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How the Covid-19 Pandemic Is Changing Online Food Shopping Human Behaviour in Italy

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Abstract: The advent of the Internet has significantly changed consumption patterns and habits. Online grocery shopping is a way of purchasing food products using a web-based shopping service. The current COVID-19 pandemic is determining a rethinking of purchase choice elements and of consumers' behavior. This work aims to investigate which characteristics can affect the decision of online food shopping during the pandemic emergency in Italy. In particular, the work aims to analyze the effects of a set of explanatory variables on the level of satisfaction for the food online shopping experience. For achieving this aim, the proportional odds version of the cumulative logit model is carried out. Data derive from an anonymous on-line questionnaire administrated during the first months of the pandemic and filled by 248 respondents. The results of this work highlight that people having familiarity with buying food online, that have a higher educational level and consider food online channels easy to use, appear more satisfied for the food online shopping experience. These findings can be crucial for the future green global challenges as online shopping may help to reach competitive advantages for company sustainability.

Keywords: online grocery shopping; situational factors 2019; global pandemic; consumer behavior; m-commerce; proportional odds version of the cumulative logit model

1. Introduction: Research Background

Lately, the use of the Internet for the purchase of goods and services has registered a considerable but also heterogeneous diffusion in relation to the category of products, the countries and, within the same, to the areas concerned [1]. This rising use of the internet has been facilitated by the growing spread of e-commerce web-site, mobile commerce (m-commerce) applications as mobile-phones online shopping, mobile-payments, and so forth, for different categories of products, including food ones [2–4]. Online grocery shopping is a way of purchasing foodstuffs including perishables and other household supplies using a web-based shopping service differing significantly from general online shopping due to the characteristics of the food products and the frequency of the purchasing activity [5–7]. Although online grocery shopping is a relatively new environment and as a consequence is modest compared to other categories of products, they experienced a continuous growth worldwide, estimated at around 21% per year in the period 2014–2019 (for more information, please see Reference [8]) gaining more and more popularity among consumers. In addition, the latter ([9]) estimated a worldwide online shopping market of nearly 190 billion US dollars in 2019, predicting a composed annual growth rate of 24.8% (2020–2027 time period). The reasons and the characteristics affecting the purchasing decisions behind the growing diffusion of online shopping for food products are different and attributable, on the one hand, to changes in the lifestyle and consumption habits [10] and, on the other hand, to the convenience and time-savings offered by the online grocery and food shopping [11]. Online grocery shopping offers several advantages, among which the opportunity to access and compare on-line numerous categories of products, also not available in local markets, access varied and large amount of information (image, list of ingredients and allergens and others that are parts of a compulsory labelling system), as well as make the purchase at any time of the day and receive the product directly at home, and reduces the physical effort to go shopping, saving time and money [12–14].

In addition, other very recent research highlights that shopping on line can help to reach a sustainable competitive advantage that can determine an ecological long-term stability in line with the 2030 Agenda's sustainable development goals (SDGs): in particular, Reference [15] show there is a link between perceived sustainability in purchasing online and customer engagement while Reference [16] give evidence that online shopping can promote sustainability paths by decreasing the quantity of shopping trips. Conversely, several authors suggest that among the main obstacles to the diffusion of the purchase channel for grocery products are found the security of transaction, the difficulty in using IT tools and the quality of the delivery service, also linked to the characteristics of the product [11].

The global emergency deriving from the COVID-19 pandemic represents 'most severe' health emergency in World Health Organization (WHO) history. The pandemic has brought numerous countries to a standstill: firms, employees and markets have been coping with several issues that evolve from public health to broader social-human-economic issues. With the lock-down resulting from the pandemic, buying products online has become a necessity for the community. This also applies to food products. Indeed, the emergency of COVID-19 from March 2020 gave a strong boost to hoard food [17] and to online shopping for food products with a rise in the quantity of customers that buy foods online to obey to the rules (in particular social distancing)—and simply to make sure they get the food they want instead of facing empty shelves. A recent work [18], by means of a national survey in Spain, demonstrated that in discomfort situation different food attitudes can arising depending on low emotional states (ranging from the less-healthy food choices to healthier habits). One out of eight immediate impacts deriving from the Covid-19 on consumption behaviour highlighted by a recent work [19], is just embracing digital technology and their applications in order to stay afloat in this period of forced isolation. All this has led numerous food companies (supermarkets, restaurants, fast food, etc.) to re-introduce themselves by announcing technological solutions for the management of online orders and for home delivery or in-store collection to meet the growing demand from consumers. A surprising figure is that of the United States where online food orders are estimated to have increased by 700% in the first quarter of 2020 following the pandemic compared to the same period of the previous year ([20].).

2. Extant Gaps and Research Aim

Despite the growing diffusion of online food shopping, there are few empirical studies aimed at observing and understanding what are the main factors influencing and affecting the intention to purchase food online and so the acceptance of modern m-commerce technologies. Literature food is related to definition of the main elements affecting the acceptance and intention or the intention to continue and to purchase online [2,7,21,22], on which characteristics of the product or seller affect this intention [14,23,24] and on what product information can determine a higher frequency of online purchases [25]. Other research investigated the online food buyers behaviour f, some times making a comparison between online purchases and offline shopping [1,26,27] and the factors that determine moving towards online shopping [28]. Finally, other studies examined the influence of situational factors in the process of purchasing food products online [29,30]. However, almost all of these studies focused on ordinary situations, while as emerged from Reference [27], situational factors (e.g., environmental) can represent important discriminating factors in the choice to buy online foods. Furthermore, the existing literature is concentrated as a beginner in the United States and in China, the main world's largest online retail market, and in Northern Europe, while little is known about the acceptance, the purchasing decisions and diffusion in emerging markets, such as the Italian one, which have recorded an increasing share of consumers interested in buying food online. Analysing the characteristics affecting the decision of consumers of online grocery shopping, especially in out of the ordinary conditions, is fundamental for a deeper understanding of their behaviour and for providing retailers, producers and academics with elements of knowledge.

