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Modeling agent-based consumers decision-making with 2-tuple fuzzy linguistic perceptions

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Abstract

Understanding consumer behaviors and how consumers react to marketing campaigns and viral word-of-mouth processes is crucial for marketers. Classical approaches try to infer this information from a global top-down perspective. However, a more suitable and natural approach is to model consumer behaviors in a heterogeneous and decentralized bottom-up approach. In this case, each virtual consumer has her own mental state and decision-making strategies to simulate her purchase decisions. The system of virtual consumers generates the global sales and a marketer can understand the rules that govern the market. A well-known paradigm to model these systems is agent-based modeling (ABM). In this manuscript we present an ABM where the brand preferences of the consumer agents are modeled using 2-tuple fuzzy linguistic variables. These variables represent the perceptions these consumers have on the different aspects or drivers every product available in the market has (e.g., price or quality). The product selection process of the agents is based on those perceptions and a utility maximization rule. This rule requires a fuzzy aggregation of the fuzzy linguistic perceptions about the products. Our proposal employs an ordered weighted average (OWA) to aggregate them. Our experiments show this approach does not suffer any loss of information when applied on data from real markets. Hence it is a suitable representation of the products preferences, normally represented by qualitative values in marketing surveys. To the best of our knowledge, this is the first work integrating a marketing ABM with fuzzy linguistic modeling.

1 | INTRODUCTION

One of the most important areas in marketing analysis is the prediction, understanding, and representation of consumer purchase decisions. Classical approaches use global variables, such as advertising or investment among other traditional sales marketing strategies, and the analysis is carried out in a top-down scheme within the strategical planning, i.e., consumer decisions are predicted from those global variables. Nevertheless, these approaches are not able to model heterogeneous consumer behaviors, especially in the presence of perturbations of those global variables, and this may result into inaccurate predictions.[1,2]

To solve the former drawback, agent-based modeling (ABM)[3,4] provides a suitable framework to perform a bottom-up analysis in marketing studies.[2,5] These models allow us to study the complex behavior of a system (e.g., a market) as the result of simpler individual behaviors of agents (e.g., consumers) and their interactions. In addition, ABM is a descriptive modeling technique (an aggregation of many individual decisions of every agent) which makes the modeler and marketer to better understand the rules that govern the system. Notice that modeling individual behaviors is often simpler—and in most of the cases, more accurate—than modeling the behavior of the whole system by global top-down rules. ABM has been successfully applied in many other diverse areas, such as economics,[6,7] politics,[8] trust-based social systems,[9,10] and contract farming.[11]

In marketing, existing ABM systems mainly focus on the interactions between consumers and companies with their respective competing brands. For instance, marketers want to understand how word-of-mouth (WOM) campaigns work[5] or to maximize viral marketing actions (e.g., the influence maximization problem).[12] By using the latter systems one can reproduce WOM mechanisms between consumers by embedding agents into the nodes of a social network and by limiting their interactions to other agents they are connected with.[13] When modelers need to feed the model with real marketing data, they are often required to process and translate qualitative data about consumer preferences into numerical data because that is the kind of information used in the variables handled by consumer agents in an ABM.

In this paper, we propose an ABM which incorporates a fuzzy linguistic model to represent consumer perceptions in a more realistic virtual market. In our model, agents are consumers who, after a decision-making process, choose a product among a set of available brands. This decision-making is based on the perceptions the agent has about every product. Perceptions are defined from consumer tracking data in the form of questions/surveys available at the company. We model the latter brand perceptions by means of fuzzy linguistic variables.[14-16] This representation is significantly more realistic than other existing and standard representations, such as numerical or crisp values. Besides, the use of numerical values also requires an additional preprocessing work by the ABM model designers to transform the linguistic data included in the surveys into crisp data. This process makes the model design more complex and can result in an information loss.

Therefore, the main motivation of our contribution is to introduce a more realistic representation of agent perceptions with fuzzy linguistic variables (e.g., high, low, or medium values) for each of the consumer drivers (e.g., price, quality, or taste). Additionally, the consumer agent employs a fuzzy decision-making mechanism to choose among the available products in the market. In our model, we use a 2-tuple fuzzy linguistic representation to model agent perceptions. Every agent has a perception of these drivers for every product. The assessment of a product is computed by aggregating the perceptions of all its purchase drivers.

In the ordinal fuzzy linguistic approach, linguistic variables take values from an ordered set of linguistic labels.[17-19] This approach is suitable in many contexts.[20-22] Nevertheless, an important drawback of the ordinal fuzzy linguistic approach is the loss of information when the problem requires to aggregate linguistic variables, making this approach inappropriate in some scenarios.[23-26] To undergo this problem, the 2-tuple fuzzy linguistic representation model was introduced in Reference.[27] In this approach, linguistic variables are represented by 2-tuples: a pair of a linguistic label and a symbolic translation. This allows us to assess different values to two linguistic variables with the same linguistic label (by having two distinct values in the symbolic translations). Notice that this cannot be achieved by only using linguistic labels.

The aggregation of several fuzzy linguistic variables[28] can be done by the ordered weighted averaging (OWA) operator.[29] This operator gives different weights to every variable in the aggregation.[30] The OWA operator has been used in other fuzzy linguistic models.[31,32] Finally, the decision-making process of every agent consists of evaluating every product assessment and selecting one of them. In our model, we use the utility maximization function for that brand selection: selecting the product with the highest global assessment.

In our work we focus on the simplest model that allows us to represent market behaviors (namely, consumer perceptions and decision-making strategies), while omitting more complex mechanisms, such as WOM in a social network and other complex interactions between agents. To the best of our knowledge, this is the first work that uses an ABM to analyze market behaviors considering fuzzy linguistic information. We will evaluate our extended fuzzy model and compare its operation with traditional numerical approaches in a set of experiments using three real marketing case studies.

