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The diffusion of goods with multiple characteristics and price premiums: an agent-based model

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Abstract

According to innovation diffusion theories, the adoption of a new product is the result of a dynamic process whereby individuals become likelier to adopt as others do. Agent-based modelling has emerged as a useful technique to model and study processes of innovation diffusion within artificial societies, as it allows to easily programme and simulate the interaction of multiple agents among them and with their environment. Despite a large body of literature dealing with innovation of diffusions, including the use of agent-based modelling, there has been little to no consideration of two elements that are important features of consumption: the presence of multiple characteristics of goods, and that of price-premiums on the presence of added characteristics. We propose an agent-based model of the diffusion of such goods, and study its emerging properties when compared to standard ones. Our goal is to try and understand how social interaction affects the consumption of goods that are complex rather than uni-dimensional, and whose prices depend on the number of dimensions (characteristics) that are present. Testing the model for different parameters shows that as goods become more complex, social interaction becomes an increasingly important explanatory variable for purchases. This opens up interesting avenues of discussion for those seeking to bring together innovation diffusion theories and goods' complexity, and can be linked with a number of issues in the social and sustainability sciences.

Keywords: Agent-based modelling, Innovation diffusion, Lancaster goods, Threshold models, Price premiums

Introduction and state of the art

The academic study of innovation diffusions, traditionally considered as beginning with Roger's 1962 *Diffusion of Innovations*, has long been used to analyse and describe the market penetration of new product releases, most notably that of new technologies. It builds on the simple observation that individuals are influenced by their peers on the decisions they make, and that successful products often evolve from being the fad of a few early adopters, to reaching an important proportion of the population. For decades now, scholars have built models that seek to reflect the theoretical and empirical findings of the innovation diffusion's literature, starting with analytical works by Bass (1969) and Granovetter (1978). In the past 20 years, agent-based modelling has emerged as a useful

technique that can help overcoming certain limitations of aggregate models (Kaufmann et al. 2009), deemed as too analytical and unable to capture heterogeneity and the complex dynamics of social processes that shape diffusion (Kiesling et al. 2012). Simulators have produced a variety of models that seek to recreate the main observed properties of innovation diffusion processes in order to study how they respond to different variations in their conditions.

Two issues have, to the best of our knowledge, been absent from the modelling of innovation diffusions' literature: the characterisation of goods as being multi-dimensional (Lancaster 1966; Rosen 1974)¹, and price differences on the presence or absence of these different dimensions.² This lack of consideration of multidimensionality and price premiums is particularly striking when compared to the study of how network structure affects diffusion, which has received the lion's share of scholars' attention³. Our model is an effort to compensate this lack of balance, particularly since multi-characteristic consumption is an already well-established feature of economic theories (Lancaster 1966; Rosen 1974). Moreover, the present study was conceived within the context of a larger project on food sustainability issues, where the of complexity of goods and price premiums are well-established features (Aschemann-Witzel and Zielke 2017; Jackson 2005).

With these elements in mind, we built a model that conceives consumption of each of these dimensions as being part of a dynamic process of social diffusion. The model belongs to the class of *network threshold models* (Watts and Dodds 2009), as first conceptualised by Granovetter (1978) and Granovetter and Soong (1983, 1986). In these, the action of an individual (in Granovetter's early example, deciding to join a riot) is binary, and depends on whether the proportion of others who act has reached or not a given threshold. Earlier versions of threshold models have been expanded in order to account for the heterogeneity of individuals and different network topologies (Delre et al. 2007). These have been used to recreate and study the diffusion of innovations (Pegoretti et al. 2012; Young 2009), analysing how cascade-like phenomena of adoption happen within societies. We extend them to include several characteristics of goods, whereby diffusion happens with regards to each one of them. As our model is inspired by issues of sustainable consumption, one can think of consumers adopting low plastic packaging, locally-sourced, organic, fairly traded, or any such dimensions of sustainability, all of which come with a higher price-tag attached. The intention to adopt a characteristic depends therefore on the proportion of others within a consumer's network that have previously adopted.

Our model—whose description and implementation are given on “[Model description](#)” section—is an extension of one previously presented (López-Merino and Rouchier 2021). The main concepts behind it are (i) that adoption of a given characteristic is the

¹ The following query on the Web of Science performed in September 2021 produces only three results, of which none is pertinent for consumption: **TS=((sustainab*) AND (“innovation diffusion” OR “innovations diffusion” OR “diffusion of innovation”) AND (simulation OR agent-based OR modelling OR modeling) AND (multidimension* OR multi-dimension* OR “multiple dimensions”))**.

