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Measuring consumers' level of satisfaction for online food shopping during COVID-19 in Italy using POSETs

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ABSTRACT

The pandemic COVID 19 has upset the economic, social, financial, and general behavioral systems. Global crisis has a large impact overall and related fallouts significantly affect existent structural paradigms in every country and region across the world. In particular, the spread of COVID-19 pandemic has led to having to rethink the way we produce and consume food. Within this global change, a rise in the number of consumers who purchase food products online in order to comply with the rules aimed at limiting the circulation of the virus should be emphasized. Consequently, probably causing a long-term positive effect on m-commerce. The purpose is to elaborate on the index of the satisfaction level of consumers of purchasing food online via food shopping channels, by using key factors that characterize the online spending behavior. The analysis was carried out by collection of data deriving from an anonymous online questionnaire administrated via social networks and emails, during the 'hot' months of the pandemic progression in Italy, which is March–May 2020.

We analyse both dimensions of customer satisfaction (process and outcome), by means of two systems of indicators. We reduce their complexity using synthesis obtained with the Partially ordered set. Results highlight the differences between the two dimensions of customer satisfaction. Online shopping can surely contribute to reduction of food waste thanks to elimination of frenzied shopping routines at supermarkets and can open space to new fields of study. On the other hand, defining an index of the consumer's satisfaction can alter sales strategies of m-commerce managers and entrepreneurs.

Although this paper should be considered the result of the common work of the three authors, Mariantonietta Fiore and Antomnino Galati have mainly written Sections 1, 2 and 4; Leonardo Salvatore Alaimo has mainly written Sections 3, 5 and 6; all authors have written Section 7.

1. Introduction

Since the early 1990s, the 'network of network', Internet, has lead new consumption patterns and habits. Indeed, in the last decades, the e-commerce and mobile commerce (m-commerce)[1] have had a great spread for the online shopping of different categories of products and services, including food ones [1]. Although online grocery shopping reaches lower levels than other categories of products, it has experienced recently increasing annual growth rates. The latest Grand View Research report [2] estimated a worldwide online shopping market of about 190 billion US dollars, by predicting a composed annual growth rate of 24.8% from 2020 to 2027. The growing importance of online food shopping has many reasons, partly attributable to changes in lifestyle and consumption patterns. Online shopping offers several advantages. For instance, the consumer has the possibility to access and compare numerous products not available in local markets, as well as being (at least potentially) better informed about the products; this results into a greater efficiency than the in-store shopping [3]. In addition, online shopping can make the purchase at any time of the day and it is

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[1] The main difference between e-commerce and m-commerce is that, in the first case consumers access to a website for buying products by means of a computer terminal, while in the case of m-commerce they use a mobile device [89,90]. Compared to e-commerce, m-commerce offers the opportunity to reach specific market segments and to experiment with new shopping and consumption experiences [91].

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possible to receive the products directly at home, saving time and money [4,5]. Food supply chains join producers and consumers throughout the world, often with just-in-time delivery but the agro-food systems and supply chains have been disrupted, or are threatened to be disrupted by the COVID-19 pandemic. The latter started on December 31st, 2019 in China with numerous cases of serious pneumonia and has speedily spread to other countries to become one of the bigger world calamities for the last ten years [6]. On 21th February 2020, the outbreak of the disease was registered also in Italy (Codogno, a city of Northern Italy). Successively, the World Health Organization (WHO) avowed the presence of a global pandemic after the COVID 18 swept across countries all over the world, on March 11th, 2020. In the face of the unprecedented challenge of the pandemic, the purchasing habits of Italians have changed profoundly in the Covid-19 time. Before of the pandemic situation, Italy consumers have been reluctant to buy food online, in particular if compared with the consumers of other European Union countries [7]. However, the agri-food market is experiencing a return to simpler consumption, to the tradition of our grandparents, to the preference for regional products, local or at 0 km. During the pandemic, there was a considerable increase in home deliveries and shopping on line (according to the Italian Institute of Services for the Agri-food Market - ISMEA plus 160% in 2020). This trend derives from the serious lockdown measures of social distancing in Italy, the most serious in Europe. The towns with high numbers of contagiousness were isolated. All flights were cancelled. Schools, universities and many public offices were closed, as well as restaurants, bars, shops and malls (apart grocery stores and pharmacies). Moreover, religious/churches celebrations and all public events were forbidden. Only agricultural and food manufacturing activities were permitted to supply modern retails. As there is growing evidence that COVID-19 can be transmitted through surface contact or airborne droplets and aerosols, grocery stores and in-store shopping are very dangerous for shoppers, but they also determine external social cost to other shoppers and the health care system. This determines an "incentivized move from in-store shopping to grocery pickup or delivery" to decrease the extent of the COVID-19 externality [8]. Despite the growing diffusion of online food shopping since 10 years worldwide, the literature on the level of satisfaction of consumers buying by means of the modern e-commerce and m-commerce technologies is very limited; moreover, there are very few empirical studies that tend to analyse this phenomenon within a dramatic pandemic context such as the COVID-19 outbreak. These aspects appear much more important to be dealt with, because online shopping can reduce the amount of food waste and, consequently, regulate compulsive consumer behaviour [9]. The possibility to plan purchases and for the meals' organization, as well as greater attention to food storage, can be a useful factor in reducing food waste [10,11].

Literature on online food shopping has mainly focused on:

- the main drivers affecting the acceptance and intention of online purchase or the continuance intention to buy online [1,12–14];
- which characteristics of the product or seller affect this intention [5,15,16];
- which product information can determine a higher frequency of online purchases [17].

Other researchers have studied the behaviour of online food buyers in comparison with that of offline food buyers [18–20] and the factors influencing the transition from offline to online purchase [21]. Another field of research has concentrated on analysing the situational factors that can influence the process of purchasing food products online [22]. In addition, as the global pandemic is determining consumption's disruption that upsets the food waste management [23,24], there are no studies investigating the food waste in the light of the changing spending behaviour of consumers.

Given this scientific framework and the theoretical and empirical gap on this perspective, the purpose of this paper is to investigate the level of satisfaction of consumers in buying food products by using online grocery shopping channels during the COVID-19 pandemic. The work begins with the description of the theoretical and the practical framework of the new consumers' choices regarding the purchasing channels within the context of the Italian lockdown (Section 2). After, we introduce the concept of customer satisfaction and how to measure it (Section 3). Data and methods are presented, respectively, in Sections 4 and 5: in particular, the key factors affecting the online-spending behaviour of consumers are defined. Data were collected thanks to the replies of an online questionnaire administrated in Italy by using social networks and emails, in the first three months of the pandemic in Italy. Therefore, the results section continues the work (Section 6) that closes drawing the discussion of conclusions, implications and future directions in Section 7.

2. COVID19, on line food shopping and food waste: theoretical and practical framework

The COVID-19 pandemic has had many effects, both negatively and positively, on society and on the individuals lifestyle. Quarantine regulations imposed by national health experts are forcing people to remain at home in lockdown, and consequently carefully plan their meals thus changing the food waste behaviour. The agri-food sector, including 740,000 farms, 70,000 food industries and 230,000 stores in Italy, counting hypermarkets (911) supermarket (21,101), food discount stores (1,716), mini markets (70,081) and other shops (138,000), has continued its regular production processes in order to deliver the food to consumers. This is what emerges from data of the Italian National Institute of Statistics - Istat (2020) on retail trade in March. Foodstuffs is the only sector in contrast with the growth of 3.5% in value and 2.1% in volume, on a trend basis; in April 2020, the food industry recorded a percentage equal to - 8.1% in production compared to April 2019. This negative trend is mainly due to the closure of the Hotellerie-Restaurant-Café (HoReCa) channel that is worth a third of Italian domestic consumption and that works with the greatest added value food products. As for the local food market, the partial and total closings of fairs and markets as well as all forms of trade in public areas starting from 23 February, after the issuing of national, regional and local level provisions, caused the closing of the trade in public areas and the consequent drastic drop in turnover. This led many farmers to sell their product online or adopt the home delivery service, responding to an increasing online marketing demand by consumers. During the month of June, local markets started their activities again and people were willing to buy local food, respecting all precautionary norms. According to a recent analysis (May 2020) of the Italian Institute of Services for the Agri-food Market (ISMEA), the main trends in the agri-food system during second month of lockdown were:

- the considerable increase in home deliveries (plus 160%); moreover, the limit to this growth is not imposed by effective demand (which is much higher), but by the capacity to satisfy it;
- the recovery of the local businesses that also quickly organized "home delivery";
- a significant change in purchasing preferences; consumers have shifted the demand from stock-able products to perishable ingredients (eggs, flour, oil, mozzarella cheese, etc.). Therefore, they avoid wasting food.