The remaining of the paper is organized as follows. In Section 2 we describe the usual procedure to model consumer perceptions as well as some preliminary concepts on fuzzy linguistic approaches. The structure and components of the marketing ABM considered are presented in Section 3. An empirical evaluation to show the benefits of our approach is presented in Section 4. Finally, Section 5 presents concluding remarks and future works.

2 | BACKGROUND

In this section we review some preliminary concepts for modeling fuzzy linguistic information in the ABM model to handle consumer opinions and preferences.

2.1 | Numerical representation of consumer preferences from tracking data

An ABM for marketing purposes usually requires the definition of the consumer agent perceptions for every brand of the market to simulate a realistic virtual market. These perceptions of the consumers about the existing brands of the market are obtained from real consumers tracking data and brand health studies from well-established marketing consultants, such as Kantar Millward Brown.[33] These data are structured in the form of surveys, including sets of answers to a series of questions about the brands.[34]

In some cases, the survey answers are directly provided in the same scale required by the marketing ABM, a real value in $[0, 10]$ with 0 representing the most negative perception, 5 a neutral perception, and 10 the most positive perception for the consumer (see Figure 1). In those cases, the perceptions definition procedure only requires some grouping/selection of the answers and some statistic computation to obtain the average perception value of each brand for each consumer segment. A segment is a group of consumers who have a similar behavior. For instance, *heavy* consumers of a certain product purchase it regularly (e.g., daily), whereas *light* consumers purchase it occasionally (e.g., monthly). All agents of the same segment are characterized by having similar perceptions, defined from the consumers tracking data. The specific perception values for each agent of a segment in the ABM are randomly generated following a normal distribution with mean equal to the mean of the segment perceptions and small standard deviation. Therefore, using those segments is equivalent to have groups of very similar agents, whose behavior is expected to be resembling.

Nevertheless, the most usual situation is that those answers show a linguistic nature, being either linguistic labels or brand choices. In those cases, a manual preprocessing is required to translate those answers to the $[0, 10]$ scale, with the consequent "loss of information". Our view is that the problem would be better tackled by directly working with the linguistic assessments following a fuzzy linguistic approach instead of transforming them into numerical values. Computing with words definitively provides a more natural representation when dealing with human perceptions, represented as words in natural language, as in our case.

2.2 | Linguistic variables

Linguistic variables[14-16] are variables whose values are words or sentences in the natural language. They are used in *fuzzy linguistic approaches*, where the problem requires to deal with qualitative aspects.[17-19] This is a typical requirement in many contexts, where the most realistic and direct representation of the information is indeed the natural language. For instance, the *price* of two products can be easily compared in quantitative terms, but these two *numbers* do not provide any information to assess whether these products are *expensive* or *cheap*, according to a certain consumer. Notice that this is even more relevant

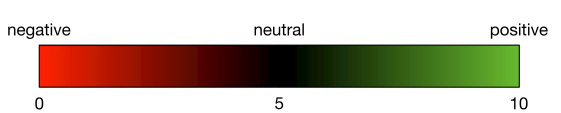

FIGURE 1 Representation of consumer perceptions in numerical and linguistic scales [Color figure can be viewed at wileyonlinelibrary.com]

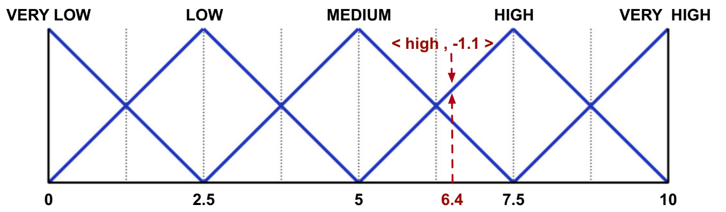

FIGURE 2 Triangular membership functions for linguistic variables in the interval [0, 10], for the set of linguistic labels {*veryLow*, *low*, *medium*, *high*, *veryHigh*}. It also includes the 2-tuple numerical-linguistic transformation $\Delta(6.4) = \langle high, -1.1\rangle$ [Color figure can be viewed at wileyonlinelibrary.com]

when the variables cannot be represented in quantitative terms, for example, comfort, quality, or design.

In the *ordinal fuzzy linguistic approach*, a special case of fuzzy linguistic approaches, linguistic variables take values from a predefined totally ordered set of *linguistic labels* $S = \{s_0, ..., s_T\}$ of finite size $|\ S\ | = T + 1$. We consider the usual definition of ordered set where $\forall\ s_i, s_j \in S.\ s_i \leq s_j \Leftrightarrow i \leq j$.

In this approach, the semantics of the linguistic labels can be derived from their order. In particular, the first and the last labels s_0 and s_T represent, respectively, the lowest and the highest values, whereas the midlabel $s_{T/2}$ represents a medium assessment.[35,*] In consequence, two labels (s_i, s_{T-i}) are equally informative. Additionally, the following operators are defined for the linguistic labels $s_i, s_j \in S$: (a) negation, $neg(s_i) = s_{T-i}$; (b) maximization, $max(s_i, s_j) = s_i \Leftrightarrow s_i \geq s_j$; and (c) minimization, $min(s_i, s_j) = s_i \Leftrightarrow s_i \leq s_j$.[36]

Example 1. Let *price* be a linguistic variable taking values from the ordered set of linguistic labels $S = \{veryLow, low, medium, high, veryHigh\}$. For this variable, the lowest value is *veryLow*, the negation of the label *low* is the label *high*, and the label *veryHigh* is the maximization between itself and the label *medium*, among other examples.