In order to fill this research gap in the academic literature, this work aims to investigate and identify these characteristics within the consumers behaviour in adopting online grocery shopping during the COVID-19 pandemic and the intention to continue to adopt this channel based on the consumers' perceptions and expectations. To meet the objectives of this study we refer to the conceptual model developed integrating the model proposed by References [21,22], on the perception of consumers who buy online, with that of Reference [31], on the key factors affecting the decision to continue using e-commerce services.

3. Theoretical Frameworks and Related Literature Review

Very few empirical studies in the economic literature have been carried out in order to better understand the consumer online shopping behaviour for grocery products adopting different theoretical lens or developing new conceptual frameworks. Empirical evidence suggest that online grocery shopping is affected by both personal characteristics and consumers' perceptions of risks and benefits associated to the acceptability [21] and use of modern technologies that are significant predictors both of the online shopping behaviour and of the intention to continue to use these tools for buying foodstuff products [21,32]. One of the earliest theoretical models adopted to predict the consumers' acceptance and continuance intention to buy foodstuff products online is the *Technology Acceptance Model* (TAM), proposed by Reference [33] and subsequently extended by Reference [32]. TAM, which is one of the most influential extensions of Ajzen and Fishbein's theory of reasoned action (TRA) [34,35], assumes that an individual's new technology acceptance is affected by the *Perceived Usefulness* (PU) and the *Perceived Ease of Use* (PEOU), defined as the degree to which a person believes that using a particular system would enhance the job performance or is free of effort, respectively [33]. Several studies confirm the validity of this approach in the grocery online shopping. For example, Reference [7] found that consumers who find it easy to use online grocery shopping perceive it as more useful, with a positive influence on their intention to use it, and this positive perception is positively affected by subjective norms and therefore by the environment in which consumers live. To better understand the relation between the technology acceptance in online grocery shopping and post adoption behaviour, Reference [2] proposed an extension of the TAM considering the *Expectation Confirmation Model* (ECM), developed by Reference [36] and focusing on the consumer's perceived value. Findings of this study confirm that perceived usefulness and ease of use positively affect the technology acceptance for consumer's online grocery shopping, emphasising the importance of a positive experience, related to the feeling or affect states generated by the application, and satisfaction, which are determinant of the continuance intention. Indeed, factors as the functionality of the m-commerce tools, interactivity, but also the saving time and flexibility offered by the online grocery shopping and the opportunity to reduce the in-store efforts positively influence the PU and PEOU [10,11]. However, as stated by Reference [10] the perceived ease of use is only the antecedent of perceived usefulness but not of the behavioural intention of use, while it is the social influence, linked to the status to which the online consumer wants to belong, to have a direct effect on the perceived usefulness and the behavioural intention. As shown by Reference [23], the previous theoretical lens (TAM and ECM) were adopted in order to analyze the acceptability of IT tools to purchase of foods and non-food products online, neglecting other factors, especially those related to the environment, which play a key role. In line with this, some of the previous factors, related to the shopping experience and the influence of environmental factors on the intention to purchase food online, have been included by Reference [21] in a theoretical model aimed at exploring the online food shopping behaviour. According to this model, the consumer's acceptance and adoption of online grocery shopping is affected by five innovation-adoption characteristics such as:

1. perceived social norms that, in line with the theory of planned behaviour proposed by Reference [34], refer to the influence that relatives and friends have in choosing to adopt online food shopping;
2. perceived complexity which refers to the degree of difficulty perceived by online food shoppers both with reference to the acquisition of information and the ease of use of the technology to complete the online transaction process;
3. perceived compatibility which refers to the perception degree that online grocery shopping is compatible with past lifestyle and personal values;
4. perceived relative advantage refers to consumers' perception of the potential offered by online shopping compared to traditional purchase channels;
5. perceived risk refers to the degree of perception of the risks connected to the online process and linked to both the payment method and the quality of the product delivered.

The model was tested [21] on a sample of 1516 US consumers to identify the discriminating factors among three different consumer segments (those who had never purchased online, those who had purchased online but not food products and those who had purchased food on line). Results confirm the explanatory power of the model, highlighting that consumers who purchased food online have greater compatibility with these tools, perceive a greater relative advantage and greater pressure from the environment in which they live, and less complexity of online shopping. With regards to the latter aspect and consistent with the TAM model, the difficulty of using online shopping tools is a deterrent for consumers, as found by Reference [28] according to which "low customer service, high perceived price, technical problem and the problem with the products delivered" are the most important determinants affecting the transition to another dealer. The robustness of Hansen's model has been recently verified by Reference [37] in their study on the Chinese consumers' adoption of online food shopping. If, on the one hand, the authors found that the consumers behaviour is positively affected by the perceived incentive (which includes social norms, perceived compatibility and perceived relative advantage), because Chinese consumers consider this shopping method as a normal part of their lives, and negatively by the perceived complexity. On the other hand, they found that the perception of risk is not statistically significant, this is probably because China, one of the largest e-commerce markets, guarantees to its consumers a safe shopping system, emphasising that the reference framework and experience play a key role in online consumer behaviour. It is thus quite clear that the personal values that determine compatibility with modern IT tools are important predictors of consumers' behaviour. In line with this, Reference [22] combine the *Theory of Planned behaviour*, of which Fishbeian and Ajzen are precursors, with personal values and found that the latter exert a relevant influence on the consumers' attitudes and that this relationship is moderated by the fact that the consumer purchased online and therefore by previous experience. Results from the literature's analysis show that the intention to buy food products online is linked, on the one hand, to the acceptability of the modern technologies and, on the other, to the perception of the benefits and risks associated with their use. However, as already highlighted, all these studies analyzed the consumers' behavior in ordinary conditions, underestimating that the choice can be linked to situational factors that are often ignored. In fact, contrary to the previous findings, Reference [29] find that online food buyers are not guided by cognitive processes, the relative advantage, completeness and complexity perceptions, but the situational factors, often ignored in the consumer behaviour research, related to specific life events that triggers shopping online. Starting from these insights and in considering the case of the COVID 19 pandemic, the intention to use digital tools for the purchase of food products cannot be exclusively related to the consumers' perception of the benefits or risks associated with the use of these tools, and therefore based on the level of satisfaction obtained, but also to specific events which impose to people specific behaviors (Figure 1).