Several previous studies have confirmed the importance of investigating the behaviour of individuals under conditions of global crisis [25,26] and the social response to pandemic crisis such as COVID-19 [6]. On the other hand, the global issue of food waste appears more important than the past times in considering the huge inequalities emerged during the COVID-19 pandemic. Recent research highlights an interesting result: surveying the population in Tunisia, Jribi et al. [27] showed that socio-economical context of the 2020 pandemic is determining the prevention of food waste (i.e. food availability, restricted measures, decreasing of income). Furthermore, novel solutions have been proposed aimed at minimizing waste along the supply chain and/or at donating food to vulnerable beneficiaries. For instance, with the temporary closure of charitable food kitchens and other catering initiatives, Norwegian charities launched a pilot project called "Matsentralen Kitchen", which aims to create ready meals which are healthy nutritious suitable for distribution, both in single-portion packs (about 500 g) and in family packs (1.5–2 kg). Being able to redistribute portions, partner organizations can reach a higher number of people in need, while reducing waste food and supporting a healthier diet for people in need. In France, in order to limit the amount of food that is wasted, the market Rungis International, which sells fresh produce to restaurants, supermarkets and at the Paris Farmers' Markets, has joined a partnership with a startup called Califrais to create a business web platform to-consumers who 'knock' directly on the doors of Parisians. Another interesting initiative is promoted by Deliveroo, in partnership with the company that manages the waste in the city of Milan, aimed at increasing awareness among restaurateurs and people of the importance of a correct differentiation of food and packaging waste [28]. These initiatives aimed at reducing food waste, which have become increasingly widespread in recent years. Another example is the *REBUS* project in the Verona area, which has defined an educational programme with the aim of reducing food waste along the supply chain [29]. And again, the new Web App *Too Good To Go* against food waste, born in Denmark in 2015 and which today has more than 20 million users. This in contrast with a recent study of Gao et al. [30] highlights a lack of awareness of the importance of food waste and food loss among food-service operators, including restaurateurs and food delivery companies. Food waste can be caused by a variety of factors: buying and/or cooking too much, not making a shopping list, not planning meals in advance, unawareness of the impact of food waste, retailers' compulsive buying messages [24, 31–35]. However, as Szakos et al. [10] point out, behaviours such as impulse shopping do not necessarily lead to food waste, especially if the family takes care of the correct storage of food and its timely consumption.

Considering the pandemic measures, online food shopping has risen more and more at the expense of frequent shopping at retailers and supermarkets inducing unplanned and hectic shopping routines, which tend to increase food waste [36,37]. Usually, retailers heavily invest on in-store marketing to promote consumers uncontrollable purchasing, for "grabbing consumers" at the point of purchase [38–40]. Other significant factors affecting food waste are the bulk shopping, practiced by consumers to save time and to benefit from price offers [41] and the lack of a precise planning of shopping and home meals [37,42]. Several studies have shown that a shopping list of necessary food can reduce food waste by about 20% [36,43]. Consistent with this [9], reveal that, due to the logistical difficulties associated with the lockdown period, people have been forced to plan food purchases and meals with a consequent reduction in food waste, especially among young people.

Taking into account that the ease of use of IT tools for the purchase of food products and the usefulness associated with their use are predictors of consumers' intention to buy through online grocery services, the following research questions was constructed: What is the of consumer satisfaction linked to the use of IT tools, and above all which dimension linked to the different phases of online purchase influences consumer satisfaction the most?

3. Measuring customer satisfaction for online food shopping

All the measurements in the social sciences are based on a defining process [44]. The measurement of a social phenomenon is built on a strong theoretical definition and a suitable set of observations [45]; the definition must be tested and verified by means of the relationship observed between observations and the concept. This is because those phenomena are not directly observable, but they derive theoretically from observations [46]. Indicators allow the connection between concepts and observations. As stated by Horn [47]; they are purposeful statistics representing a measure organically connected to a theoretical framework. Indicators should be developed by means of a step-by-step process based on the model elaborated by Ref. [48]. We illustrate the different steps and how they were applied in this work.

The first step is the so-called "imagery of the concept", in which we must create a rather vague image of the phenomenon. In simple words, we must define the object of study. Thus, our starting point is the question: what does *customer satisfaction* mean? Answering this question is not an easy task. The term satisfaction derives from the Latin *satis* (enough) and *facere* (to do). Thus, it implies a fulfilment of customers needs, that should be *enough*, i.e. up to a threshold. The complex question to understand is how much is this enough, what is this threshold. Customer satisfaction is a multidimensional concept, whose definition is linked to the complete consumption experience. Ref. [49] gives a formal definition: "Satisfaction is the consumer's fulfilment response. It is a judgement that a product/service feature, or the product or service itself, provided (or is providing) a pleasurable level of consumption-related fulfillment, including levels of under- or over-fulfilment" [49]; 13). Thus, the dominant framework conceives customer satisfaction as based on the fulfilment of customer expectations: it is a standard of how a specific product or service fulfils some specific customer expectations [50]. Customer satisfaction is a perception and, consequently, it is not readily available and not directly measurable. For this reason, we need to do additional effort in order to measure, analyse and explain it. Thus, the second step consists in the specification of the concept. By carefully analyzing the phenomenon, we identify its dimensions each of which allows its specification consistently with the conceptual model. As mentioned before, customer satisfaction regards the fulfillment of the expectations of an individual related to the shopping experience. As specified by Ref. [49], different dimensions of satisfaction are related to the complete consumption experience; thus, we can identify:

- satisfaction during the consumption experience;
- satisfaction with final outcome.

This also applies to the online food shopping experience; overall satisfaction depends, therefore, on what happened during the buying experience and the final result evaluated against initial expectations. These are the two dimensions of satisfaction that we consider in this paper.

At this point, the following step is the identification of a set of basic indicators for each dimension. Obviously, we can choose different indicators to measure a dimension; the choice depends on a wide variety of factors (data availability, level of spatial disaggregation, etc.). Generally, all indicators selected must be systemically related to the conceptual model. They are *purposeful statistics* [47]. It is therefore necessary to select indicators that can measure both the process and the final outcome, generating two systems of indicators, one for each identified dimension of satisfaction. The indicators selected are reported in Section 4.

The last stage of Lazarsfeld's design for measurement is the combination of indicators into indices. The concept needs to be reconstituted by means of synthesis. By using specific statistical techniques, the complexity of the indicators system must be reduced without oversimplifying reality, so that the synthetic index represents a stylized image of reality. The choice of synthesis techniques should always be made taking into account the nature of the indicators first of all and then the objective of the research. Obviously, this choice influences the results obtained and, consequently, the interpretation of the phenomenon. The indicators considered (see Section 4) are all ordinal indicators. For this reason we used the Partial Order Theory (poset) for their synthesis. It provides several mathematical tools for the analysis of indicator systems. Once we have obtained the measures for the two dimensions of customer satisfaction, we could construct a single synthetic index. However, given the profound differences in the two dimensions considered, highlighted in the following pages, we decided to analyse the two dimensions separately.

4. Data description

In order to investigate research's aim, we adopt the survey method [51] considered suitable for the collection of standardised data delivering necessary information [52]. Our research is based on an anonymous, self-designed, structured questionnaire, carried out by means of a Computer Assisted Web Interview (CAWI). According to Romeo-Arroyo et al. [53]; questionnaire was firstly tested and validated by experts in m-commerce, e-commerce and marketing strategies for online purchasing channels in two virtual meetings. The choice of this tool is related to the need to collect primary data on online food shopping during the pandemic. The period covered by the survey is from March 2020 to May 2020 during the period of the Covid-19 restrictions applied in Italy. The questionnaire was made in Italian language and implemented online through Google Forms; it was accompanied by a message inviting people to participate in "a research on online food shopping during Covid-19 pandemic". The questionnaire was filled up by a sample of Italian consumers by means of social networks (Facebook, Whatsapp, etc.) and some internal mailing lists of the University of Palermo, Foggia, and Rome-Sapienza. Thus, the sampling strategy was non-probabilistic and, consequently, self-selection of respondents cannot be excluded. However, under the dramatic pandemic conditions this appears the best solution for quickly investigating consumers while guaranteeing their security [54].