In this paper, we consider triangular membership functions for linguistic variables,[18,37] although other nonpiecewise linear functions could have been considered.[17] In Figure 2, we represent an example of this fuzzy membership. In particular, we represent a triangular membership function for linguistic variables in the interval [0, 10], for the set of linguistic labels {*veryLow*, *low*, *medium*, *high*, *veryHigh*}.

Dealing with fuzzy linguistic variables usually requires to aggregate their information, i.e., the variable values. A common approach is to transform these linguistic values into numbers, aggregate them by common methods, and finally transform the numerical aggregation into a linguistic label. To this purpose, we define two operations to transform linguistic variables into numbers and vice versa, as follows:

Definition 1 (Linguistic-numerical transformation). Given an interval $I = [a, b]$, a number $c \in [a, b]$, and a linguistic label s_k of a linguistic variable v, with k being the position of the label s_k in the ordered set of linguistic labels $S = \{s_0 ... s_T\}$ from which such

*The size of the linguistic labels set is usually odd.

a linguistic variable v takes values, we define the following linguistic-numerical transformation functions $\Delta : I \to S$ and $\Delta' : S \to I$ as

$$\begin{aligned} \Delta'(s_k) &= a + k{\cdot}(b - a)/T \\ \Delta(c) &= s_k \quad \text{s.t.} \quad \forall_{s_i \in S \wedge i \neq k} \ |\Delta'(s_k) - c| < |\Delta'(s_i) - c| \vee \\ & \qquad\qquad\quad \exists_{s_i \in S \wedge i = k+1} \ |\Delta'(s_k) - c| = |\Delta'(s_i) - c|. \end{aligned}$$

Without loss of generality, we use the interval $I = [0, 10]$ in this paper.

Example 2. Consider the linguistic variable and the linguistic labels defined in the previous Example 1. Some examples of linguistic-numerical transformations are the following: $\Delta'(low) = 2.5$, $\Delta'(medium) = 5.0$, $\Delta(3.0) = low$, or $\Delta(4.0) = medium$.

2.3 | The OWA aggregation operator

The OWA is an aggregation operator that allows us to aggregate linguistic variables, considering they may have a distinct weight in the aggregation. For linguistic variables, it is defined as follows:

Definition 2 (OWA; Yager[29]). Given a set of linguistic labels S, let $A = \{a_1, ..., a_m\}$ be a set of linguistic variables to be aggregated with $a_1 ... a_m \in S$. The OWA operator ϕ on these linguistic labels is defined as

$$\phi(A, W) = \Delta(W \cdot \Delta'(A^T)),$$

where $W = [w_1, ..., w_m]$ is a weight vector such that $w_i \in [0, 1]$ and $\sum_i w_i = 1$, and the functions Δ and Δ' are the linguistic-numerical transformation functions defined before.[†]

Without loss of generality, we consider A is an ordered set following the predefined order of assessments used in the weights vector. However, it is possible to handle any unordered set A' by just considering a permutation function $\sigma(A') = A$, which orders A' according to the order in W.

Notice that the OWA operator, applied to a set of linguistic labels A on a common domain S of linguistic labels, returns another linguistic label in the same domain, i.e., $\phi(A, W) = s^* \in S$. Recall that this is achieved by the linguistic-numerical transformation Δ.

2.4 | 2-Tuple fuzzy linguistic representation model

A drawback of the previous approach is the loss of information caused by the aggregation of linguistic labels. In particular, the aggregation of two distinct sets of linguistic labels may lead to the same value. As a result, it may be hard to assess whether one of these two sets is preferred to the other. The following example summarizes this drawback:

Example 3. Consider the set of linguistic labels S described in Example 1 and two sets of linguistic variables to be aggregated whose values (in S) are: $S1 = \{medium, medium, low\}$ and $S2 = \{medium, medium, high\}$. Considering a weight vector with equal weights

[†]For simplicity, we overload these functions Δ and Δ' for a vector of linguistic labels $A = \{a_1, a_2, ..., a_n\}$ and a vector of real numbers $B = \{b_1, b_2, ..., b_n\}$ as follows: $\Delta(B) = [\Delta(b_i)]_{1 \le i \le n}$ and $\Delta'(A) = [\Delta'(a_i)]_{1 \le i \le n}$.

$W = [0.33, 0.33, 0.33]$, the aggregation of both sets returns the same linguistic label: $\phi(S1, W) = \phi(S2, W) = medium$.

To solve the previous problem, the *2-tuple fuzzy linguistic representation* was proposed in Reference.[27] In this approach, linguistic variables are represented by a linguistic label and a symbolic translation.

Definition 3 (2-Tuple fuzzy linguistic variable; Herrera and Martínez-López[27]). A 2-tuple fuzzy linguistic variable is a pair $\langle s, \alpha\rangle$, where $s \in S = \{s_0, ..., s_T\}$ is a linguistic label, and $\alpha \in [-t, t]$ is a symbolic translation.

Again, the semantics of the 2-tuples can be directly derived from their order in the ordered set of linguistic labels S. In particular, the following operators are: (a) equality, $\langle s_i, t\rangle = \langle s_{i+1}, -t\rangle$; (b) negation, $neg(\langle s_i, \alpha\rangle) = \langle s_{T-i}, -\alpha\rangle$; (c) maximization, $max(\langle s_i, \alpha_i\rangle, \langle s_j, \alpha_j\rangle) = \langle s_i, \alpha_i\rangle \Leftrightarrow s_i \geq s_j \vee (s_i = s_j \wedge \alpha_i \geq \alpha_j)$; and (d) minimization, $min(\langle s_i, \alpha_i\rangle, \langle s_j, \alpha_j\rangle) = \langle s_i, \alpha_i\rangle \Leftrightarrow s_i \leq s_j \vee (s_i = s_j \wedge \alpha_i \leq \alpha_j)$.

