produced [45]. Consumers' interest in the characteristics of the process makes label essential to learn more about the new food and how it is derived. This output is in line with the notion that consumers routinely rely on experts in the case of complex decisions, which is an admission of knowledge inadequacy [55].

For this group of respondents, the degree of confidence in EU food security is a discriminating factor: if trust is high, consumers are more confident in buying food derived from agricultural biotechnology. This suggests that if the European food safety authorities approved the diffusion of NPBT products, consumers would feel more comfortable buying them.

The lack of knowledge about agricultural biotechnologies brings out a psychological bias derived from the perceived distance between these products and the conventional ones. Consumers that consider NPBT unfamiliar mistrust and fear these products [58–61]. Indeed, familiarity with the product usually leads to a different perception of uncertainty. Consumers who are not familiar with a product tend to believe that they are a higher risk [62]. This behavior in food consumption is called neophobia, the reluctance of individuals to try novel food [63], and can also be seen as the averseness toward new methods of production [64–66].

Our model shows that this gap in knowledge may be compensated for with a detailed label. Indeed, in an increasingly complex food system, consumers need to have accurate information on the characteristics of the food purchased [67,68]. This is in line with the overall EU regulations on labeling, traceability, and quality assurance systems which offer extensive and accessible information to the consumer [69].

The results of the study highlighted that attitude and acceptance change with knowledge. Therefore, in the framework of consumers' concerns arises the need for balanced information and the importance of translating science into laymen's language, which can help informed decisions of consumers.

5. Concluding Remarks

Few studies have investigated the attitude of Italian consumers toward NPBT foods products, and this work tried to contribute to filling this gap in the literature. In this paper, we have used machine learning to classify potential consumers and to acquire efficient information on the attributes that are most important in predicting their behavior towards NPBT products. This study confirms that J48 is a useful tool for the construction of a hierarchical decision support model. The study revealed that consumers are still fearful and uncertain but somehow positive, especially those concerned about the environment and human health. Our study attempted to go beyond a binary "for" or "against" genetic techniques to provide more nuanced data about consumer attitudes that depend on a hierarchy of attributes.

We have seen how the viewpoint of the consumer changes in relation to their level of self-perceived knowledge on the topic. In general terms, being informed greatly reduces the fear and the perception of the risk consumers associate with the product. Knowledge helps consumers understand and, therefore, not reject a priori possibilities that may be advantageous. Mandatory labeling is probably the way to promote consistent decisions. However, current EU regulations do not allow consumers to distinguish NBTs from transgenic products, as the European Court of Justice has ruled that NBTs must fall under the GMO Directive. Policymakers should address advancements in genome editing technologies with proper regulation.

Moreover, there is not an information strategy that may change the trend and empower consumers to deliberately choose among different food options without diffidence. To reverse consumer uncertainty toward NPBT foods, targeted communication campaigns to disseminate their benefits may have major implications for further development and commercialization in the European market. Additionally, a full understanding of the diffusion of NPBT technologies would require further research work. In particular, it would be interesting to analyze the pressure of interest groups in contributing to the social construction of risk.

This study presents some limitations. Firstly, the analysis of the potential willingness to buy intention to purchase new products was carried out in the absence of a real market, hence, stated preference survey responses may not predict actual behavior, leading to hypothetical bias. Future validation of these findings will be possible once NPBT foods are widely available in the EU market. In addition, the sample size is not representative of the overall Italian population, and therefore the quantitative outcomes should not be interpreted as such. However, we have accepted this biased sample since our goal was to survey opinion at an informative level and not for a study of a target population. From our point of view, the outcome does not affect the validity of the results, and they can be accepted because, in this study, consumers' opinion is generalizable across a population in the same geographical area.

Finally, although online surveys are recognized as valid methods that have quickly gained popularity in research due to their low cost and time savings [70,71], they could present a lack of potential depth and suffer correct guessing.