The total respondents that filled up the survey were 249; about the 25% of people reached did not complete the questionnaire mainly because they do not meet the criterion of having purchased at least once on line. As described in Alaimo et al. [55]; the survey was grounded on a multiple-choice questionnaire composed of 39 qualitative and quantitative questions organised in 2 sections. In particular, there were a set of questions in which the respondent is asked to rate, using a 3-points Likert scale from 1 (Disagree or Low) to 3 (Agree or High), some characteristics of the online food shopping experience (time, complexity, difficulty in finding products, etc.). We preferred an odd number of rates because it avoids limitations in data interpretation and analysis.

We identified 4 questions for the process dimension and 5 for the outcome dimension, shown in Table 1. In line with Knapp and Campbell-Heider [56]; for the multivariate analysis the number of observations should be at least 10 times the number of variables and exceed the number of variables by at least 30, that is $n \geq 10v + 30$, where n is number of observations and v is number of variables. In this work, the number of variables used for the statistical analysis is 9 and therefore, the minimum size of total sample would be 120.

Table 1
Indicators of customer satisfaction dimensions: code; question; range.

Code	Question	Range
Process dimension		
X1	Buying food online by means of the Internet websites or apps is generally very simple.	1–3
X2	It is difficult to find all the products in online food platforms.	1–3
X3	It is difficult to order products in online food platforms.	1–3
X4	Online food shopping is particularly useful during this time of COVID-19 pandemic.	1–3
Outcome dimension		
Y1	I think that buying food products online is useful.	1–3
Y2	Using online grocery shopping tools saves a lot of time.	1–3
Y3	I can save money by using tools for buying food online.	1–3
Y4	Online grocery shopping fits perfectly with my shopping habits.	1–3
Y5	Online grocery shopping experience was much better than my expectations.	1–3

5. Methods

The objective of this work is to assess the level of satisfaction of the respondents to the questionnaire described in Section 4 by constructing a synthetic index. From a methodological point of view, we identify two indicator systems (one for the process dimension and one for the outcome dimension of customer satisfaction) and synthesize each system according to the nature of the basic indicators. In measurement and evaluation of socio-economic phenomena, one of the main critical points is the detection of the most suitable statistical methods ensuring that the analysis respects the nature of the phenomena, both from a conceptual and methodological point of view. Thus, we chose synthesis method respecting the nature of the indicators. In particular, dealing with two ordinal indicator systems, a non-aggregative method was utilized, the Partially Order Set (poset). In the following paragraphs, we describe the main characteristics of this methodology.

5.1. *Poset: basic definitions and measures*

Synthesis of multidimensional systems of ordinal data using *non-aggregative methods* allows the construction of measures without the aggregation of the scores of basic indicators [57]. The *Partially Ordered Set* (poset) is a reference within this approach [58], as shown by different works in different fields [59–64]. Poset perfectly fits perfectly with the synthesis of ordinal indicators, such as those used in this paper. Dealing with ordinal data, the use of traditional aggregative-compensative synthesis methods[2] is conceptually and methodologically wrong, as shown in the following pages. Poset provides concepts and tools that fit very naturally the needs of synthesis. It is focused on *profiles*, which are the combinations of scores of each statistical units in the basic indicators considered, describing the status of units. Moreover, this method is also suitable for cardinal data [65–69] and, generally, even if we deal with indicators of different scaling levels [70]. Thus, poset respects the nature of data and the production of synthetic indicator does not require any operation on the basic indicators (normalization, aggregation).

Before describing the basic concepts of poset, we propose a small example useful to understand it better. Suppose we have 5 objects on which the presence or absence of 3 properties or attributes is observed. For simplicity, the absence of a property will be encoded with 0, the presence with 1. We report the resulting system in Table 2.

We want to determine if it is possible to establish a rank between the objects considered, that is, if it is possible to say that one object is better than another one. In fact, it is often the final ranking that is the goal of a synthesis, rather than the exact scores [71]. Looking at data reported in Table 2, object A can be classified as "better" (whatever this means in specific contexts) than all the other ones, because it presents all the attributes considered. For the same reason, we can classify object E as the "worst", since it has no attributes. What about the other objects? They

Table 2
Poset example: system of 3 ordinal attributes for 5 objects.

Objects	X	Y	Z
A	1	1	1
B	1	0	1
C	0	1	1
D	1	1	0
E	0	0	0

[2] The aggregative-compensative approach consists in the mathematical combination (or aggregation) of the set of indicators, obtained by applying methodologies known as composite indicators [92,93].

present similar situations, since they have 2 attributes of the 3 considered. However, it is not possible to establish a rank between these three objects: we cannot say, for example, that B is better than C since they have different combinations of attributes. They have conflicting achievements and, consequently, are not comparable. This exactly means dealing with a *partially ordered set*. Addressing the synthesis of such a system of indicators using the aggregative approach involves conceptual and methodological limitations. The use of aggregative methods presupposes that the indicators are cardinal, that is, the modalities they assume are numbers. These methods are, therefore, not suitable for ordinal variables, whose modalities are not numerical, even though they are often coded using numbers (as in the example in Table 2). Despite being conceptually wrong, however, the use of aggregative methods to synthesize systems with ordinal indicators is common practice in literature. This leads to misleading results and conclusions. For example, applying the arithmetic mean[3] to synthesize data in Table 2, objects A and E would have, respectively, the best and worst rank. The other three objects would all obtain the same score (0.67) and, consequently, the same rank, although, as mentioned above, they have different combinations in the basic indicators. Thus, the application of an aggregative method *makes comparable incomparabilities* among statistical units (this aspect is clearly investigated in Alaimo and Maggino [72]). Poset gives analytical tools to better deal with system presenting ordinal indicators, allowing the construction of a synthesis that is not the result of an aggregation of the scores of basic indicators.

Given a finite object set X consisting of several units of analysis x_i, $X = \{x_i\}$, if we can compare those units using a binary relation $\trianglelefteq$ the set is equipped with a *partial order* and we can call it a poset (partially ordered set). More precisely, a poset ($\Pi = (X, \trianglelefteq)$) is a set X equipped with a partial order relation $\trianglelefteq$ satisfying three main properties [73,74]:

– the first property is called *reflexivity* and indicates that an object can be compared with itself, i.e. $x \trianglelefteq x$ for all $x \in X$;
– the second property, *anti-symmetry*, states that, given two generic elements a and b belonging to the set X, if b is better than a and, at the same time, a is better than b, then the two elements are identical; i.e. if $a \trianglelefteq b$ and $b \trianglelefteq a$ then $a = b$, $a, b \in X$;
– *transitivity* is present if the units are, at least, ordinal scaled and stated the possibility of defining an order among them. i.e. if $a \trianglelefteq b$ and $b \trianglelefteq c$, then $a \trianglelefteq c$, $a, b, c \in X$.

If $a \leq b$ or, alternatively, $b \leq a$ then they are comparable, otherwise incomparable. The structure of comparabilities is defined by a matrix, called *incidence matrix*, $Z_P = (z_{ij}) \in \mathbb{Z}^{k \times k}$ where $|X| = k$ is the cardinality of X and z_{ij} is equal to 1 if $x_i \trianglelefteq x_j$, 0 otherwise, with $x_i, x_j \in X$. Given two elements $x_i, x_j \in X$, x_j covers x_i ($x_i \prec x_j$) if x_j dominates x_i ($x_i \trianglelefteq x_j$) and there is no other element $x_s \in X$ that jointly dominates x_i and is dominated by x_j ($x_i \trianglelefteq x_s \trianglelefteq x_j$). Dealing with a multi-indicator system, the elements of the poset correspond to the combinations in the basic indicators for each statistical unit, the *profiles*. Given two profiles, x and y, we will say that x covers y only if it has a profile with values in all the indicators equal to and at least one greater than those of y. Looking at Table 2, we can say that A covers all other elements of the set. If x has a higher value in one indicator than y and the latter has a value in another indicator higher than x, regardless of the values assumed in the other indicators, the two profiles are incomparable, since they actually express situations not akin with each other. In the reported example, B and C are incomparable, because B has a value in the indicator X higher than C but C presents a value in the indicator Y higher than B. The incidence matrix resulting from the system in Table 2 is the following:

$$Z_P = \begin{array}{c} \begin{array}{ccccc} A & B & C & D & E \end{array} \\ \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix} \end{array} \begin{array}{c} A \\ B \\ C \\ D \\ E \end{array} \tag{1}$$

A partially ordered set can be represented by means of a directed graph without cycles called *Hasse diagram*, in which the nodes are the elements of the sets. In the case of a system of indicators, each edge represents a specific profile. It graphically summarises the information in the incidence matrix. This diagram should be read from top to bottom and two elements are comparable $\trianglelefteq$ if an edge connects them in the diagram. Hasse diagram provides a vertical information regarding the comparabilities within the poset and a horizontal one about the incomparabilities among nodes, expressing the uncertainty in the set. Obviously, nodes connected by a path are comparable by transitivity. Fig. 1 reports the Hasse diagram of the example presented in this work.