The OWA operator can be directly applied to 2-tuple fuzzy linguistic variables by just redefining the linguistic-numerical transformation functions Δ and Δ' as follows. Recall that these functions are defined for an interval $[a, b]$ and for a set of linguistic labels $S = \{s_0 ... s_T\}$.

$$\Delta'(\langle s_k, \alpha\rangle) = a + k\cdot(b - a)/T + \alpha$$
$$\Delta(c) = \langle s_k, \alpha\rangle \quad \text{s.t.} \quad \Delta'(\langle s_k, 0\rangle) + \alpha = c.$$

Notice that the value of t for the interval of symbolic translations is $t = (b - a)/2T$ when considering triangular membership functions (the ones that we use). An example of these transformations can be found in Figure 2, where it can be seen that $\Delta(6.4) = \langle high, -1.1\rangle$.

Example 4. Consider the set of linguistic labels described in Example 1 and the set of linguistic variables $S1$ and $S2$ described in Example 3. These sets can be represented using 2-tuple fuzzy linguistic variables as $S1' = \{\langle medium, 0\rangle, \langle medium, 0\rangle, \langle low, 0\rangle\}$ and $S2' = \{\langle medium, 0\rangle, \langle medium, 0\rangle, \langle high, 0\rangle\}$. Notice that in this case, the symbolic translations α are in the interval $\alpha \in [-1.25, 1.25]$.

Considering a weight vector with equal weights $W = [0.33, 0.33, 0.33]$, the OWA operator returns:

$$\begin{aligned}\phi(S1', W) &= \Delta(W\cdot\Delta'(S1'^T)) = \Delta(1/3\cdot\Delta'(\langle medium, 0\rangle)\\ &\quad + 1/3\cdot\Delta'(\langle medium, 0\rangle) + 1/3\cdot\Delta'(\langle low, 0\rangle))\\ &= \Delta(1/3\cdot 5.0 + 1/3\cdot 5.0 + 1/3\cdot 2.5)\\ &= \Delta(12.5/3) = \langle medium, -0.83\rangle\\ \phi(S2', W) &= \Delta(W\cdot\Delta'(S2'^T)) = \Delta(17.5/3) = \langle medium, +0.83\rangle.\end{aligned}$$

Therefore, $\phi(S1', W) < \phi(S2', W)$, whilst $\phi(S1, W) = \phi(S2, W)$.

3 | A MARKETING ABM BASED ON 2-TUPLE FUZZY LINGUISTIC REPRESENTATION

In this section we define the ABM that simulates the behavior of a market with fuzzy consumer perceptions and linguistic decision-making. As previously presented, our proposed ABM system uses fuzzy linguistic variables and fuzzy decision-making to characterize and handle brand perceptions. This is the natural way of representing this kind of qualitative information. In particular, we use the fuzzy linguistic variables (e.g., *price*, *quality*, *comfort*, etc.) to represent the different aspects of each brand or product. These aspects are called *drivers* as they drive consumer choices. We model consumer perceptions on each brand using these drivers. For instance, a consumer can have a *low* price and a *high* quality about a certain brand of the market.

We use 2-tuple fuzzy linguistic variables for storing the perceptions about the drivers that rule the market. This way, we can aggregate consumer perceptions on each brand without undergoing the problem of loss of information existing in the ordinal fuzzy linguistic approach.

In our model, agents represent consumers who carry out a decision-making process to select a product among a set of available brands. This process is performed according to their perceptions and their assessments on each brand. The agents population can be organized in segments, groups of very similar agents in terms of behavior. All of these allow us to simulate the behavior of a market and make predictions on it. In what follows, we precisely define the elements of our marketing ABM based on 2-tuple fuzzy linguistic representation.

3.1 | Brands

In our ABM, consumer decision-making strategies will be only performed among a finite set of available of n brands $B = \{b_1, ..., b_n\}$. To model the attributes of each brand, we also consider a set of m drivers $D = \{d_1, ..., d_m\}$. These drivers are fixed for all the selected brands of the market. This is a typical design used in marketing analysis, in, for example, inquiries or surveys, where all respondents are asked their opinions on the same set of aspects of a product or brand.

3.2 | Consumers

Every consumer is represented by an agent of the system. Each agent has its perceptions (positive, neutral, or negative) about each driver of each brand. To represent driver preferences, we define for each agent x a list of weights $W^x = [w_1^x, ..., w_m^x]$, such that all weights must be in the interval $[0, 1]$ and their sum must be equal to 1. These weights represent the importance of each driver when a consumer agent x makes a decision. For instance, in an ABM with two drivers *price* and *quality*, an agent x having $w_{price}^x = 0.85$ and $w_{quality}^x = 0.15$ will give a high assessment for the former driver and a low assessment for the latter. Notice that these driver weights are independent from each specific brand. It means agents will have the same driver weights for the whole market and its brands.

Consumer perceptions are modeled by defining, for each agent x in the ABM, a matrix of perceptions P^x of dimension $n \times m$, where each element $p_{i,j}^x \in P^x$ represents the perception of agent x on brand $b_i \in B$ about driver $d_j \in D$. In our model, these perceptions are represented using 2-tuple fuzzy linguistic variables, all of them taking values from a common ordered set of linguistic labels (see Definition 3). This allows us to represent the qualitative view of the consumer on each brand.

Definition 4 (Consumer agent). A consumer agent x is defined as the pair $\langle W^x, P^x \rangle$, where W^x is a list of m weights satisfying that $\forall\, w_i^x \in W^x.\ w_i^x \in [0, 1]$ and

$\sum_{1 \le i \le m} w_i^x = 1$ which represents the preferences agent x has on each driver, and P^x is a $n \times m$ matrix of 2-tuples representing the perceptions that agent x has on each pair brand-driver.