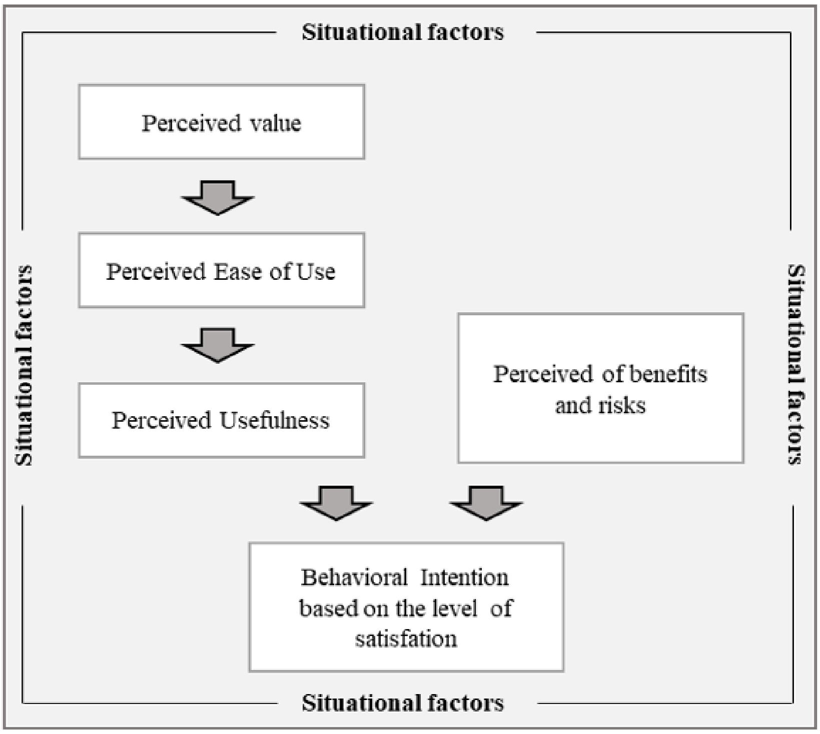

Figure 1. Conceptual framework.

4. Materials and Methods

4.1. Data Description

To investigate our research's aim, the Survey Method was carried out [38] and an anonymous, self-designed, structured questionnaire was conducted. This was considered a suitable method for the collection of standardised data that deliver necessary information [39]. Then, data were collected from this questionnaire administrated to a sample of Italian consumers constructed by using a snowball sampling method (Snowball sampling is widely used in Internet research [40,41], especially to reach as many people as possible with similar characteristics and often hard to reach [42,43]. In our work, the goal was to reach as many people as possible who would use Internet to buy, especially food. Thus, the objective was to obtain a sample as much as possible made up of people who buy online food products (in fact, many people abandoned the questionnaire from the beginning because they had never purchased food products). Moreover, the choice of sampling method is further justified given the emergency situation and the need to collect data in a timely manner during the period of the phenomenon (the COVID19 pandemic).). The respondents were reached by means of social networks and emails, during the pandemic period, from March to May 2020. Therefore, the questionnaire was on line during this three months period, and sponsored by means of social media, like Facebook, and through internal mailing lists of the University of Palermo, Foggia, and Rome-Sapienza.

The choice of using such online research derives from the idea to quickly survey certain subjects, thus guaranteeing their security under pandemic conditions [44]. Firstly, the questionnaire was validated during virtual meetings by a focus of experts composed of representatives belonging to online purchasing channels, academy and web-marketing field who studied, discussed, and filtered all the statements [18]. The survey based on a multiple-choice questionnaire was composed of 39 qualitative and quantitative questions organised in 2 sections addressed to know:

- demographic data, included age, gender, place of living, household composition, level of education and income [45];

- info related to food categories consumption frequency [46], to increasing or decreasing of consumption of foods compared with a non pandemic period [18], to the websites (Amazon, Carrefuour, Conad, Coop), and apps used (Social food, Just Eat, Deliveroo, Glovo, My menu, etc.).

In particular, the frequency of consumption was assessed using categorical variables [47], while the perceptions and the level of satisfaction of consumers were rated using a 3-point Likert scale, from 1 (Disagree or Low) to 3 (Agree or High) (We preferred an odd number of rates because it avoids limitations in data interpretation and analysis [48].). 25% out of the total respondents was not able to conclude the questionnaire due not to meeting the criteria of having purchased at least once by means of on line channels. In addition, another inclusion criteria was Italian nationality, and an age of at least 18 years old. The final respondents were 248.

4.2. Methods

We want to analyse the effects of a set of explanatory variables on the level of satisfaction (in a scale from 1-Low to 3-High (The scale was originally 5 levels. However, we decided to reduce it to three. The intermediate levels (2 and 4) were poorly represented; initially, we tried to estimate the model using the 5-level variable, but there was not a good fit. So, we decided to use a three-level scale, which also makes it easier to interpret the coefficients, which are expressed in terms of ratios of cumulative probabilities.) for the food online shopping experience. To do this, we fit a regression model, chosen according to the nature of the dependent variable (an ordinal one) (This is a crucial point. Although widely used, regression models are often badly used. They are often applied without testing the nature of the response variable and other assumptions underlying these same models. This can often lead to erroneous conclusions [49–51].). Thus, we use the *proportional odds version of the cumulative logit model* (This model is often mentioned to as a *proportional odds model*, according to an influential paper on modelling ordinal data by Reference [52]. In this paper, we adopt the term proportional odds version of the cumulative logit model, suggested by Reference [53], who considers vague both the terms ordered logit and proportional odds.). This model is a useful extension of the binary logistic model for the cases in which the dependent variable assumes ordered categorical values [53,54]. The proportional odds version of the cumulative logit model, probably the most frequently utilised in practice for ordinal response variables [55], uses cumulative probabilities which do not overcome a threshold. In this way, it makes the whole range of ordinal categories binary at that threshold. It is based on the cumulative distribution function (Equation (1)):

$$P(Y \leq i) = \pi_1 + \pi_2 + \cdots + \pi_i = \frac{\exp \alpha_i + \boldsymbol{\beta X}}{1 + \exp \alpha_i + \boldsymbol{\beta X}}, \tag{1}$$

where $i = 1, \ldots, K$ is the outcome category; $\mathbf{X}$ is the $(n \times p)$ matrix of explanatory variables; α_i (the intercept) and $\boldsymbol{\beta}$ (the vector of coefficients) are the parameters we must estimate. $P(Y \leq i)$ measures the probability of Y below a given i. From Equation (1), we can calculate the odds (Equation (2)):

$$\text{odds} = \frac{P(Y \leq i)}{1 - P(Y \leq i)} = \frac{\pi_1 + \pi_2 + \cdots + \pi_i}{\pi_{i+1} + \pi_{i+2} + \cdots + \pi_K}. \tag{2}$$