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References

1. Lusser, M.; Parisi, C.; Plan, D.; Rodríguez-cerezo, E. *New Plant Breeding Techniques State-of-the-Art and Prospects for Commercial Development New Plant Breeding Techniques State-of-the-Art and Prospects*; Publications office of the European Union: Luxembourg, 2011; ISBN 9789279197154.
2. Sprink, T.; Eriksson, D.; Schiemann, J.; Hartung, F. Regulatory hurdles for genome editing: Process- vs. product-based approaches in different regulatory contexts. *Plant Cell Rep.* **2016**, *35*, 1493–1506. [CrossRef] [PubMed]
3. Wilde, H.D. Induced mutations in plant breeding. *Adv. Plant Breed. Strateg. Breeding Biotechnol. Mol. Tools* **2016**, *1*, 329–344. [CrossRef]
4. Huang, J.; Pray, C.; Rozelle, S. Enhancing the crops to feed the poor. *Nature* **2002**, *418*, 678–684. [CrossRef] [PubMed]
5. Gepts, P. A comparison between crop domestication, classical plant breeding, and genetic engineering. *Crop Sci.* **2002**, *42*, 1780–1790. [CrossRef]
6. Qaim, M. Role of New Plant Breeding Technologies for Food Security and Sustainable Agricultural Development. *Appl. Econ. Perspect. Policy* **2020**, *42*, 129–150. [CrossRef]
7. Qaim, M. The Economics of Genetically Modified Crops. *Annu. Rev. Resour. Econ.* **2009**, *1*, 665–694. [CrossRef]
8. Oliver, M.J. Why we need GMO crops in agriculture. *Mo. Med.* **2014**, *111*, 492–507.
9. Qaim, M. Genetically Modified Crops and Agricultural Development. *Genet. Modif. Crop. Agric. Dev.* **2016**, *18*, 95–101. [CrossRef]
10. Hartung, F.; Schiemann, J. Precise plant breeding using new genome editing techniques: Opportunities, safety and regulation in the EU. *Plant J.* **2014**, *78*, 742–752. [CrossRef]
11. Eriksson, D.; Custers, R.; Edvardsson Björnberg, K.; Hansson, S.O.; Purnhagen, K.; Qaim, M.; Romeis, J.; Schiemann, J.; Schleissing, S.; Tosun, J.; et al. Options to Reform the European Union Legislation on GMOs: Scope and Definitions. *Trends Biotechnol.* **2020**, *38*, 231–234. [CrossRef]
12. Council Directive 2001/18/EC Directive 2001/18/Ec of the European Parliament and of the Council of 12 march 2001 on the deliberate release into the environment of genetically modified organisms and repealing Council directive 90/220/EEC. *Off. J. Eur. Communities* **2001**, *L106*, 1–60.
13. European Commission (EC). *Study on the Status of New Genomic Techniques under Union Law and in Light of the Court of Justice Ruling in Case C-528/16*; European Commission (EC): Brussels, Belgium, 2021; 116p.
14. Jorasch, P. Potential, Challenges, and Threats for the Application of New Breeding Techniques by the Private Plant Breeding Sector in the EU. *Front. Plant Sci.* **2020**, *11*, 1463. [CrossRef] [PubMed]
15. Vats, S.; Kumawat, S.; Kumar, V.; Patil, G.B.; Joshi, T.; Sonah, H.; Sharma, T.R.; Deshmukh, R. Genome editing in plants: Exploration of technological advancements and challenges. *Cells* **2019**, *8*, 1386. [CrossRef]
16. Hickey, L.T.; Hafeez, A.N.; Robinson, H.; Jackson, S.A.; Leal-Bertioli, S.C.M.; Tester, M.; Gao, C.; Godwin, I.D.; Hayes, B.J.; Wulff, B.B.H. Breeding crops to feed 10 billion. *Nat. Biotechnol.* **2019**, *37*, 744–754. [CrossRef]
17. Rani, R.; Yadav, P.; Barbadikar, K.M.; Baliyan, N.; Malhotra, E.V.; Singh, B.K.; Kumar, A.; Singh, D. CRISPR/Cas9: A promising way to exploit genetic variation in plants. *Biotechnol. Lett.* **2016**, *38*, 1991–2006. [CrossRef]