3.3 | Agent decision-making process

The decision-making process of each agent consists of selecting one of the available brands in the ABM, based on the agent perceptions. This decision simulates the purchase decision of a consumer. As a result, the ABM will describe the global behavior of the population of consumers, emerged from the individual decisions of agents.

For each agent, this fuzzy decision-making process can be divided into two steps: (a) aggregation of the assessment for each brand and (b) selection of a brand. In the first step, the agent needs to aggregate their perceptions on all the drivers for each brand. This aggregation is computed using the OWA operator for 2-tuples (see Section 2 for more details) as follows:

Definition 5 (Brand assessment). For a consumer agent x, given a brand b_i we define the assessment $as(x, b_i)$ of this agent x on this brand b_i as the aggregation of its perceptions on this brand computed with the OWA operator:

$$as(x, b_i) = \phi(P_i^x, W^x) = \Delta(W^x \cdot \Delta'((P_i^x)^T)),$$

where $P_i^x = [p_{i,1}^x, \ldots, p_{i,m}^x]$ is the ith row of matrix P^x, and Δ and Δ' are the linguistic-numerical transformation functions for 2-tuples defined in Section 2.

Recall that the OWA aggregation of a set of 2-tuples (i.e., the perceptions of each driver) is also a 2-tuple. Therefore, the assessment of an agent on each brand is indeed a 2-tuple fuzzy linguistic variable.

Example 5. Consider a set of drivers $D = \{price, quality\}$, a set of one brand $B = \{b_1\}$, and a consumer agent $x = \langle W^x, P^x \rangle$ with $W^x = [0.33, 0.67]$ and $P^x = [P^x_{b_1,price}, P^x_{b_1,quality}] = [\langle medium, 0\rangle, \langle high, 0\rangle]$, with $S = \{veryLow, low, medium, high, veryHigh\}$ being the ordered set of linguistic labels used by 2-tuples.

The assessment of this brand b_1 for this agent x is

$$\begin{aligned} as(x, b_1) &= \phi(P_1^x, W^x) = \Delta(W^x \cdot \Delta'((P_1^x)^T)) \\ &= \Delta([0.33, 0.67] \cdot \Delta'([\langle medium, 0\rangle, \langle high, 0\rangle])^T) \\ &= \Delta([0.33, 0.67] \cdot [5.0, 7.5]^T) \\ &= \Delta(20/3) = \langle high, +0.83\rangle. \end{aligned}$$

The second and final step is the selection of a brand. This selection represents the brand preferred by each consumer and is based on the assessments of such a consumer on each brand.

In this study we use the deterministic utility maximization function $maxUtil^{\mathrm{D}}$ as the brand selection function in the marketing ABM. This function selects the brand whose assessment is maximal for the consumer agent. Notice this is a deterministic brand selection function in contrast to other nondeterministic functions that introduce some random brands selection.[38-40]

This deterministic version will help show and understand the benefits of the proposed ABM with 2-tuple fuzzy linguistic perceptions, as we will see in Section 4.

Definition 6 (Deterministic utility maximization). The function $maxUtil^{\mathrm{D}}$, which stands for deterministic utility maximization, is the deterministic brand selection function that selects the brand with maximal assessment, defined as

$$maxUtil^{\mathrm{D}}(\{b_1, \ldots, b_k\}) = b_i \mid \forall_{1 \leq j \leq k \wedge j \neq i} \;\; as(x, b_j) \leq as(x, b_i).$$

In case of ties between two (or more) assessments (e.g., $as(x, b_i) = as(x, b_j)$ for two brands b_i and b_j), one of these *maximal* brands is randomly chosen with a uniform probability.

Notice that the assessment of each brand is represented by a 2-tuple, and hence two assessments can be easily compared using the maximization operator of 2-tuples (see Section 2).

4 | EXPERIMENTS AND MODEL EVALUATION

In this section, we present an empirical evaluation of the marketing ABM with a fuzzy linguistic modeling in several case studies. The motivation of this analysis is to show that our ABM offers a realistic representation of perceptions via 2-tuple fuzzy linguistic variables, whereas it does not suffer any loss of information existing in other approaches. To this purpose, we present a comparison between our ABM and two other models by only differing in the representation of perceptions (the rest of the model remains unaltered).

First, we compare our ABM to a model with a numerical representation of perceptions in the interval $[0, 10]$ (this is the same interval used by 2-tuples in the numerical-linguistic transformation in our ABM with fuzzy linguistic modeling). As stated before, although this numerical representation of perceptions is the most extended, it is unrealistic since it is unable to model qualitative aspects, among other drawbacks. Unfortunately, this is the usual representation marketers must consider to process the available information. In our case, this crisp representation model allows us to have a baseline model to compare to. As we will see later, our ABM with 2-tuple fuzzy linguistic variables exactly generates the same results due to the deterministic decision-making function used in both models.

Second, we compare our ABM to a model where perceptions are represented just by linguistic labels. In both cases, we use the same set of labels. Although this second model also uses a realistic representation of perceptions, it is less expressive. As a consequence, this model returns different results. This is because the assessments of each brand may differ even if the decision-making function is the same in both models (for more details, see Examples 3 and 4).

In the following subsections we first present a description of the experimental set-up of our analysis. Next, a small-scale marketing example is introduced to summarize the trace of the ABM and analyze its main components. Finally, we present three different large-scale marketing case studies from real marketing analysis provided by Zio Analytics, a Spanish marketing company, to show the different results produced by the three models. Recall that the only difference between these three models is the representation of the agent perceptions: (a) 2-tuple fuzzy linguistic variables, (b) numerical variables, and (c) fuzzy linguistic variables.