If the cumulative odds are less than 1 (more than 1), the response is associated with a shift towards the right (left) of the response scale, namely a rise in the probabilities in the higher categories. The model can be estimated by Equation (2), by calculating the natural logarithms of the odds ([53], p. 275):

$$\text{logit}[P(Y \leq i)] = \log \frac{P(Y \leq i)}{1 - P(Y \leq i)} == \log \frac{\pi_1 + \pi_2 + \cdots + \pi_i}{\pi_{i+1} + \pi_{i+2} + \cdots + \pi_K} = \alpha_i + \boldsymbol{\beta X}; \quad i = 1, \ldots, K-1. \tag{3}$$

$\boldsymbol{\beta}$ is a vector of p coefficients, each of which describes the influence of the p explanatory variables on the logit and the α_i parameter is related to the outcome category and not used in the interpretation of results. This effect does not change for all the $K-1$ cumulative logits. One of the main assumptions of this logit formulation is the common effect of $\boldsymbol{\beta}$ in the $K-1$ equation. Therefore, each logit has its own intercept (α_i), but the regression coefficients ($\boldsymbol{\beta}$) do not depend on i, implying that the model assumes that the relationship between x_i and Y is independent from i. Reference [52] calls this assumption "the proportional odds" or "the parallel regression" assumption. Because the regression parameters are independent from and invariant to the outcome category, the odds ratios (OR) are the same over each logit, and the common log odds ratio provides a single estimate of the log odds ratio over the cut-off points. This estimate is the optimum one obtained using the maximum likelihood methods [56]. OR can be calculated by comparing cumulative probabilities and their complements. Given the two values x_1 e x_2 for the j^{th} explanatory variable X_j, OR is computed as follows:

$$\frac{P(Y \leq i/X_j = x_2)/P(Y > i/X_j = x_2)}{P(Y \leq i/X_j = x_1)/P(Y > i/X_j = x_1)} = \exp\left[\beta(x_2 - x_1)\right]. \quad (4)$$

If $x_2 - x_1 = 1$, OR is equal to $exp(\beta)$ for each outcome category and this makes it possible to define Equation (3) as a proportional odds model.

Before fitting the model, we must verify if the assumption of proportionality is satisfied by each independent variable, that is, if the categories of the response variable are parallel to each other. According to this assumption, parameters should not change across categories. If this assumption is violated, there is no parallelism between the categories and, consequently, interpretations of the results will be wrong. In order to test this assumption, we use the version of the Wald test proposed by Reference [54]. The null hypothesis H_0 states that the coefficients of the independent variables are the same for each category of the response variable. The approach is based on considering the proportional odds version of the cumulative logit model as a set of $K-1$ binary logistic regressions, for variables z_k $(k = 1, \ldots, K-1)$ defined as follows:

$$z_k = \begin{cases} 1 & \text{if} \quad Y > k \\ 0 & \text{if} \quad Y \leq k, \end{cases} \quad (5)$$

with success probability $\pi_k = P(z_k = 1) = 1 - P(Y \leq i)$. Under the null hypothesis, the separate maximum likelihood estimates $\hat{\beta}_k^* = (\hat{\beta}_1', \hat{\beta}_2', \ldots, \hat{\beta}_{K-1}')$ have an asymptotically multivariate normal distribution. In this way, the Wald test, based on the correlated separate fits, provides an assessment of the proportionality assumption in the proportional odds version of the cumulative logit model ([56], p. 280).

In order to check the goodness of fit, we use some specific tests suggested in literature for ordinal regression models:

- *Lipztig test* [57]; data are divided into g groups of equal size based on an ordinal response score, calculated by summing the predicted probabilities of each subject for each level of outcome multiplied by equally spaced integer weights. From this partitioning of data, we derive I dummy variables such that, for each group, $I = 1$ if the subject is in region g, otherwise $I = 0$. We, then, re-fit the model including these dummy variables: the model has a good fit if the coefficients for all these dummy variables will simultaneously be equal to 0. We indicate with L_0 and L_1 the log likelihoods of the fitted models with and without the dummy variables, respectively. The Lipsitz test statistic is the likelihood ratio statistic $-2(L_1 - L_0)$. A p-value is obtained by comparing the observed value of the test statistic with the χ^2 distribution with $g-1$ degrees of freedom.
- *Hosmer-Lemeshow test* [58]; it compares observed with expected frequencies of the outcome and computes a test statistic which is distributed according to the χ^2 distribution. The degrees of freedom depend upon the number of quantiles used and the number of outcome categories.

A non-significant p-value indicates that there is no evidence that the observed and expected frequencies differ and this is an evidence of goodness of fit.

- *Pulkstenis-Robinson tests* [59]; these tests can be used for models with continuous and categorical predictors. The first step is to determine the covariate patterns using only the categorical predictors (ignore any unobserved patterns), to avoid partitioning among an unacceptably high number of covariate patterns. After, we assign an ordinal score to each subject, by summing the predicted probabilities of each subject for each outcome level multiplied by equally spaced integer weights. The covariate patterns are then split into two at the median score within each. Based on this partitioning, observed and expected frequencies are calculated, a contingency table can be constructed and the statistic tests computed. The two Pulkstenis and Robinson test statistics are the Pearson χ^2 and deviance test statistics on that table. These statistics are distributed by the χ^2 distribution with $(2I-1)(J-1)-k-1$ degrees of freedom, where I is the number of covariate patterns, J is the number of of response categories and k is the number of categorical variables in the model.