² An equivalent search where the last item is replaced by (“price premiums” OR “price differenc*”) does not yield any results at all.

³ Conversely, in the field of opinion diffusion—where issues of convergence, divergence and polarisation are studied—multidimensionality has been more widely studied, starting from (Axelrod 1997)'s seminal work on the development of “culture”, to more recent work on influence and learning (Rouchier and Tanimura 2012), worldviews (Huet et al. 2019) and interdependent topics (Ye et al. 2018)

combined result of a consumer's intention to buy it and his or her budget ability to do so, and (ii) that intention on the said characteristic is formed through the observation of the level of adoption in the consumer's more or less immediate network.

We expand the aforementioned model and analysis in three main ways. First, we include a formalised and standardised description of it, in order to ensure transparency, ease of understanding and replicability. For this, we use the "Overview, Design concepts and Details" (ODD) protocol (Grimm et al. 2006, 2010; Müller et al. 2013). Second, we remove the focus on the *intention-behaviour gap* on which the previous work was centred, and work purely on the dynamics of adoption and diffusion, to shed light on how the consumption of multiple dimensions is increasingly dependent on social interaction. Third, and in order to add robustness to our analysis, we include an econometric regression and graphical presentation of results. Finally, we include an analytical exploration of our model's equations and results.

Our overarching interest is to study how the addition of extra dimensions to diffusion models and the explicit inclusion of price premiums on them can produce new results worthy of further exploration. **In particular, we look at whether the influence of social dynamics on the purchase of combined characteristics is a function of the number of characteristics considered.** We show that the importance of the influence of other's adoption on an agent's purchases increases as the number of characteristics is expanded. We evaluate this further by changing certain parameters within the model, which provides an additional confirmation of our results. This is arguably a novel result that could be of interest for analysts of social dynamics.

We have structured the remainder of the article in the following way: We first introduce the model using the ODD approach (Grimm et al. 2006, 2010).⁴ The results emerging from our model are later shown graphically and by means of econometric analyses, as well as by an analytical exploration of the model's equations. We then finish with conclusions and work ahead.

Model description

Overview

General purpose, entities, state variables and process.

Purpose

This model was conceived as a theoretical abstraction (Boero and Squazzoni 2005) in order to explore questions related to the diffusion of purchases of multi-dimensional goods within a human network. It uses and expands the *innovation diffusion* framework. Theoretical, empirical and modelling work has been done over the past few decades on how innovations become adopted in societies (or fail to do so), and has consistently described S-shaped curves as characterising the process of diffusion—the result of network economies and social influence.

Our model belongs to the class of *network threshold models*, whereby an agent whose network (immediate or otherwise) reaches a given proportion of adoptees automatically

⁴ We draw also from Müller et al.'s (2013) extension for agent-based models with human decisions (ODD + D), although the simplicity of our decision-making mechanism makes it unnecessary to use all of its items.

Table 1 Consumer variables, their description and type

Variable	Description	Type
w_i	Budget. Each consumer i is endowed randomly with an individual budget, reacquired at each time-step	Exogenous-continuous
\mathbf{I}_i	Intention. The set of intentions to purchase each of the characteristics of a given consumer i , the result of a dynamic process (written $I_{i,a}$ to denote intention on a single characteristic a)	Endogenous-binary-vector
\mathbf{B}_i	Purchase. The set of characteristics a consumer i actually purchases at a given time-step, with or without intention for each (written $B_{i,a}$ to denote purchase of a single characteristic a).	Endogenous-binary-vector
\mathbf{A}_i	Adoption. The set of characteristics a consumer i adopts, related to \mathbf{I}_i and w_i (written $A_{i,a}$ to denote purchase of a single characteristic a)	Endogenous-binary-vector
\mathbf{J}_i	The <i>network of influence</i> of an agent i , defined as the set of agents in i 's vicinity whose distance falls within the d parameter. Each agent in \mathbf{J}_i is denoted by the letter j	Exogenous

Table 2 Goods' variables, description and type

Variable	Description	Type
\mathbf{C}_g	Characteristics. The set of characteristics a good g has (written $C_{g,a}$ to denote a single characteristic a)	Exogenous-binary-vector
p_g	Price. The cost of purchasing a given good g , defined as a function of the number of 1s in \mathbf{C}_g	Exogenous-discrete

adopts. Although an obvious simplification of reality, these models have a number of advantages in terms of fitting theoretical and empirical findings relating to the diffusion of innovations (Watts and Dodds 2009).