4.1 | Description of the ABM simulation conditions

To initialize agent perceptions and driver weights, we use consumers segments. Recall that a segment is a group of consumers who have a *similar* behavior. In our ABM all agents of the same segment are characterized by the same driver weights W^x and similar perceptions P^x, randomly generated following a normal distribution with mean equal to the mean of the segment and small standard deviation.[‡] We emphasize that segments do not introduce any change either in the structure and components of the ABM or in the decision-making process, but they only affect the consumer agents population structure and thus the initialization of the agent perceptions.

Since agent perceptions are randomly generated, the results of two simulations (where agents have been distinctly initialized) may differ. To reduce the influence of outliers and to obtain meaningful results, we perform a number of distinct Monte Carlo (MC) simulations, differing in the initialization of agents.[§] This is a common procedure when working with ABMs.

4.2 | A small-scale marketing example

Now we describe and analyze the execution of our ABM in a small-scale marketing case study. This model consists of two brands with three drivers, and two agents. We present the initialization of agent perceptions as well as the results of one MC simulation.

In Figure 3, we collect a summary of this execution. In this small example, we analyze two brands $B = \{b1, b2\}$ with three drivers $D = \{q, p, c\}$, which stand for quality, price, and comfort, respectively. Thus, the matrix of perceptions P of every agent x in the ABM is

$$P^x = \begin{bmatrix} P^x_{b1,q} & P^x_{b1,p} & P^x_{b1,c} \\ P^x_{b2,q} & P^x_{b2,p} & P^x_{b2,c} \end{bmatrix}.$$

Let us consider a set of two agents $X = \{x_1, x_2\}$, with their driver weights initialized as

$$W^1 = [0.5, 0.3, 0.2],$$
$$W^2 = [0.3, 0.2, 0.5].$$

For agent perceptions we consider three distinct representations, namely, a numerical representation, an ordinal fuzzy linguistic labels representation, and a 2-tuple fuzzy linguistic representation. For these approaches, we always consider a numerical interval $I = [0, 10]$ and a set of linguistic labels $S = \{vl, l, m, h, vh\}$, which stand for *very low*, *low*, *medium*, *high*, and *very high*, respectively.

The matrices of perceptions P^x of every agent x are initialized according to Table 1. Notice that every perception, which represents the agent perception of a driver for a brand, has an equivalent value in the three models.

Once every agent in the ABM has its driver weights and its driver perceptions initialized, the decision-making process is performed. In this process, the agent computes the assessments of every brand (according to Definition 5) and chooses one of them for purchasing using a

[‡]In our experiments, we use a standard deviation of 1.5.

[§]In our experiments, an execution of the ABM is composed of 1000 MC simulations.

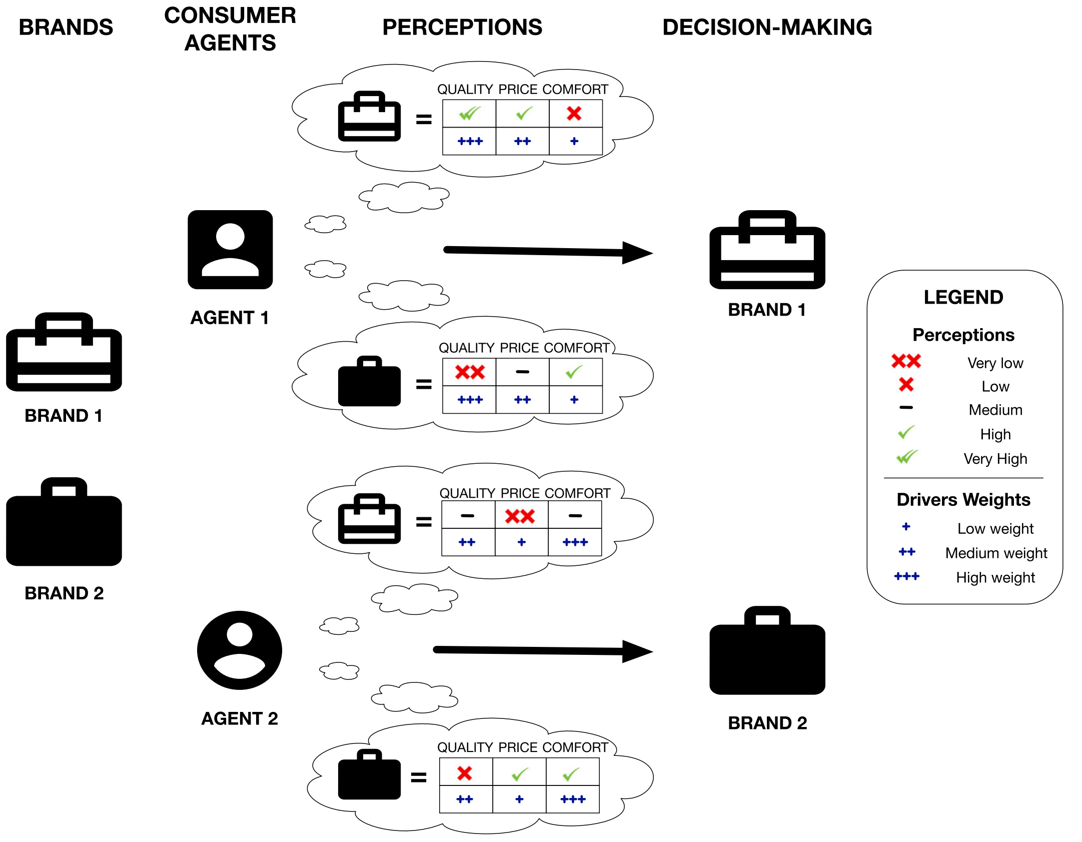

FIGURE 3 Summary of the execution of the marketing ABM based on 2-tuple fuzzy linguistic representation. ABM, agent-based modeling [Color figure can be viewed at wileyonlinelibrary.com]

decision-making function. We recall that in this paper we use the deterministic utility maximization function for such a decision (see Definition 6 for more details). In Table 2 we summarize the results of this process.