According to Reference [60], all these three tests must be performed together.

5. Results and Discussions

5.1. Characteristics of the Sample

The sample of analysis is composed of 248 respondents. The percentage of respondents who rated the level of satisfaction as "Low" is 25.5%; while the percentages of people who rated the level of satisfaction as "Medium" and "High" are the same (37.3%).

Table 1 shows the main characteristics of the sample. The 43% of respondents are aged between 35 and 54 years and only 20% are aged more than 55 years. Almost 39% of the respondents live in Apulia. Respondents present a very high level of education: 42% of them declare to have post-graduate degree (81% have at least a college degree), while only 2% have a lower secondary school diploma (17% have a high school diploma). Regarding the composition of the family unit, there is a predominance of one component units (58.1%), with respect to those composed of two (20.2%) or more than two components (21.7%). 33.9% of the sample declare to spend on average less than 1 hour every day on the internet (for any reason other than work); 41.1% of the respondents use Internet at least once a week to purchase food products while 25.4% never use it. The core of the questionnaire includes a set of questions relating to buying food online. 69.4% of the respondents declare that they are familiar with buying food online. Only 14.9% judge highly complex to buy food online and 42.7% say that this complexity is due to the inability to see food products physically; thus, other aspects of the online food shopping experience can influence this judgement (for instance, possibility of return, security of payments, etc.). Among these factors, the low quality of the products received or the possibility of receiving the wrong ones are considered highly risky by 34.3%. Only 29.5% of the sample declare having few problems with buying food online.

5.2. Model Estimation

The first step was to fit a model with all variables reported in Table 1. The response variable is the level of satisfaction for the food online shopping experience. The estimated coefficients of some explanatory variables did not prove statistically significant results. Thus, we used the stepwise technique to re-estimate the model. The final model (Table 2), with 3 response outcomes and 2 α_i intercepts, includes only variables with at least one significant estimated parameter. The model was estimated by means of the *polr* function of the *MASS* package [61] in R statistical software.

Table 1. Characteristics of the sample.

Characteristics	Total Number	Percentage
Age 1 (18–34)	100	0.403
Age 2 (35–54)	119	0.480
Age 3 (More than 55)	29	0.117
Apulia: Yes	96	0.387
Apulia: No	152	0.613
Education: Lower secondary school diploma (LSSD)	7	0.028
Education: High school diploma	41	0.165
Education: Degree	95	0.383
Education: Post-graduate degree	105	0.424
One component units	144	0.581
Two components units	50	0.202
More than two components units	54	0.217
Frequency of online purchase of food products: never	63	0.254
Frequency of online purchase of food products: rarely	72	0.290
Frequency of online purchase of food products: at least once a month	11	0.045
Frequency of online purchase of food products: at least once a week	102	0.411
Familiarity with buying food online: yes	172	0.694
Familiarity with buying food online: no	76	0.306
General complexity of buying food online: low	158	0.637
General complexity of buying food online: medium	53	0.214
General complexity of buying food online: high	37	0.149
Complexity of buying food online (inability to see physically): low	86	0.347
Complexity of buying food online (inability to see physically): medium	56	0.226
Complexity of buying food online, (inability to see physically): high	106	0.427
Possibility of low quality or wrong products received: low	82	0.330
Possibility of low quality or wrong products received: medium	81	0.327
Possibility of low quality or wrong products received: high	85	0.343
Possibility to save time by purchasing food products online: low	51	0.206
Possibility to save time by purchasing food products online: medium	78	0.315
Possibility to save time by purchasing food products online: high	119	0.479
Problems in buying food products online: low	73	0.295
Problems in buying food products online: medium	88	0.355
Problems in buying food products online: high	87	0.350

The results of the Brant test (The test was estimated by using the *brant* function of the *brant* R package [62].), reported in Table A1 in Appendix A, provide evidence that the parallel lines assumption has been accepted for all selected variables. Tables A2 and A3 in Appendix A report the results, respectively, of the Lipsitz and Hosmer-Lemeshow tests and of the Pulkstenis-Robinson tests (Lipsitz, Hosmer-Lemeshow and Pulkstenis-Robinson tests were estimated using the respective functions included in *generalhoslem* R package [63].): all of them indicate that there is evidence of a good fit.

The model coefficients can be difficult to interpret because they are scaled in terms of logs; so, we can convert them in *proportional odds ratios* (OR). The latter express the odds of being more satisfied for the food online shopping experience, that is, the odds of being sufficiently or highly satisfied (i.e., the 2-Sufficient or 3-High response outcomes of the dependent variable) versus being unsatisfied. The interpretation must be made taking into account the reference modality chosen for each variable in the construction of the model.

Table 2. Proportional odds version of the cumulative logit model for the level of satisfaction for the food online shopping experience: estimated coefficients (Estimates); standard errors (Std.Errors); *p*-values; *t*-statistic; observations; residual deviance, AIC.

	Level of Satisfaction for the Food Online Shopping Experience			
	Estimates	**Std. Errors**	***p*-Values**	***t***
X1 - Education: High school diploma	0.894	0.862	0.300	1.038
X1 - Education: Degree	1.651 **	0.828	0.047	1.994
X1 - Education: Post-graduate degree	1.010	0.820	0.219	1.231
X2 - Familiarity with buying food online: yes	0.914 ***	0.301	0.003	3.032
X3 - General complexity of buying food online: medium	0.776 *	0.457	0.090	1.700
X3 - General complexity of buying food online: low	1.304 ***	0.409	0.002	3.187
X4 - Complexity of buying food online (inability to see physically): medium	0.583 *	0.351	0.098	1.659
X4 - Complexity of buying food online (inability to see physically): low	0.587 *	0.337	0.082	1.742
X5 - Possibility to save time by purchasing food products online: medium	0.512	0.380	0.178	1.349
X5 - Possibility to save time by purchasing food products online: high	1.389 ***	0.398	<0.001	3.490
X6 - Problems in buying food products online: medium	1.036 ***	0.317	0.002	3.262
X6 - Problems in buying food products online: low	1.296 ***	0.381	0.001	3.403
α_1 (intercept 1: Low/Medium)	3.273	0.954	0.001	3.432
α_2 (intercept 2: Medium/High)	5.510	1.001	<0.001	5.508
Observations	248			
Residual Deviance	432.787 (df = 234)			
AIC	460.787			

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. *Source: our processing.*

Focusing only on the explanation of the significant odds ratios (in Table 3), we can observe:

- Education: Degree

  The reference modality is *Lower secondary school diploma (LSSD)*. For people with a degree, the odds of being more satisfied for the food online shopping experience is 5.215 times that of people with a lower secondary school diploma, holding constant all other variables. Several studies suggest that personal characteristics, such as level of education, are important predictors of online grocery shopping [64]. Indeed, better educated consumers may be more likely to shop online, both because they could feel more confident about having the necessary resources, and for time savings and convenience aspects related to this channel [12,65].