18. Grohmann, L.; Keilwagen, J.; Duensing, N.; Dagand, E.; Hartung, F.; Wilhelm, R.; Bendiek, J.; Sprink, T. Detection and identification of genome editing in plants: Challenges and opportunities. *Front. Plant Sci.* **2019**, *10*, 236. [CrossRef]
19. Zimny, T.; Sowa, S.; Tyczewska, A.; Twardowski, T. Certain new plant breeding techniques and their marketability in the context of EU GMO legislation—recent developments. *N. Biotechnol.* **2019**, *51*, 49–56. [CrossRef]
20. Purnhagen, K.; Wesseler, J. EU Regulation of New Plant Breeding Technologies and Their Possible Economic Implications for the EU and Beyond. *Appl. Econ. Perspect. Policy* **2021**, *43*, 1621–1637. [CrossRef]
21. European Commission REGULATION (EC) No 1830/2003 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 22 September 2003 concerning the traceability and labelling of genetically modified organisms and the traceability of food and feed products produced from genetically modified o. *Off. J. Eur. Union* **2003**, *31*, 24–28.
22. EU Regulation (EC) No 1829/2003 of the European Parliament and of the council on genetically modified food and feed. *Off. J. Eur. Union* **2003**, *L 268*, 1–23.
23. Laanen, T. New plant-breeding techniques Applicability of GM rules. *Eur. Parliam. Res. Serv.* **2016**, 1–8. Available online: https://www.europarl.europa.eu/thinktank/es/document/EPRS_BRI(2016)582018 (accessed on 1 October 2021).
24. EuropaBio Pricing Innovation out of the EU: Counting the Costs of GMO Authorisations. *Croplife Eur.* **2019**, *38*, 2008.
25. Eckerstorfer, M.F.; Engelhard, M.; Heissenberger, A.; Simon, S.; Teichmann, H. Plants developed by new genetic modification techniques-Comparison of existing regulatory frameworks in the EU and Non-EU countries. *Front. Bioeng. Biotechnol.* **2019**, *7*, 26. [CrossRef] [PubMed]
26. Conf, L.; Conf, L. Corte di giustizia dell' Unione europea Gli organismi ottenuti mediante mutagenesi costituiscono OGM e, in linea di principio, sono soggetti agli obblighi previsti dalla direttiva sugli OGM. 2018, pp. 2001–2002. Available online: https://curia.europa.eu/jcms/upload/docs/application/pdf/2018-07/cp180111it.pdf (accessed on 15 September 2021).
27. Enfissi, E.M.A.; Drapal, M.; Perez-Fons, L.; Nogueira, M.; Berry, H.M.; Almeida, J.; Fraser, P.D. New plant breeding techniques and their regulatory implications: An opportunity to advance metabolomics approaches. *J. Plant Physiol.* **2021**, *258–259*, 153378. [CrossRef]
28. Gelinsky, E.; Hilbeck, A. European Court of Justice ruling regarding new genetic engineering methods scientifically justified: A commentary on the biased reporting about the recent ruling. *Environ. Sci. Eur.* **2018**, *30*, 52. [CrossRef]
29. Lassoued, R.; Smyth, S.J.; Phillips, P.W.B.; Hesseln, H. Regulatory uncertainty around new breeding techniques. *Front. Plant Sci.* **2018**, *9*, 1291. [CrossRef]