It can be seen that the 2-tuple fuzzy linguistic representation has equivalent assessments to the numerical one, for every brand. As a consequence, the decision-making process of every agent is exactly the same. For instance, agent x_1 has a *high* perception of brand b_1, whereas it has a *low* perception of brand b_2, and hence it prefers to choose b_1. Hence, we achieve our original goal of keeping the same behavior while considering a more natural information representation model. On the contrary, the ordinal fuzzy linguistic approach results—in some

TABLE 1 Agent perceptions using the three distinct representations

	2-Tuples	Numerical	Linguistic labels
P^1	$\begin{bmatrix} \langle vh,0\rangle & \langle h,0\rangle & \langle l,0\rangle \\ \langle vl,0\rangle & \langle m,0\rangle & \langle h,0\rangle \end{bmatrix}$	$\begin{bmatrix} 10.0 & 7.5 & 2.5 \\ 0.0 & 5.0 & 7.5 \end{bmatrix}$	$\begin{bmatrix} veryHigh & high & low \\ veryLow & medium & high \end{bmatrix}$
P^2	$\begin{bmatrix} \langle m,0\rangle & \langle vl,0\rangle & \langle m,0\rangle \\ \langle l,0\rangle & \langle h,0\rangle & \langle h,0\rangle \end{bmatrix}$	$\begin{bmatrix} 5.0 & 0.0 & 5.0 \\ 2.5 & 7.5 & 7.5 \end{bmatrix}$	$\begin{bmatrix} medium & veryLow & medium \\ low & high & high \end{bmatrix}$

TABLE 2 Agent assessments and decision-making results using the three distinct representations

	2-Tuples	Numerical	Linguistic labels
$as(x_1, b_1)$	$\langle high, +0.3\rangle$	7.8	*high*
$as(x_1, b_2)$	$\langle low, +0.5\rangle$	3.0	*low*
$maxUtil^{D}(\{b_1, b_2\})$	b_1	b_1	b_1
$as(x_2, b_1)$	$\langle medium, -1.0\rangle$	4.0	*medium*
$as(x_2, b_2)$	$\langle medium, +1.0\rangle$	6.0	*medium*
$maxUtil^{D}(\{b_1, b_2\})$	b_2	b_2	$rand(\{b_1, b_2\})$

cases—into different assessments, and hence distinct results in the overall decision-making process. For instance, the agent x_2 has neutral perceptions for both brands, slightly positive for brand b_2 and slightly negative for brand b_1. However, these differences cannot be captured by linguistic labels, since it assigns the linguistic label *medium* to both brands. As a result of this equal perception, the decision-making function will randomly choose any of them, instead of choosing b_2, which is the preferred brand in the other representations. Therefore, this may result into different decisions, which ultimately might lead to inaccurate predictions in the model.

4.3 | Validation in real marketing case studies

In this subsection, we present the results of the execution of the marketing ABM based on 2-tuple fuzzy linguistic representation in three real-world marketing case studies. The results represent the number of choices of every brand, cumulative for every agent, considering that each agent only performs one decision-making process, and hence only chooses one brand. A comparison between the three models that only differ in the representation of perceptions is presented.

The aim of this experiment is again to show that our model achieves the main objective: a realistic representation without loss of information. In fact, we will later show that the representation of agent perceptions can dramatically affect the output of the ABM (i.e., the number of choices per brand), and therefore any prediction using those results may be inaccurate.

In the three case studies, we run our ABM with 1000 agents, whose driver weights and perceptions are initialized from existing marketing studies as described before. Recall that results represent the aggregation of 1000 MC realizations of the ABM. In the two fuzzy linguistic approaches, we use as linguistic labels the set $S = \{low, medium, high\}$. The number of brands and drivers in each case study is: (a) four brands and six drivers, (b) five brands and six drivers, and (c) nine brands and five drivers. For anonymity reasons, we have omitted the brand names in this manuscript.

Figure 4 shows the comparison of these three models. In the left column, we represent in histograms the average number of choices of the 1000 MC simulations, whereas in the right column we provide box-plots representing the maximum, minimum, median, and quartiles 1 and 3 of that number of choices in the same executions.

As it can be seen, our ABM based on 2-tuple fuzzy linguistic representation has exactly the same number of choices than the model with numerical perceptions. In fact, if we analyze the