We seek to study an emerging properties that comes out of this, and how it can inform theoretical and empirical work. Namely, we test how purchases are dependent on social interaction as more dimensions of characteristics are included. As the complexity of goods increases, it is natural to wonder what factors can move consumers towards adopting a multiple array of characteristics—and we pose that social interaction is an increasing determinant of this.

Entities, state variables and scales

There are three types of entities in the model: consumers, goods and links. The model is run on a number of parameters that are set before starting a simulation. Tables 1, 2, 3 and 4 describe the entities with their main related variables as well as the parameters.

Spatial considerations are not explicitly considered in the model.

Our model being largely a theoretical abstraction, we choose parameters' values so as to produce diffusion curves that stabilise within a relatively short time span ($t^{max} = 50$). We do not strictly define what a time-step represents. Since the model is inspired by the notion of sustainable food purchases, however, a step of time and its corresponding purchase can be imagined as a weekly basket of items that cannot be avoided.

Table 3 Types of links

Variable	Description	Type
L_c	Consumer links. The links between a consumer and other ones in the network. Can be more or less randomly defined	Exogenous
M_i	The number of nodes in a consumer's \mathbf{J}_i	Endogenous
L_b	Purchase links. Created between consumers and goods at every time-step according to a rule described in “Process” section	Endogenous

Table 4 Model's parameters and their description

Parameter	Description
n_c	Number of consumer agents
n_d	Number of dimensions. This determines the number of characteristics goods can have and that consumers can purchase
ι	Proportion of consumers with intention at $t = 0$. The model is preset so that a given proportion of consumers has the intention to purchase a characteristic right from the outset (they can be seen as the <i>early adopters</i> of the innovation diffusion literature)
ρ	Random consumer links. Consumers are linked to their immediate neighbours in a circle lattice, following a regular-small world algorithm (Watts and Strogatz 1998). ρ defines the average number of additional L_c in the lattice
d	Distance of influence. Consumers are influenced by their more or less immediate network according to the value of this parameter. A value of 1 means that only a consumer's direct links are taken into account
τ	Influence threshold. A consumer with $l_{i,a} = 0$ on a given dimension a is likely to change this variable to $l_{i,a} = 1$ once a proportion τ of M_i has reached $A_{j,a} = 1$
κ	Probability of influence. A consumer i whose \mathbf{J}_i reaches a given threshold of adoption regarding a goods' characteristic a will modify its $l_{i,a}$ with a given probability $\kappa \in [0, 1]$
π	Price premium. The higher price paid by consumers adopting a good containing one or more characteristics. It is defined as a percent value to be added on each additional characteristic present ($\pi \in [0, 1]$)
t^{max}	The duration of a simulation run. This time is fixed so as to ensure that all S-shaped curves of diffusion reach an equilibrium

Process

Consumers face 2^{n_d} types of goods, as each one can have or not any of the n_d characteristics available (for $n_d = 1$, there are two goods: the one that has the existing characteristic and the one that doesn't). There is no difficulty in identifying a good or in purchasing it other than that created by π . Consumers *have* to purchase a unit of good at each time-step, represented in the model through the creation of one L_b between the consumer and a good. The chosen good will depend on the consumer's own \mathbf{I}_i and w_i , as well as on an element of randomness for any characteristic a where $I_{i,a} = 0$. The consumers' individual algorithm at each time-step (intention formation and purchase) can be described as follows, with its corresponding flowchart on the following page:

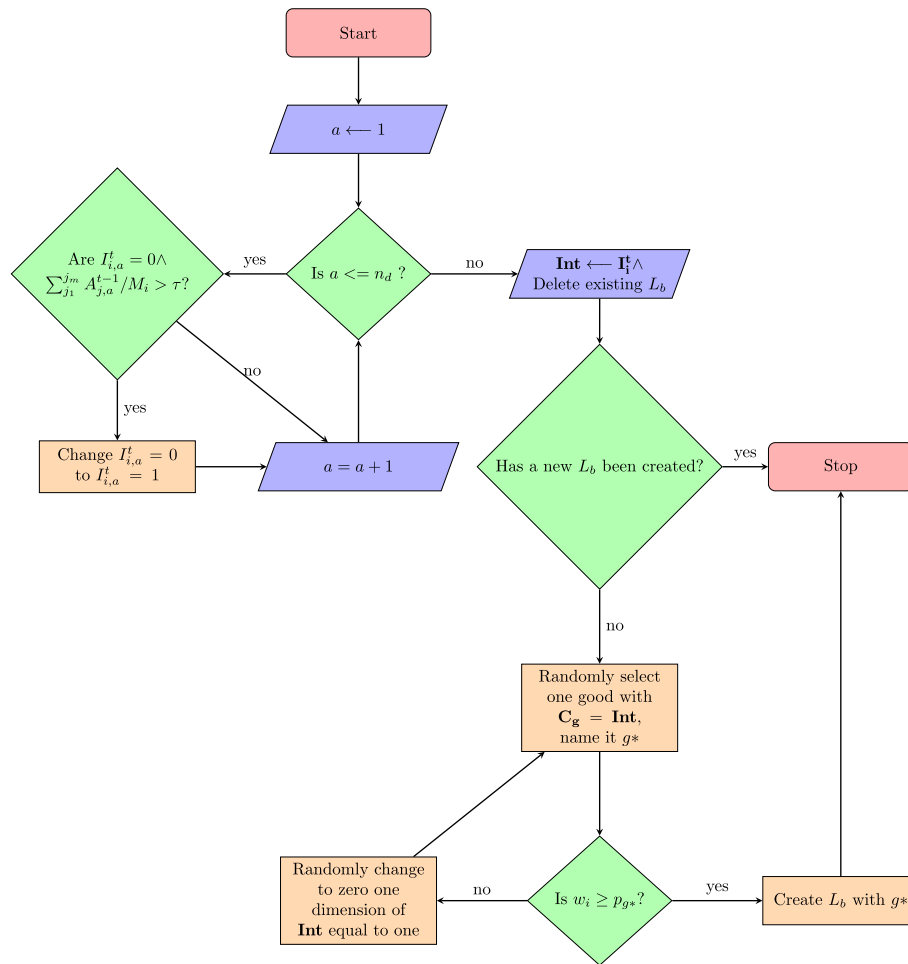
Algorithm 1 Intention formation and purchase for consumer i at every time-step

```

START
procedure INTENTION FORMATION
   $a \leftarrow 1$ 
  while  $a \leq n_d$  do
    if  $I_{i,a}^t = 0 \wedge \sum_{j_1}^{j_m} A_{j,a}^{t-1} / M_i > \tau$  then
      Set  $I_{i,a}^t = 1$ 
    end if
    Make  $a = a + 1$ 
  end while
end procedure

procedure PURCHASE
  Delete existing  $L_b$ 
   $\mathbf{Int} \leftarrow \mathbf{I}_i^t$ 
  while No new  $L_b$  has been created do
    Randomly select one good with  $\mathbf{C}_g = \mathbf{Int}$ , name it  $g^*$ 
    if  $w_i \geq p_{g^*}$  then
      Create  $L_b$  with  $g^*$ 
    else
      Randomly select one dimension of  $\mathbf{Int}$  equal to one and change it
      to zero
    end if
  end while
end procedure
END

```



It should be noticed that the goods that do not contain any characteristics ($C_g = 0$) can be purchased by all consumers, and so the algorithm always comes to an end. A consumer purchasing a good costing less than the consumer's w_i does not save any money, and w_i is reset to its same value at each time-step. Borrowing to purchase an expensive good is not allowed either. Note also that characteristics are independent from one another from a consumer's point of view, and so having intention on one of them does not imply having it on the other.

The equations underlying the algorithm are shown on section “[Submodels](#)”.

Design concepts

Basic principles, individual decision-making, learning, collectives, heterogeneity, stochasticity and observation & emergence.

Basic principles

We use a basic threshold model of innovation diffusion, and expand it to multiple characteristics. Despite its simplicity, the diffusion of purchases in our model is less straightforward than in traditional threshold models: a consumer will not automatically adopt

once a threshold is reached on a dimension a , but will develop an intention ($I_{i,a}$) to do so. $I_{i,a} = 1$ with a corresponding w_i availability will thus translate as $A_{i,a} = 1$. A purchase can happen without a corresponding adoption, as a consumer with enough budget may purchase a good containing a characteristic for which he or she is not necessarily interested in.

Although characteristics are not interdependent *per se* (neither in the case of goods nor for consumers' intentions), they are subject to a common w_i constraint, and in this may have to be arbitrated by consumers with a limited w_i and more than one $I_{i,a} = 1$. In the example of sustainable food consumption, this can be pictured as a person wanting to purchase plastic-free, locally-sourced, organic and fair-trade, and yet being unable to satisfy all four due to budget issues (the arbitration in our model is done randomly, which precludes the possibility of a consumer having a higher *preference* on one or the other of the dimensions).