We must introduce two other crucial concepts. An *extension* of $\Pi = (X, \trianglelefteq)$ is a poset $\Pi_e = (X, \trianglelefteq_e)$ defined on the same set X but equipped with a relation $\trianglelefteq_e$ that extends the relation $\trianglelefteq$. The consequence is that all the pairs of elements comparable in $\trianglelefteq$ are comparable in $\trianglelefteq_e$, while some pairs comparable in $\trianglelefteq_e$ are not comparable in $\trianglelefteq$. An extension of a poset is defined *linear* if all the elements of the set X are comparable; in other words, it is a linear order obtained extending the starting poset so that all elements of the set X are comparable. A poset generally has a set of linear extensions, Ω_Π. An interesting property [71,75] is that a poset is uniquely identified by a set of linear extensions that is different from that of any other poset and it is the result of the intersection of its linear extensions. Thus, we can study properties of a poset starting from the analysis of the set of its linear extensions. The latter, being linear, are easier to study and examine. Linear extensions, therefore, dissolve the incomparabilities present in the poset: given two generic incomparable elements, a and b, in some linear extensions a dominates b, while in others b dominates a. The *mutual ranking probability (MRP) matrix* of Π is a $k \times k$ (where k is the number of elements of the set) matrix $M_\Pi = (m_{ij})$, where m_{ij} is the fraction of linear extensions in Ω_Π such that the element x_i is dominated by the element x_j.

In using poset for analysing multi-indicators systems, we define the structure of comparabilities among the units of the systems and analyse it by means of some mathematical tools. First, we want to give a *score* to each element of the set, in order to reduce the complexity. This is obtained by means of the *average rank*. Generally, the *rank* of an element x_i in a linear extension ℓ is 1 plus the number of elements which dominates x_i in ℓ. Consequently, the *average rank* of an element $x_i \in \Pi$ is the average over Ω_Π of the ranks of x_i in the linear extensions. The vector of average ranks of the poset elements $\mathbf{h}_\Pi$ is equal to the vector of row sums of the *MRP* matrix.[4] The MRP matrix and the average ranks vector (AvR)

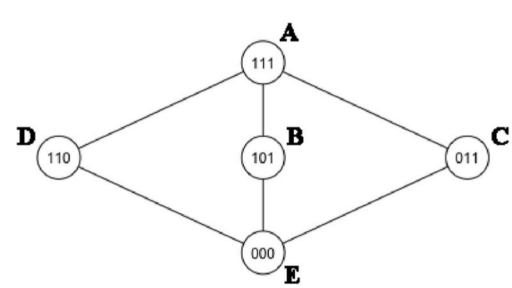

Fig. 1. Hasse diagram of the system in Table 2.

[3] These considerations are independent of the aggregation method used.

[4] For a more detailed analysis of the average height, please see Fattore [71]; Alaimo et al. [67].

of the example reported in Table 2 are the following:

$$Z_P = \begin{array}{c} \\ A \\ B \\ C \\ D \\ E \end{array} \begin{array}{c} \begin{array}{ccccc} A & B & C & D & E \end{array} \\ \begin{bmatrix} 1.0 & 0.0 & 0.0 & 0.0 & 0.0 \\ 1.0 & 1.0 & 0.5 & 0.5 & 0.0 \\ 1.0 & 0.5 & 1.0 & 0.5 & 0.0 \\ 1.0 & 0.5 & 0.5 & 1.0 & 0.0 \\ 1.0 & 1.0 & 1.0 & 1.0 & 1.0 \end{bmatrix} \end{array} \begin{array}{c} AvR \\ 1 \\ 3 \\ 3 \\ 3 \\ 5 \end{array} \quad (2)$$

Average rank is bounded between a minimum, equal to 1, corresponding to the element with no others above it in the linear extensions (the best one) and a maximum, equal to the number of all elements of the poset. It represents the position of each element in the general order. We can integrate this information with that expressing the situation in terms of evaluation of satisfaction of each profile. To do this, we need to define a criterion capable of determining whether a profile belongs to the satisfied or dissatisfied class. Thus, we identify one or more *threshold profiles*, compared to which we identify the satisfied profiles in the poset. The identification of threshold profiles is a crucial and critical point. Although it is based on objective criteria (e.g. analysis of the literature, opinion of experts, etc.), there is no doubt that this step is strongly pervaded by subjectivity. This could be considered a weakness. However, subjectivity is an unavoidable element in measurement, which, however, does not make it arbitrary, since it always involves a relationship with the reality [57]. Once the threshold(s) has been identified, a series of mathematical functions can be used to describe the satisfaction levels of the profiles in relation to the threshold(s) identified. The so-called *identification function* expresses the number of events in which the profile falls into the area of dissatisfaction, considering the different linear extensions, assigning to each profile a score in $[0, 1]$ as follows:

- the scores of the threshold profiles are 1 (they are classified as dissatisfied);
- the scores of profiles below at least one element of the threshold are 1;
- the scores of profiles above any element of the threshold are 0 (they are classified as absolutely satisfied);
- the scores of all other profiles are in $[0, 1]$ (they are classified as *fuzzy* satisfied profiles).

In each linear extension, a profile is clearly below at least an element of the threshold or it is above all elements. Thus, it can be reliably classified as satisfied or not. Thus, we can define a function $idn_\delta(\cdot)$, which assigns in each linear extension δ:

$$\begin{cases} 1 & \text{if the profile is classified as dissatisfied in } \delta \\ 0 & \text{if the profile is classified as satisfied in } \delta \end{cases}$$

The count of linear extensions where a profile is classified as dissatisfied makes it possible to quantify such ambiguities and obtain a non-linear identification function $idn(\cdot)$ that assigns scores in $[0, 1]$ to each profile. The mathematical formalization of this function for a profile π of the poset Π is the following:

$$idn(\pi) = \frac{1}{|\Omega_\Pi|} \sum_{\delta \in \Omega_\Pi} idn_\delta(\pi) \quad (3)$$

This function gives information about the ambiguity of the set in terms of dissatisfaction. This information can be integrated with that expressing the intensity of such dissatisfaction by means of the so-called *severity function*. Severity is the arithmetic mean of the graphical distance of the profile from the first profile above all threshold ones (its score is 0 for profiles above the threshold). Given a deprived profile q in a linear extension δ and a profile s nearest to q in δ as the first profile ranked above all the elements of the threshold, the severity of q in δ is defined as the graph distance of q from s in the Hasse diagram of δ [60]; 422). Severity is equal to 0 for non-deprived profiles in δ. It is formalized as follows:

$$svr(\pi) = \frac{1}{|\Omega_\Pi|} \sum_{\delta \in \Omega_\Pi} svr_\delta(\pi) \quad (4)$$

As stated by Ref. [76]; 845), we can define a relative severity function by using the maximum value (deprivation severity reaches the maximum on the bottom profile) as benchmark:

$$svr_{rel}(\pi) = \frac{1}{|\Omega_\Pi|} \sum_{\delta \in \Omega_\Pi} \frac{svr_\delta(\pi)}{svr_\delta(\pi_{max})} \quad (5)$$

6. Results

Table 3 shows the main characteristics of the sample. The 48% of respondents are between 35 and 54 years old and only 20% are over 55 years old. Respondents present a very high level of education: the 42.4% of them declare to have a post-graduate degree, 16.5% have a high school diploma, only 2.8% have a lower secondary school diploma. Geographical origin of respondents shows an imbalance in favour of southern Italian regions[5] (71.7%). The majority of respondents (42.7%) reported an average monthly household income between 1,621 and 3,240 euros; a significant part of the sample (26.3%) declares very high household incomes. There is a predominance of individuals that live in family units composed by one component (58.1%), with respect to those composed by two (20.2%) or more components (21.7%). 33.9% of the sample stated to spend on average of less than 1 h a day online (for any reason other than work); 41.1% of the respondents use Internet at least

Table 3
Characteristics of the sample.