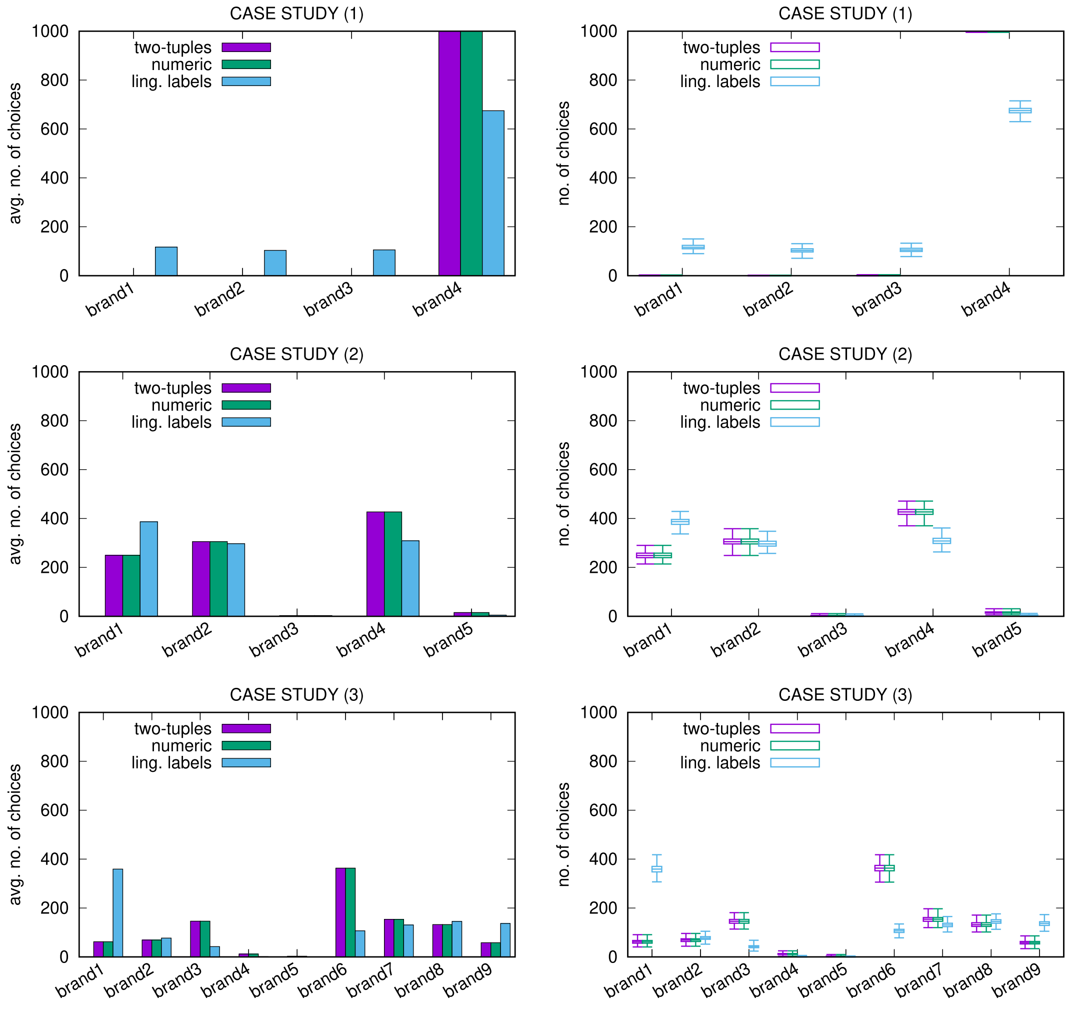

FIGURE 4 Comparison of perceptions representations with histograms (left) and box-plots (right), for the three real marketing case studies [Color figure can be viewed at wileyonlinelibrary.com]

results to a deeper extent, we observe that the choices are indeed the same. This is expected because the deterministic decision-making function makes both models behave equally, as explained before.

On the contrary, we observe remarkable differences between the model with 2-tuples and the model with linguistic labels. See, for instance, the first case study, where almost 100% of the consumer agents choose the fourth brand when using the 2-tuples representation (and also with the numerical representation), whilst this brand 4 only has 60% of the choices in the model with linguistic labels, with a significant number of choices for the other three brands of the market. We also observe striking differences in the other two case studies. In summary, we can conclude that any prediction or further analysis based on the results of ordinal fuzzy linguistic representation model may be inaccurate as a consequence of the less expressive representation of perceptions in this model. We emphasize that this problem does not appear in our ABM based on 2-tuple fuzzy linguistic representation.

5 | CONCLUSIONS AND FUTURE WORK

In this paper we have presented an ABM for marketing analysis which incorporates fuzzy linguistic information and fuzzy decision-making. In this ABM, agents represent consumers who have different perceptions about the products in the market. Those perceptions are modeled using drivers, i.e., the different aspects of every product that drive consumer choices, such as price, comfort, or quality, among others.

A realistic representation of perceptions—which are qualitative aspects—requires linguistic variables. We use a 2-tuple fuzzy linguistic representation to avoid the problem of loss of information suffered by some fuzzy linguistic approaches when aggregating linguistic variables. The assessments of every product are performed based on an aggregation of those perceptions, and such assessments drive the decision-making process, i.e., the process of selecting one of those products. To the best of our knowledge, this is the first time that fuzzy linguistic modeling is integrated in an ABM for marketing analysis purposes.

We have presented an empirical evaluation showing that an incorrect representation of perceptions may cause dramatic differences in the results of the ABM, and as a consequence this may result into inaccurate predictions. First, we have shown in a small-scale case study that the decision-making process produces distinct results by just changing the representation of perceptions. Then, we have analyzed the results of our ABM in three large-scale real marketing case studies, showing the remarkable differences of these different representations, without altering agents perceptions.

As future work, we plan to extend our marketing ABM based on 2-tuple fuzzy linguistic representation in two directions. On the one hand, we plan to investigate and incorporate other decision-making heuristics in our system, adapting them to handle fuzzy linguistic information. Consumer behaviors are hardly fully deterministic.[38-40] For instance, if a consumer was slightly involved in a certain purchase, a relatively high degree of randomness would possibly model her decision-making strategy more realistically. Some open questions to accurately model consumer behaviors concern the relation between the degree of randomness of the decision-making heuristic and the involvement of the consumer in the purchase, or the relation between this degree of involvement and the potential product to be selected. New stochastic heuristics may shed light on these open questions. On the other hand, we plan to extend our marketing ABM by incorporating temporal behavior to build a temporal simulation with diverse events at each time-step.[3-5] It means adding a temporal evolution into the agent perceptions, and analyzing how this affects their decision-making strategies. This evolution can be the consequence of media advertising and/or WOM processes among the consumers of the market.

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