- Familiarity with buying food online: yes

  The reference modality is *Familiarity with buying food online: no*. The respondents who claim to be familiar with buying food online have an odds of being more satisfied for the shopping experience 2.494 times that of those who are not familiar with it, holding constant all other variables. This result corroborates what Reference [21] found, according to which consumers who have greater compatibility with these digital technologies are more likely to buy food products online as they are satisfied with their previous experience.

- General complexity of buying food online: medium—low

  The reference modality is *General complexity of buying food online: high*. In general, people who find it less complex to buy food online tend to be more satisfied for this experience. For respondents who judge the online shopping experience sufficiently or less complex, the odds of being more satisfied is, respectively, 2.174 and 3.685 times that of those who judge it highly complex, with constant all other variables. Several empirical evidence confirm that consumers who have no difficulty in using digital tools for the online purchasing of foods find these tools particularly useful and consequently accept them more easily and tend to use them more frequently [7,21,36]. Conversely, as highlighted by Reference [28], the difficulty of using digital technologies is a deterrent for consumers who, consequently, shift their attention to other easier-to-use solutions.

- Complexity of buying food online (inability to see physically): medium—low

  The reference modality is *Complexity of buying food online (inability to see physically): high*. We can express some considerations similar to those made for the variable *general complexity*: people evaluating the online shopping experience sufficiently or less complex due to the inability to see products physically have an odds of being more satisfied, respectively, 1.791 and 1.799 times that of those who judge it highly complex, constant all other variables. This result is in line with the advantages that online grocery shopping offers consumers, giving the opportunity to compare a greater number of products and product characteristics than traditional purchasing methods [12,14].

- Possibility of saving time by purchasing food products online: high

  The reference modality is *Possibility to save time by purchasing food products online: low*. For respondents who state that the possibility to save time by shopping online is high, the odds of being more satisfied is 4.011 times that of those who state that this possibility is low, holding constant all other variables. As numerous empirical evidence show, the opportunity of saving time by purchasing food products online, compared to traditional channels, is perceived as an advantage or an incentive by consumers [21,37]. Above all, this result is in line with the social and organizational changes of the families in which household members spend less time for cooking and consequently for food shopping.

- Problems in buying food products online: medium and low

  The reference modality is *Problems in buying food products online: high*. We can observe that the lower the problems in buying food products online, the higher the satisfaction in online shopping experience. Respondents who affirm having sufficient or low problems in buying online have an odds of being more satisfied, respectively, 2.817 and 3.656 times that those who declare to have high problems, given constant all other variables. This result is consistent with other empirical evidence [7,36,37], according to which the complexity in the use of digital tools for the purchase of food products, linked also to technical problems, negatively affects consumers by reducing the propensity to use or re-use these modern tools.

Table 3. Proportional odds version of the cumulative logit model for the level of satisfaction for the food online shopping experience: odds ratios (OR); confidence intervals at 95% (CI).

	OR	**CI**
Education: High school diploma	2.446	0.452–13.240
Education: Degree	5.215	1.028–26.441
Education: Post-graduate degree	2.745	0.550–13.691
Familiarity with buying food online: yes	2.494	1.381–4.503
General complexity of buying food online: medium	2.174	0.888–5.321
General complexity of buying food online: low	3.685	1.652–8.217
Complexity of buying food online (inability to see physically): medium	1.791	0.900–3.564
Complexity of buying food online (inability to see physically): low	1.799	0.929–3.483
Possibility to save time by purchasing food products online: medium	1.669	0.793–3.512
Possibility to save time by purchasing food products online: high	4.011	1.838–8.751
Problems in buying food products online: medium	2.817	1.512–5.248
Problems in buying food products online: low	3.656	1.733–7.712

Given the fitted model, we can calculate an *effect display plot*, which allows the visualisation of the effect of each predictor on a response in models in which the response depends on a linear combination of main effects and interactions [66]. This representation is built allowing a focal predictor to range over its values, while other predictors in the model are fixed and held to *typical* values [67]. Fitted values are then computed using these typical values for the fixed group of predictors and varying the values of the focal predictor. In our model, all explanatory variables are ordinal. Thus, fitted values are computed by evaluating a fixed ordinal variable at each of its levels. The fitted value that is used in the predictor effects plot is a weighed average of these within-level fitted values, with weights proportional to the number of observations at each level of the ordinal variable (As shown by Reference [66], this is the default approach.). Table 4 and Figure 2 report the probabilities of each explanatory variables' value (holding constant to their typical values all other ones) for all outcome categories.