Characteristics	Total Number	Percentage
Age class (18–34)	100	40.3%
Age class (35–54)	119	48.0%
Age class (more than 55)	29	11.7%
Education: Lower secondary school diploma	7	2.8%
Education: High school diploma	41	16.5%
Education: Degree	95	38.3%
Education: Post-graduate degree	105	42.4%
Northern Italy	47	19.0%
Central Italy	23	9.3%
Southern Italy	178	71.7%
Average monthly household income: until 1,620 EUR	14	5.6%
Average monthly household income: 1,621–3,240 EUR	106	42.7%
Average monthly household income: 3,241–8,100 EUR	63	25.4%
Average monthly household income: more than 8101 EUR	65	26.3%
Family composition: one component	144	58.1%
Family composition: two components	50	20.2%
Family composition: more than two components	54	21.7%
Frequency of online purchase of food products: never	63	25.4%
Frequency of online purchase of food products: rarely	72	29.0%
Frequency of online purchase of food products: at least once a month	11	4.5%
Frequency of online purchase of food products: at least once a week	102	41.1%
Familiarity with buying food online: yes	172	69.4%
Familiarity with buying food online: no	76	30.6%

[5] In this paper, we refer to the three groups of Italian regions according to the NUTS (Nomenclature of Territorial Units for Statistics) codes of Italy; i.e.: Northern Italy: Piedmont, Aosta Valley, Liguria, Lombardy, autonomous province of Trento, autonomous province of Bolzano, Veneto, Friuli Venezia Giulia and Emilia Romagna; –Central Italy: Tuscany, Umbria, Marche and Lazio; –Southern Italy: Abruzzo, Basilicata, Campania, Apulia, Molise, Calabria, Sardinia and Sicily.

once a week to purchase food products while 25.4% have never used it. More than 60% of the sample declares having familiarity with buying food online.

The characteristics of the sample are undoubtedly influenced by the way in which the respondents were selected and the survey was conducted. Consequently, the sample presents some imbalances and selection bias. This is, probably, the main limitation of our work. Although, as previously written, in a critical period like the one in which the data were collected (the COVID-19 pandemic), the choice of administering the questionnaire online is a viable and acceptable solution, despite the above-mentioned problems and limitations.

The core of the questionnaire includes a set of questions relating to buying food online, some of which (see Table 1) were used to construct the synthetic indices. The starting point in any synthesis is the analysis of the basic indicators. In Fig. 2, we report the percentage distribution of the indicators used.

Looking at the indicators of the process dimension, more than 60% of the respondents express a high level of satisfaction expect in the indicator X2 (see Table 1 for the description of different indicators), where the percentage drops to 43.5%. The situation in the process dimension is profoundly different. In fact, while indicators Y1 and Y2 show a similar percentage of respondents expressing a high level of satisfaction as X2 (more than 40%), the other ones have percentage quite low (from 21% to 28%). At the same time, the percentage of respondents who assess satisfaction as low in these variables is quite considerable (in particular, in variable Y4 the percentage is higher than 50%). This seems to indicate that respondents had a good experience with the online purchasing process in its different phases, while their expectations were often not met with regard to the final outcome. This positive experience is related to the users' opportunity to reserve time for their delivery through mobile apps before they start online shopping. Indeed, as Ref. [77] state the longer the waiting time, the lower the marginal utility, especially in the case of the purchase of food, where respondents prefer a time window closer to the present.

For each dimension of customer satisfaction, we define an order relation according to the rules described in Section 5.1. Thus, the set of the respondents is partially-ordered differently in the different customer satisfaction dimension sets. At this point, we must define the incidence matrix and, consequently, construct the Hasse diagram. We must make some clarifications. The Hasse diagrams refer to all possible theoretical profiles generated by the combination of the different modalities of the indicators considered. In detail, we have 81 possible profiles for the process dimension and 243 for the outcome one. The realized profiles, i.e. those actually observed in the population, may not coincide with the

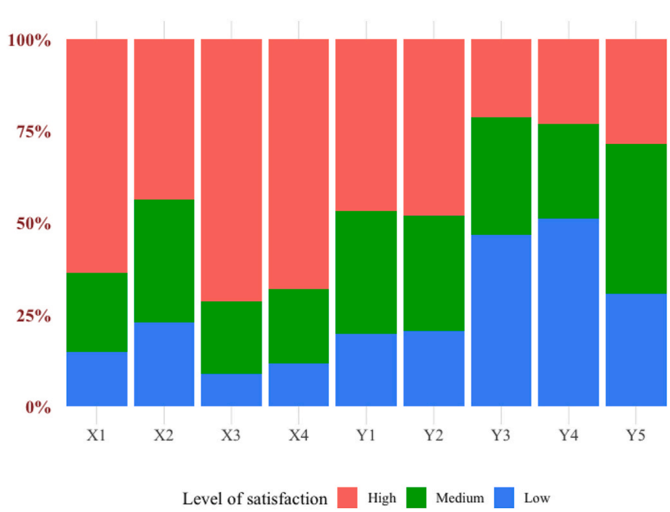

Fig. 2. Indicators of customer satisfaction for online food shopping: percentage distribution of levels of satisfaction.

theoretical ones; in fact, it is possible that some theoretical profiles were not actually observed in reality. However, they are still possible and feasible. Therefore, the set of all theoretical profiles defines the overall evaluation space, i.e. the most general possible evaluation context (consisting of all possible profiles) within which it is possible to evaluate each profile. The measurement of the two dimensions of customer satisfaction is then carried out using the posets of all possible profiles. Another crucial point is the choice of threshold(s). As mentioned above, this step has a clear subjective component that cannot be eliminated, but which should not be considered in negative terms (arbitrariness). From the analysis of literature, it was not possible to identify an unambiguous criterion for the definition of possible threshold(s), also because of the specificity and novelty of the topic. We define the threshold(s) according to the procedure presented in Arcagni et al. [78]. Given the two posets, representing the dimensions of customer satisfaction, we identify for each of them a subset π_l of mutually incomparable profiles (lower threshold); all the profiles in π_l or below an element of it are classified as dissatisfied. At the same time, we define another subset π_c (upper threshold), so that profiles in π_c or above an element of it are identified as completely satisfied. All other profiles are classified as ambiguously satisfied.[6] Table 4 reports the lower and upper thresholds for posets of process and outcome dimensions. For the lower threshold, we chose to include, in addition to the minimal profile, also the profiles presenting in all the indicators considered, modality 1 - "Low" and only one modality 2 - "Medium". The upper threshold includes the maximal element of each poset and all those with a combination in the basic indicators with modality 3 - "High" and only one modality 2 - "Medium". This choice of very high thresholds for both full satisfaction and full dissatisfaction has been made taking into account the literature [49,50], which establishes the difficulty for a consumer to achieve full and complete satisfaction (or dissatisfaction). These reflections are applicable to the specific field of online food shopping. Figs. 5 and 6 in Appendix report the Hasse diagrams of, respectively, process and outcome dimension. In each diagram, we report in dark grey the profiles belonging to the lower threshold, while in light grey those of the upper threshold.

At this point, it is possible to calculate for each dimension the three synthetic measures described in Section 5.1. All the results are reported in Tables 5 and 6.[7] We can compare the measures obtained and verify whether they are correlated to each other. To do this, we use the Spearman correlation coefficient, ρ.[8] Fig. 3 shows the correlation plot of the 6 synthetic indices. The coefficients confirm that the process and outcome dimensions measure different and non-coincident aspects of customer satisfaction. The measures are highly correlated for each dimension; on the contrary, severity functions (0.33), average ranks (0.36) and identification functions (0.34) show low coefficients between them. As highlighted from previous analyses, respondents show higher levels of satisfaction in the process dimension than in the outcome one.

Table 4
Lower and upper thresholds of the process dimension and outcome dimension posets.