30. Hjort, C.; Cole, J.; Frébort, I. European genome editing regulations: Threats to the European bioeconomy and unfit for purpose. *EFB Bioeconomy J.* **2021**, *1*, 100001. [CrossRef]
31. Statistics, M.; Leo, A. Goodman Source: The Annals of Mathematical Statistics. *Statistics* **2016**, *32*, 148–170. Available online: http://www.jstor.org/stable/2237615 (accessed on 29 September 2021).
32. Vaus, D. *De Surveys in Social Research*, 6th ed.; Routledge: London, UK, 2013.
33. O'Shea, R.; Jolley, J.; Mitchell, M. *Writing for Psychology*, 4th ed.; Pacific Grove, C.W., Ed.; Cengage Learning: Boston, MA, USA, 2013; ISBN 9780495597810.
34. Hoelscher, J.; Mortimer, A. Using Tableau to visualize data and drive decision-making. *J. Account. Educ.* **2018**, *44*, 49–59. [CrossRef]
35. Spina, D.; Vindigni, G.; Pecorino, B.; Pappalardo, G.; D'Amico, M.; Chinnici, G. Identifying themes and patterns on management of horticultural innovations with an automated text analysis. *Agronomy* **2021**, *11*, 1103. [CrossRef]
36. Vindigni, G.; Mosca, A.; Bartoloni, T.; Spina, D. Shedding Light on Peri-Urban Ecosystem Services Using Automated Content Analysis. *Sustainability* **2021**, *13*, 9182. [CrossRef]
37. Quinlan, J.R. *C4.5: Programs for Machine Learning*; Elsevier: Amsterdam, The Netherlands, 1993; ISBN 9781558602380.
38. Breiman, L.; Ihaka, R. *Nonlinear Discriminant Analysis via Scaling and Ace*; University of California: Davis, CA, USA, 1984.
39. Mahmud, M.S.; Huang, J.Z.; Salloum, S.; Emara, T.Z.; Sadatdiynov, K. A survey of data partitioning and sampling methods to support big data analysis. *Big Data Min. Anal.* **2020**, *3*, 85–101. [CrossRef]
40. Maria Travisi, C.; Nijkamp, P.; Vindigni, G. Pesticide risk valuation in empirical economics: A comparative approach. *Ecol. Econ.* **2006**, *56*, 455–474. [CrossRef]
41. Nijkamp, P.; Vindigni, G.; Nunes, P.A.L.D. Economic valuation of biodiversity: A comparative study. *Ecol. Econ.* **2008**, *67*, 217–231. [CrossRef]
42. Kalmegh, S. Analysis of WEKA Data Mining Algorithm REPTree, Simple Cart and RandomTree for Classification of Indian News. *Int. J. Innov. Sci. Eng. Technol.* **2015**, *2*, 438–446.
43. Wesseler, J.H.H.; Purnhagen, K.P.; Perspectives, A.E. *Campus Kulmbach Legal Working Papers, n. 1/20 (2020)*; Chair for Food Law: Kulmbach, Germany, 2020.
44. Lassoued, R.; Phillips, P.W.B.; Macall, D.M.; Hesseln, H.; Smyth, S.J. Expert opinions on the regulation of plant genome editing. *Plant Biotechnol. J.* **2021**, *19*, 1104–1109. [CrossRef]
45. Beghin, J.C.; Gustafson, C.R. Consumer valuation of and attitudes towards novel foods produced with new plant engineering techniques: A review. *Sustainability* **2021**, *13*, 11348. [CrossRef]
46. Holmes, G.; Hall, M.A. A development environment for predictive modelling in foods. *Int. J. Food Microbiol.* **2022**, *73*, 351–362. [CrossRef]