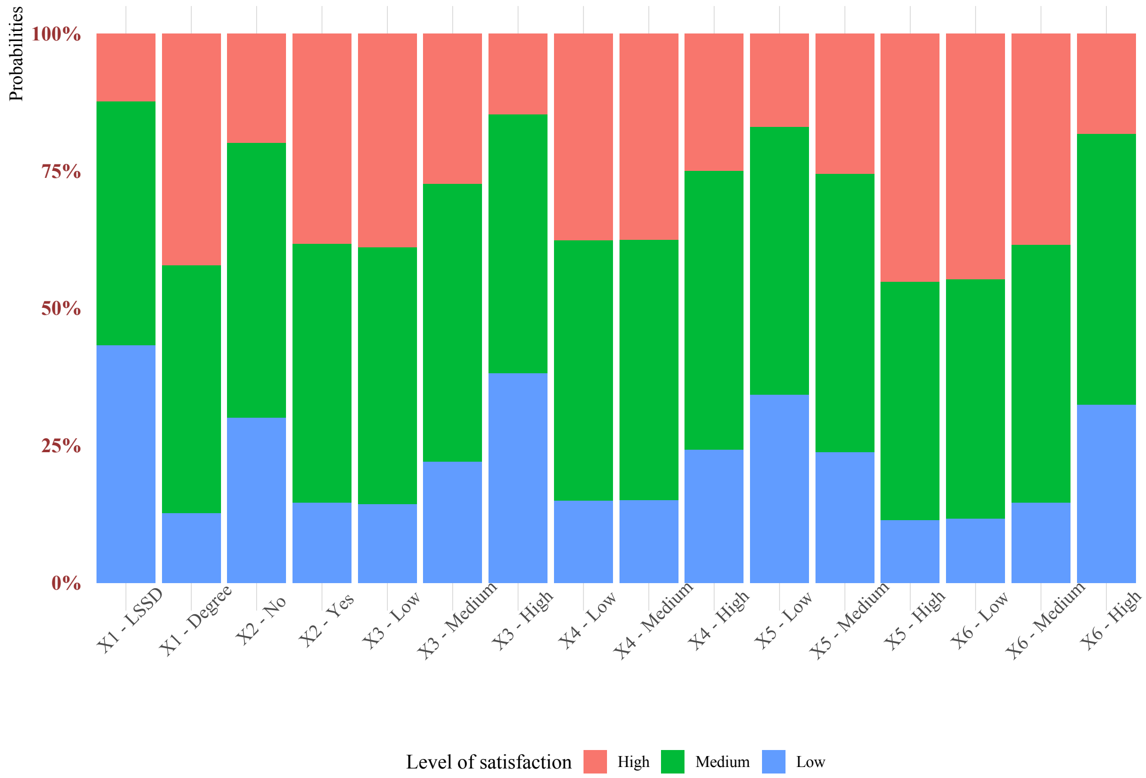

Figure 2. Outcome categories' probability for different sample characteristics.

Table 4. Probability for outcome categories.

	1-Low	2-Medium	3-High
X1—Education: Lower secondary school diploma-LSSD (*reference modality*)	0.433	0.444	0.123
X1—Education: Degree	0.128	0.451	0.421
X2 - Familiarity with buying food online: No (*reference modality*)	0.301	0.500	0.199
X2—Familiarity with buying food online: Yes	0.147	0.471	0.382
X3—General complexity of buying food online: low	0.144	0.467	0.389
X3—General complexity of buying food online: medium	0.221	0.506	0.273
X3—General complexity of buying food online: high (*reference modality*)	0.382	0.471	0.147
X4—Complexity of buying food online (inability to see physically): low	0.150	0.474	0.376
X4—Complexity of buying food online (inability to see physically): medium	0.151	0.474	0.375
X4—Complexity of buying food online (inability to see physically): high (*reference modality*)	0.243	0.507	0.250
X5—Possibility to save time by purchasing food products online: low (*reference modality*)	0.343	0.487	0.170
X5—Possibility to save time by purchasing food products online: medium	0.238	0.507	0.255
X5—Possibility to save time by purchasing food products online: high	0.115	0.434	0.451
X6—Problems in buying food products online: low	0.117	0.436	0.447
X6—Problems in buying food products online: medium	0.146	0.470	0.384
X6—Problems in buying food products online: high (*reference modality*)	0.325	0.493	0.182

Compared to the reference values, respondents with higher education, who are familiar with buying food online, who consider online shopping not very complex, also considering the inability to perceive the products physically, who claim that this experience saves time and who generally state to have had few problems with buying food online are more likely to express a high (or at least medium) level of satisfaction. This is evident from Figure 3, where the effect display plots for each explanatory variable are shown. It is pointed out that, for each explanatory variable, higher values coincide with an increase in the level of satisfaction expressed by users with respect to the experience of buying food online.

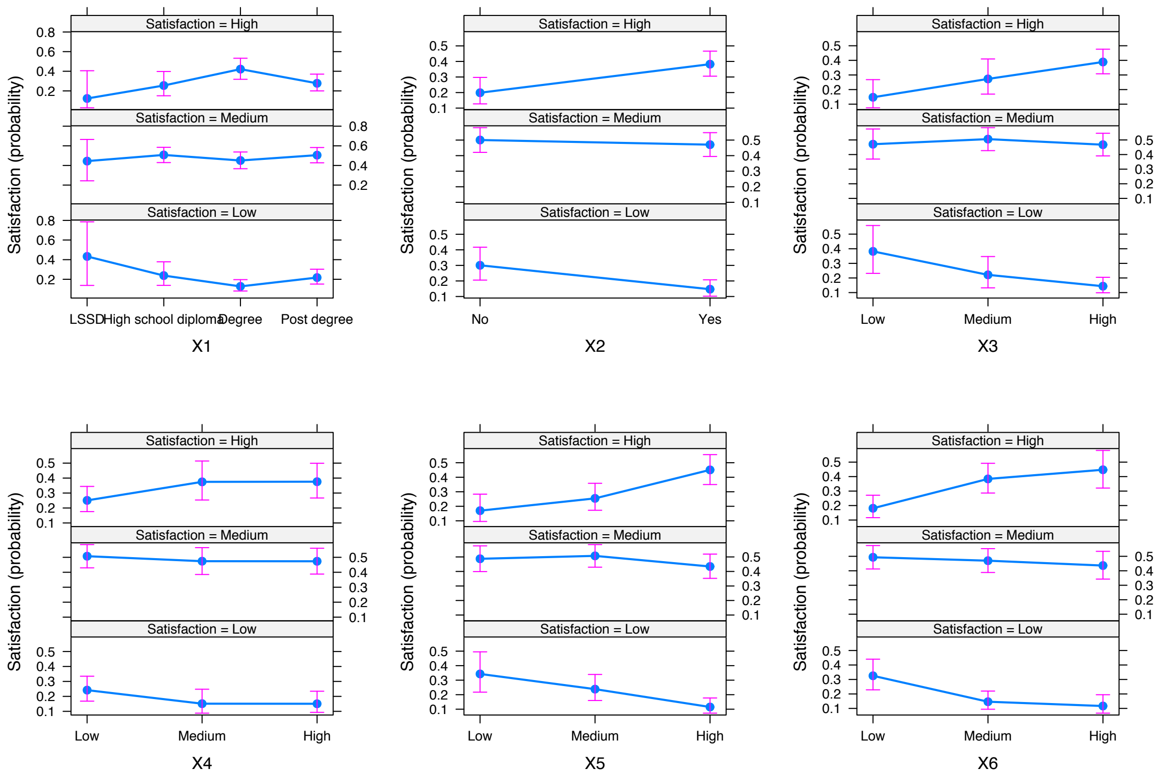

Figure 3. Effects display plots of each explanatory variable.