Poset	Lower Threshold	Upper Threshold
Process dimension	(1111; 2111; 1211; 1121; 1112)	(3333; 2333; 3233; 3323; 3332)
Outcome dimension	(11111; 21111; 12111; 11211; 11121; 11112)	(33333; 23333; 32333; 33233; 33323; 33332)

[6] For methodological details, please see: Arcagni et al. [78].

[7] The results refer only to the profiles observed in the sample (realized profiles).

[8] As known, ρ coefficient is the rank-based version of Pearson's correlation coefficient *r*. We use it because we want to focus on the rankings obtained from different measures, rather than their values.

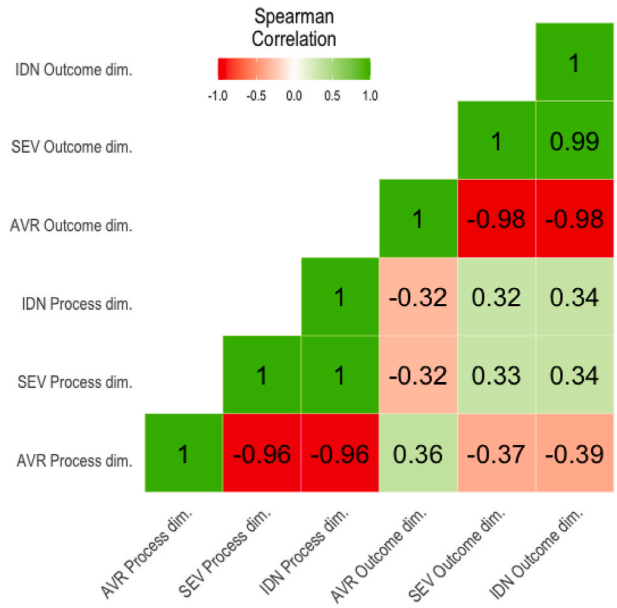

Fig. 3. ρ Spearman correlation coefficients: average rank (AVR Process dim.), severity function (SEV Process dim.) and identification function (IDN Process dim.) of process dimension; average rank (AVR Outcome dim.), severity function (SEV Outcome dim.) and identification function (IDN Outcome dim.) of outcome dimension.

In addition to this, high levels of satisfaction in the process dimension do not always coincide with high levels in the other one. These findings support the decision to analyse the two dimensions separately, rather than looking at a single synthetic index.

The frequency distributions of the profiles provide further evidence of the difference between the two dimensions. Looking at process dimension (Table 5), the 28% of the sample result fully satisfied (having profiles in the upper threshold), while only one respondent has a profile that falls within those of the lower threshold. Only 5% of the respondents express a full satisfaction in the outcome dimension and 7% presents profiles of full and complete dissatisfaction.

Notwithstanding the importance of the position of units in the general order provided by the average rank, it is much more interesting to analyse the situation in terms of the intensity and ambiguity of their satisfaction in relation to the thresholds and the two posets. Fig. 4 shows the distributions of cumulative frequencies of the identification and relative severity functions in the different posets. Starting with the identification function (at left in Fig. 4), we can observe that 69% of respondents has values not exceeding 0.25 in the process dimension (104 respondents, the 42% of the sample, have a value equal to 0) and the 5% values higher than 0.75. In the outcome dimension, only the 24% presents values between 0 and 0.25 (26 respondents have a value of 0) and the 43.5% values higher than 0.75. These results highlight the differences in satisfaction levels for the two different dimensions, confirming a generally better situation in process dimension. Similar conclusions apply to the analysis of severity function. The 75% of the sample has values at or close to 0 in the process dimension and only three respondents had profiles with severity values above 0.75. In outcome dimension, the 56% of people has values lower than 0.25 and the 19% higher than 0.75. The difference between process and outcome dimensions is evident.

7. Discussion and conclusions

The advent of internet and the development of ICTs has profoundly transformed the communication and marketing of products and services affecting significantly consumption patterns and habits [1] for different product categories, including foods [18]. Online grocery is a relatively new environment that has experienced a considerable growth in recent years [17], particularly during the COVID-19 pandemic [55,79,80]. The economic literature, as already emphasized, has studied over the years different dimensions related to the online food shopping by adopting different theoretical lenses such as the Theory of Planned Behavior, the Theory of Reasoned Action, the Theory of Planned Behavior [13], the Technological Acceptance Model [1], the Hansen model [12]. The common aim was to understand the main factors affecting the acceptance, the intention or the user's continuance intention to use smartphone or other mobile apps to buy food products. Findings of these studies reveal that consumers' acceptance and intention to use online tools to buy food products is affected by the consumers' previous experiences and the ease of using these online instruments. On the other hand, few studies focused on the analysis of the satisfaction of consumers who purchase agri-food products online, although it is well known that customer satisfaction is a strong predictor for frequent or infrequent online grocery shopping [14,81]. Our analysis enriches the literature on the customer satisfaction for the online grocery shopping. Starting from a definition of customer satisfaction identifying two main dimensions of the concept (the process and the outcome dimensions), our findings, somewhat consistent with those by other researchers, highlight that these dimensions have different levels among consumers. In particular, the process dimension, linked to the ease of use of online tools in the phases of online searching and purchase, generates a higher level of satisfaction than the outcome one, measured in terms of service usefulness. As shown by Kim [82]; the ease with which consumers acquire product information, the customer service, the attractiveness of the website design and the process convenience affect the overall self-reported satisfaction. Consistent with this, Maditinos and Theodoridis [81] found that product and service information quality and the user interface quality and security perception have a strong impact on the overall satisfaction. The higher level of satisfaction with the process dimension can be explained by the frequency with which consumers use IT tools to purchase different categories of products, which makes their use easier. Several empirical evidences, indeed, emphasize that the complexity of online purchases negatively affects satisfaction and, consequently, purchase intent [13,83]. Therefore, satisfied consumers of the online food delivery service intend to repurchase or recommend the services to other potential consumers, implying that "customer satisfaction mediates the relationship between e-service quality as well as food quality on online loyalty" [84]. On the other hand, our results are in part in contrast with the findings of Shang and Wu [1] and Driediger and Bhatiasevi [14]: indeed, there is a positive relationship between the perception of the ease of use of the online shopping service (process dimension), the perceived utility (outcome dimension) and the intention to use these tools. The lower level of satisfaction generated by the outcome dimension could be explained by a negative association between the online purchase of food products and the pandemic, confirming the influence of the surrounding environment and situational factors on the intention and continuance intention to buy food online [22,55]. As previously pointed out, a high level of consumer satisfaction positively influences the intention to purchase food products online, helping to reduce food waste. The use of online grocery services, as Hebrok and Heidenstrøm [85] highlight, allows consumers to more easily check the supply of food products before purchasing procedures, helping to decrease food waste. The reduction of food waste characterized the period of the lockdown. As Jribi et al. [27] underline, consumers have changed their habits during the COVID-19 pandemic by adopting more responsible behaviors, more influenced by the socio-economical context than by pro-environmental behavior. During the pandemic period, the lower frequency of going to supermarkets, the greater engagement in more home cooking and the health concerns in the choices of food products contribute to reduce food waste [11]. In line with Li et al. [86]; results highlight that consumers that choose smart delivery appear more aware of food waste issues due to the higher price