47. Weiss, G.; Provost, F. *The Effect of Class Distribution on Classifier Learning: An Empirical Study*; Technical Report ML-TR-44; Rutgers Department of Computer Science: Piscataway, NJ, USA, 2001; pp. 1–26.
48. Lone Bredahl Lone Bredahl Determinants of Consumer Attitudes and Purchase Intentions With Regard to Genetically Modified Foods—Results of a Cross-National Survey. *J. Consum. Policy* **2001**, *24*, 23–61. [CrossRef]
49. Moon, W.; Balasubramanian, S.K. Public attitudes toward agrobiotechnology: The mediating role of risk perceptions on the impact of trust, awareness, and outrage. *Rev. Agric. Econ.* **2004**, *26*, 186–208. [CrossRef]
50. Reisch, L.; Eberle, U.; Lorek, S. Sustainable food consumption: An overview of contemporary issues and policies. *Sustain. Sci. Pract. Policy* **2013**, *9*, 7–25. [CrossRef]
51. White, K.; Habib, R.; Hardisty, D.J. How to SHIFT consumer behaviors to be more sustainable: A literature review and guiding framework. *J. Mark.* **2019**, *83*, 22–49. [CrossRef]
52. Schaart, J.G.; van de Wiel, C.C.M.; Lotz, L.A.P.; Smulders, M.J.M. Opportunities for Products of New Plant Breeding Techniques. *Trends Plant Sci.* **2016**, *21*, 438–449. [CrossRef] [PubMed]
53. Lusk, J.L.; Briggeman, B.C. Food values. *Am. J. Agric. Econ.* **2009**, *91*, 184–196. [CrossRef]
54. Tanner, C.; Kast, S.W. Promoting Sustainable Consumption: Determinants of Green Purchases by Swiss Consumers. *Psychol. Mark.* **2003**, *20*, 883–902. [CrossRef]
55. de Corte, K.; Cairns, J.; Grieve, R. Stated versus revealed preferences: An approach to reduce bias. *Health Econ.* **2021**, *30*, 1095–1123. [CrossRef]
56. Pappalardo, G.; D'Amico, M.; Lusk, J.L. Comparing the views of the Italian general public and scientists on GMOs. *Int. J. Food Sci. Technol.* **2021**, *56*, 3641–3650. [CrossRef]
57. Dihr, M.; Berthold, A.; Siegrist, M.; Sütterlin, B. Consumers' knowledge gain through a cross-category environmental label. *J. Clean. Prod.* **2021**, *319*, 128688. [CrossRef]
58. Christoph, I.B.; Bruhn, M.; Roosen, J. Knowledge, attitudes towards and acceptability of genetic modification in Germany. *Appetite* **2008**, *51*, 58–68. [CrossRef]
59. Allum, N.; Sturgis, P.; Tabourazi, D.; Brunton-Smith, I. Science knowledge and attitudes across cultures: A meta-analysis. *Public Underst. Sci.* **2008**, *17*, 35–54. [CrossRef]
60. Ronteltap, A.; van Trijp, J.C.M.; Renes, R.J.; Frewer, L.J. Consumer acceptance of technology-based food innovations: Lessons for the future of nutrigenomics. *Appetite* **2007**, *49*, 1–17. [CrossRef] [PubMed]
61. Wang, W.; Pakrasi, H.B.; Ghosh, B.K. Modeling diurnal rhythms with an array of phase dynamic oscillators. In Proceedings of the 2008 10th International Conference on Control, Automation, Robotics and Vision, Hanoi, Vietnam, 17–20 December 2008; pp. 1391–1396.
62. Verneau, F.; Caracciolo, F.; Coppola, A.; Lombardi, P. Consumer fears and familiarity of processed food. The value of information provided by the FTNS. *Appetite* **2014**, *73*, 140–146. [CrossRef] [PubMed]
63. Ritchey, P.N.; Frank, R.A.; Hursti, U.K.; Tuorila, H. Validation and cross-national comparison of the food neophobia scale (FNS) using confirmatory factor analysis. *Appetite* **2003**, *40*, 163–173. [CrossRef]
64. Frewer, L.J.; Bergmann, K.; Brennan, M.; Lion, R.; Meertens, R.; Rowe, G.; Siegrist, M.; Vereijken, C. Consumer response to novel agri-food technologies: Implications for predicting consumer acceptance of emerging food technologies. *Trends Food Sci. Technol.* **2011**, *22*, 442–456. [CrossRef]
65. Cox, D.N.; Evans, G. Construction and validation of a psychometric scale to measure consumers' fears of novel food technologies: The food technology neophobia scale. *Food Qual. Prefer.* **2008**, *19*, 704–710. [CrossRef]
66. Rollin, F.; Kennedy, J.; Wills, J. Consumers and new food technologies. *Trends Food Sci. Technol.* **2011**, *22*, 99–111. [CrossRef]
67. Mazzocchi, M.; Lobb, A.; Traill, W.B.; Cavicchi, A. Food scares and trust: A European study. *J. Agric. Econ.* **2008**, *59*, 2–24. [CrossRef]
68. Charlebois, S.; Schwab, A.; Henn, R.; Huck, C.W. Food fraud: An exploratory study for measuring consumer perception towards mislabeled food products and influence on self-authentication intentions. *Trends Food Sci. Technol.* **2016**, *50*, 211–218. [CrossRef]
69. Rosa, G.; Filho, J.; Neto, S. Modelagem Conceitual de Geodados com Técnica Orientada a Objetos para Gestão de Recursos Hídricos. *Rev. Bras. Recur. Hídricos* **2006**, *11*, 235–244. [CrossRef]
70. Lehdonvirta, V.; Hjorth, I.; Graham, M.; Barnard, H. Online Labour Markets and the Persistence of Personal Networks: Evidence From Workers in Southeast Asia. In Proceedings of the American Sociological Association Annual Meeting, Chicago, IL, USA, 22–25 August 2015.
71. Fang, J.; Wen, C.; Prybutok, V. An assessment of equivalence between paper and social media surveys: The role of social desirability and satisficing. *Comput. Human Behav.* **2014**, *30*, 335–343. [CrossRef]