6. Concluding Remarks

The present work aimed to analyse the effects of a set of explanatory variables on the level of satisfaction for the food online shopping experience in Italy during lockdown due to emergency COVID-19 outbreak. In this way, the purpose was to understand and to identify the main characteristics of Italian consumers influencing the acceptance of modern m-commerce technologies and the intention to purchase food online. The dramatic pandemic COVID-19 has represented and yet represents a severe health emergency in the world history. All countries are facing several big multi-sectoral issues: focusing on the food sector, the actual goal for firms and countries according to the WHO (https://www.who.int/publications/i/item/9789241565165, accessed on 3 September 2020) is to try and to stay balanced by guaranteeing safer food for better health and well-being [68,69]. This is also a fundamental challenge in terms of achieving sustainable development at national and international level [70–72] in line with the 2030 Agenda's sustainable development goals (SDGs). As highlighted by recent research [15], online shopping can represent a new model of consume and path of agri-food development to reach sustainable standards and objectives. The toolbox Food for Earth by Future Food Institute of Bologna (Italy) orients new agro-food system also towards food security and nutritional diversity and online shopping meets this requirement by making available lots of information [12–14].

Consumer preferences and ICT development are in line and address more and more sustainable global needs. Shopping on line can become the new way to implement and reach highly competitive sustainable advantages within the business environment. The first effect deriving from the COVID-19 pandemic was a strong increase in hoarding food [17] and in the number of on line food consumers that have preferred this channel to observe the social distancing and be sure to get food products without facing long and dangerous queues at supermarkets and shops. Another important effect was embracing digital technology and their applications to stay connected and not isolated [19]. The focus on Italy appears very interesting as Italy was among first countries to face the pandemic emergency and as Italy represents an emergent market in the m-commerce tools. Results of this work highlight that people having familiarity with buying food online and that have a degree are satisfied with food online shopping experience . The perception of complexity or ease to use food online channels often plays an important role to feel more or less satisfied. Surely, as expected, the inability to physically see the food products purchased is in line with the perception of complexity or ease to use the m-commerce and to have few problems. Saving time by purchasing food products online depends on the perception of the consumers (those that consider this aspect high appear clearly more satisfied). Then, the level of satisfaction and perception can derive from the confinement period and low emotional states [18]. Our results provide relevant theoretical and practical implications. From a theoretical point of view, our study contributes to enrich the literature on the consumer intention to adopt the online grocery shopping demonstrating the usefulness of some theoretical models previously adopted in order to explore this phenomenon but adding new insight with regard the influence of situational factors. Indeed, the novelty of this study is to adopt a conceptual framework based on the TAM and ECM theoretical approaches and on the Hansen's Model, but exploring the online grocery shopping behaviour in the pandemic context, as a situational factor. Switching to a managerial perspective, investigating the characteristics affecting the decision of consumers that buy food via online grocery shopping appear certainly a key point for understanding consumers' behaviour thus shedding some light on important aspects for retailers and producers as well as academics. These new insights can be a useful starting point for identifying significant means for refining and promoting the m-commerce tools. The deep changes that are being experienced at a macro and micro level are challenging consumers' intentions and behaviours in retailing and in online purchasing to the extent that they 'might leave a mark even when the emergency is over' ([73], p. 2). Some limitations can be highlighted: the sample size does not allow generalisations and does not dictate a very good amount of information therefore, in part, our precision or level of confidence is limited. Nevertheless, in this dramatic period collecting data appears not easy as people reached high levels of social distrust. As a consequence, the increase in global distrust of social media registered in Edelman's 2018 Trust Barometer Report reduces of the possibility to find respondents via social media. In the next future, this research will provide a second step by trying to elaborate a synthetic index by considering the evaluation expressed by the consumers on the main aspects characterising the online spending behaviour thus identifying several profiles. A comparison with another EU or US country could be really significant in order to test differences in the characteristics and behaviours of purchasing.

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Appendix A

Table A1. Parallel lines assumption: Brant test results.

	χ^2	Degrees of Freedom	*p*-Value
Omnibus	9.873	12	0.627
Level of Education	0.747	3	0.862
Familiarity with buying food online	0.971	1	0.324
General complexity of buying food online	0.171	2	0.918
Complexity of buying food online (inability to see physically)	0.927	2	0.629
Possibility to save time by purchasing food products online	0.758	2	0.685
Problems in buying food products online	5.693	2	0.058

Table A2. Goodness of fit: Lipsitz and Hosmer-Lemeshow tests.

Lipsitz Test			Hosmer-Lemeshow Test		
Deviance	Degrees of freedom	*p*-value	χ^2	Degrees of freedom	*p*-value
8.924	9	0.444	31.094	21	0.072

Table A3. Goodness of fit: Pulkstenis-Robinson tests.

	Deviance Squared	Degrees of Freedom	*p*-Value	χ^2	Degrees of Freedom	*p*-Value
Level of education	15.842	12	0.199	18.126	12	0.112
Familiarity with buying food online	2.467	4	0.651	2.599	4	0.627
General complexity of buying food online	1.457	8	0.993	1.440	8	0.994
Complexity of buying food online, due to the inability to see products physically	6.295	8	0.614	6.373	8	0.606
Possibility to save time by purchasing food products online	5.463	8	0.707	6.430	8	0.599
Problems in buying food products online	9.792	8	0.280	9.786	8	0.280

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