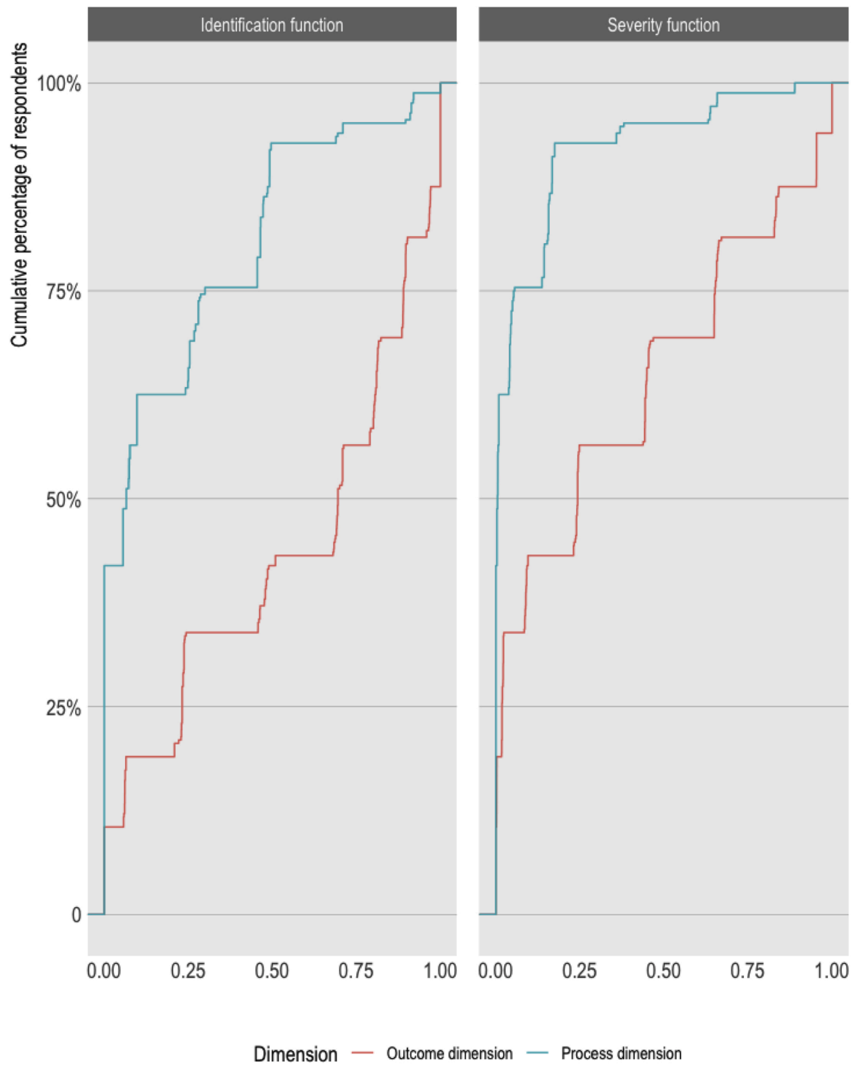

Fig. 4. Process and outcome dimensions of customer satisfaction: cumulative frequencies distribution of identification and severity functions.

of home delivery food than single raw ingredients. In addition, Zulkarnain et al. [87] show that food delivery improves buying decisions and conversely the level of satisfaction of consumers thanks to precise food descriptions. Finally, it is possible to notice that there is an unexpected positive effect of the Covid-19 pandemic on reduction and handling of food waste [88]: consumers monitor attentively, try to plan meals in advance and define a shopping list before purchasing food.

Our study provides some theoretical and managerial implications. From a theoretical point of view, it contributes to existing research on online grocery shopping, linking consumer behaviour to the influence of situational factors such as the COVID-19 pandemic. Moreover, it is the first study (to our knowledge) that separately analyses the dimensions of customer satisfaction. This allows differences to be better highlighted and provides a more precise view of the phenomenon. From the managerial perspective, the study provides insights and hints to on-line food providers which should focus more on the dimensions of the service that affect the usefulness of the consumer. This is one of the aspects that can influence the continuance intention to use these tools to buy products online.

From a methodological point of view, our study is the first one that uses posets for measuring customer satisfaction. This method, consistent with the nature of the data used, allows methodological errors and misleading conclusions to be avoided. By focusing on the profiles of the statistical units, poset makes it possible to obtain synthetic measures that are not the result of any combination of the basic indicators, but depend on the relational position of each unit in relation to all the others. In this way, we can treat ordinal data respecting its nature, without using tools that are not appropriate from a methodological point of view (the aggregative-compensative methods, like arithmetic or geometric mean).

Appendix

Table 5
Process dimension of customer satisfaction: profiles observed in the sample; frequencies; average rank; severity function; identification function.

Profile	Frequency	Average rank	Severity function	Identification function
1112	1	4.006	0.890	1.000
1113	3	11.909	0.659	0.913
1121	2	3.964	0.890	1.000
1122	2	11.183	0.637	0.920
1132	3	23.016	0.358	0.710
1133	8	42.133	0.168	0.492
1212	2	11.580	0.639	0.910
1213	2	27.446	0.369	0.690
1223	3	44.307	0.138	0.465
1232	1	41.002	0.159	0.474
1233	4	59.978	0.041	0.250
1313	1	43.863	0.153	0.473
1323	2	59.814	0.043	0.248
1332	1	56.872	0.056	0.286
1333	2	71.237	0.007	0.072
2112	1	11.188	0.632	0.896
2113	1	26.970	0.381	0.695
2123	9	42.398	0.144	0.455
2213	3	43.839	0.167	0.492
2222	9	42.008	0.157	0.465
2223	7	59.091	0.041	0.254
2231	2	37.944	0.160	0.496
2232	3	57.011	0.044	0.267
2233	6	70.979	0.006	0.066
2322	1	57.882	0.052	0.283
2331	2	54.714	0.053	0.299
2332	1	69.932	0.006	0.072
2333	8	78.024	0.000	0.000
3111	1	10.458	0.658	0.919
3113	4	42.256	0.175	0.472
3123	2	58.280	0.040	0.241
3131	1	40.701	0.145	0.484
3132	2	57.127	0.038	0.271
3133	17	70.784	0.003	0.056
3213	1	58.518	0.044	0.254
3221	2	38.497	0.155	0.486
3222	3	57.559	0.050	0.279
3223	4	70.518	0.006	0.076
3231	4	55.192	0.046	0.279
3232	4	69.941	0.005	0.074
3233	23	78.072	0.000	0.000
3313	2	71.696	0.006	0.074
3323	3	78.191	0.000	0.000
3331	15	69.338	0.009	0.096
3332	16	77.892	0.000	0.000
3333	54	81.000	0.000	0.000

Table 6
Outcome dimension of customer satisfaction: profiles observed in the sample; frequencies; average rank; severity function; identification function.

Profile	Frequency	Average rank	Severity function	Identification function
11111	15	1.000	1.000	1.000
11112	3	4.758	0.955	1.000
11113	1	14.879	0.842	0.969
11211	2	4.690	0.954	1.000
11212	1	15.950	0.834	0.965
11213	1	37.404	0.663	0.902
11222	1	38.666	0.656	0.890
11223	1	73.572	0.454	0.812
11312	1	39.416	0.661	0.901
11313	1	74.539	0.446	0.822
11321	1	36.264	0.657	0.888
12111	5	4.678	0.955	1.000
12112	3	16.471	0.829	0.967
12211	2	15.460	0.830	0.959
12212	2	39.774	0.652	0.889
12312	1	75.992	0.438	0.813

(continued on next page)

Table 6 (*continued*)

Profile	Frequency	Average rank	Severity function	Identification function
13111	1	14.670	0.842	0.968
13112	1	38.418	0.654	0.889
13211	1	37.023	0.671	0.896
13212	1	76.133	0.455	0.813
13311	1	74.992	0.468	0.807
13312	1	125.026	0.245	0.693
13313	1	172.473	0.087	0.457
13323	1	207.605	0.021	0.238
21111	6	4.662	0.955	1.000
21112	1	15.633	0.834	0.971
21113	3	37.415	0.657	0.888
21121	1	14.679	0.835	0.968
21122	1	36.809	0.650	0.896
21131	1	36.042	0.664	0.894
21211	1	15.565	0.832	0.966
21212	1	40.313	0.650	0.897
21213	1	75.460	0.459	0.813
21221	1	38.774	0.654	0.891
22111	3	15.632	0.835	0.970
22112	5	39.489	0.650	0.897
22113	2	76.397	0.444	0.811
22121	1	37.596	0.662	0.892
22122	2	75.286	0.449	0.805
22132	1	125.884	0.238	0.693
22211	3	37.610	0.650	0.885
22212	5	74.711	0.444	0.810
22213	1	124.247	0.246	0.712
22221	2	73.875	0.446	0.801
22222	10	122.374	0.244	0.709
22223	3	171.983	0.096	0.509
22311	1	73.626	0.443	0.804
22313	1	170.538	0.085	0.476
22322	3	167.663	0.089	0.479
22332	1	205.065	0.022	0.243
22333	1	228.555	0.002	0.057
23111	1	37.503	0.657	0.890
23112	2	74.710	0.449	0.803
23113	1	120.308	0.245	0.701
23121	1	72.984	0.448	0.808
23122	1	121.477	0.233	0.689
23131	2	119.717	0.249	0.684
23133	1	207.341	0.017	0.221
23211	1	72.239	0.454	0.816
23212	3	117.889	0.232	0.695
23213	3	168.176	0.092	0.486
23222	1	166.375	0.089	0.464
23232	1	203.530	0.018	0.231
23321	1	165.799	0.093	0.460
23322	2	202.767	0.019	0.229
31111	1	14.936	0.841	0.970
31112	2	38.701	0.660	0.897
31113	1	76.067	0.446	0.815
31132	1	126.844	0.245	0.692
31212	1	76.456	0.457	0.813
32111	3	36.809	0.650	0.890
32112	3	76.474	0.454	0.800
32113	1	119.612	0.243	0.708
32123	1	168.091	0.090	0.489
32131	1	119.015	0.247	0.693
32133	2	208.101	0.019	0.229
32211	1	74.270	0.443	0.792
32221	1	120.788	0.237	0.683
32222	1	167.066	0.089	0.476
32223	1	204.963	0.021	0.239
32232	1	205.733	0.019	0.228
32233	1	228.996	0.002	0.059
32311	1	119.519	0.245	0.687
32332	2	228.329	0.002	0.057
33111	4	70.792	0.443	0.790
33112	5	120.293	0.240	0.696
33121	1	116.786	0.241	0.681
33122	2	169.490	0.088	0.458
33123	8	206.300	0.022	0.237
33131	1	164.974	0.090	0.481
33132	10	205.968	0.018	0.231
33133	4	229.209	0.002	0.061

(*continued on next page*)

Table 6 (*continued*)

Profile	Frequency	Average rank	Severity function	Identification function
33211	2	118.995	0.242	0.691
33212	3	167.437	0.086	0.463
33222	4	205.054	0.022	0.234
33223	4	228.378	0.002	0.065
33232	3	228.140	0.002	0.062
33233	7	239.367	0.000	0.000
33311	2	170.307	0.092	0.482
33312	4	204.438	0.017	0.208
33313	3	229.313	0.002	0.061
33321	1	206.381	0.024	0.236
33323	6	239.433	0.000	0.000
33331	3	228.379	0.003	0.061
33332	4	239.173	0.000	0.000
33333	9	243.000	0.000	0.000

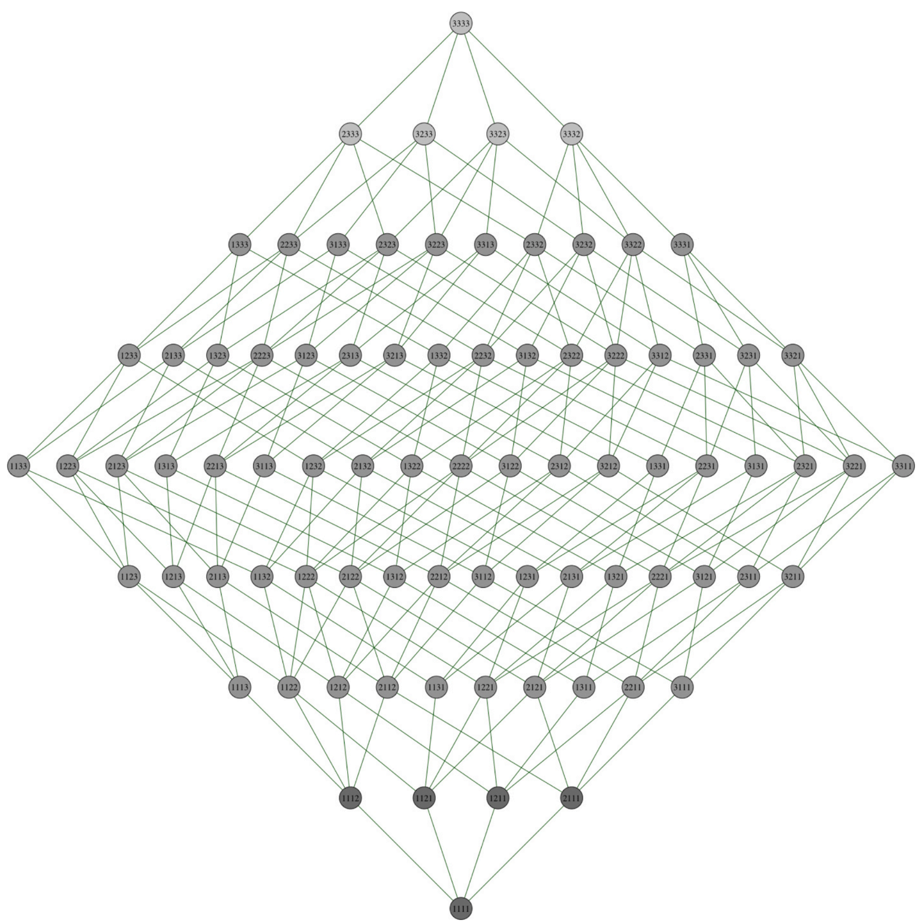

Fig. 5. Process dimension of customer satisfaction: Hasse diagram.

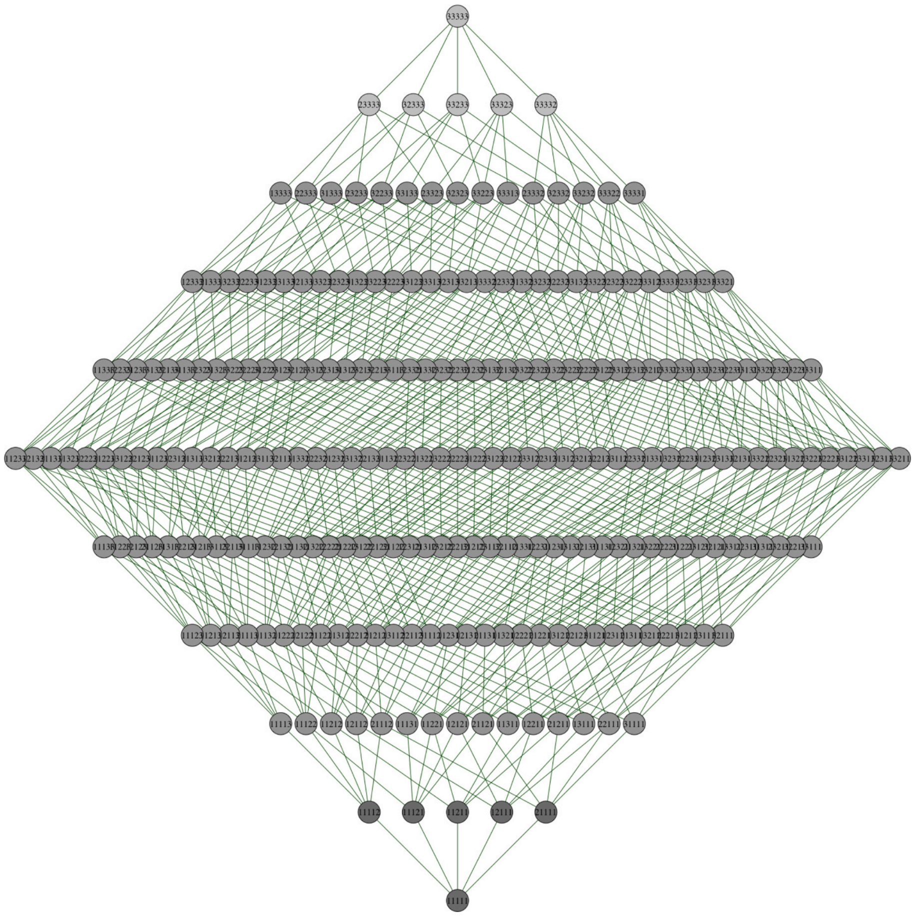

Fig. 6. Outcome dimension of customer satisfaction: Hasse diagram.

Credit author statement

Leonardo Salvatore Alaimo: Conceptualization, Methodology, Software. Resources, Visualization, Formal analysis, Writing - review & editing.
Mariantonietta Fiore: Conceptualization, Data Curation, Formal analysis, Writing - review & editing.
Antonino Galati: Conceptualization, Data Curation, Formal analysis, Writing - review & editing.

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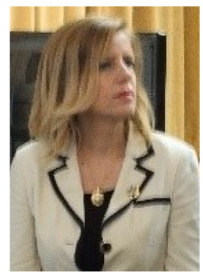

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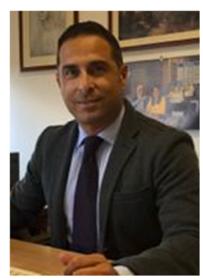

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