Individual decision-making

The decision-making process of individuals is exceedingly simple. They chose a good at each time-step, related to their intention and budget as has already been described. There's no particular rationality other than the fact that they have to purchase a unit of a good (in economic terms, the demand for a unit of a good per time-step is perfectly inelastic). Decisions are chiefly the outcome of a process of social influence, as the intention to adopt a given dimension is related to the proportion of consumers who have adopted it in the consumer's network of influence. In this, adoption can be seen as a cultural phenomena, which also has a counterpart in the consumption of food.

Learning, sensing and prediction

A consumer i with a sufficient level of w_i can randomly purchase a good with a characteristic a while $I_{i,a} = 0$ (much like a person in the supermarket may purchase an eco-labelled coffee without caring for it), although such a consumer is not considered as having changed its adoption. In this, only consumers with a formed intention can be considered as being able to *sense* a dimension, thus consisting of the only learning issue we can identify in the model.

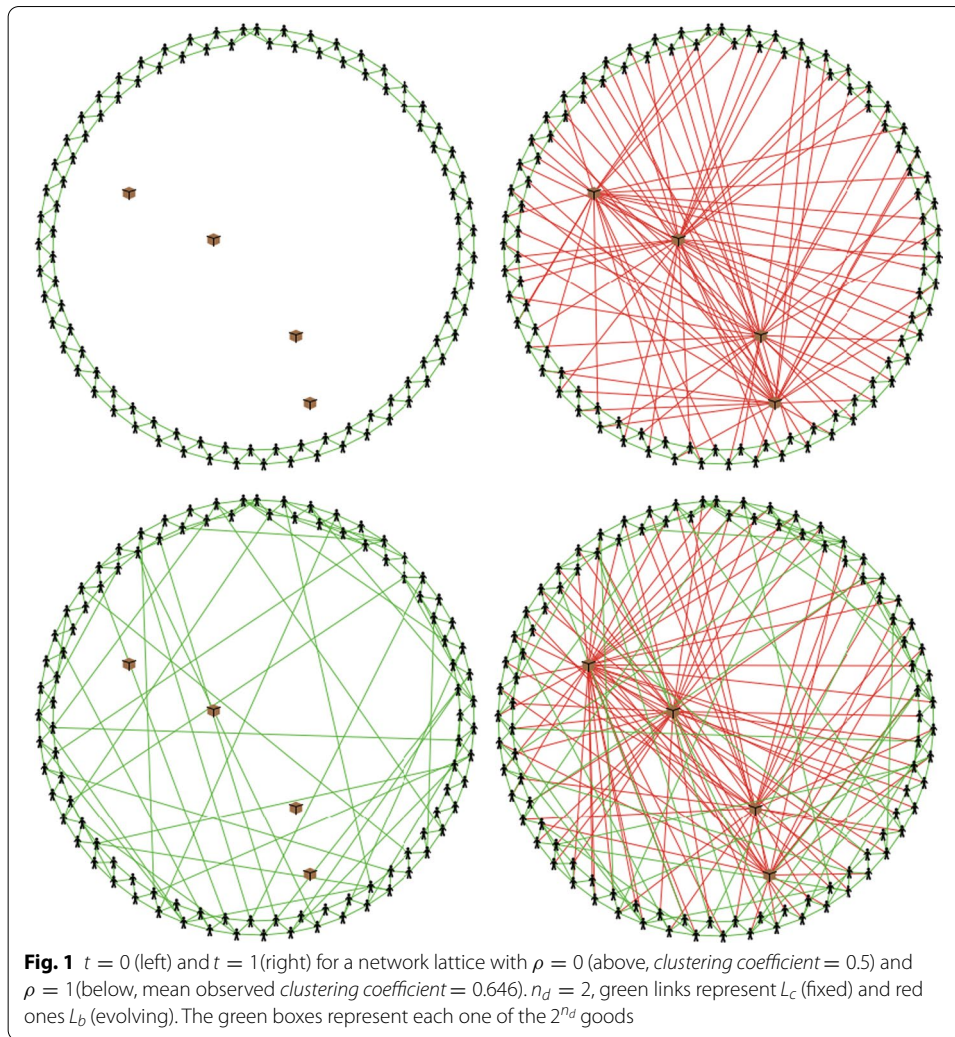
No element of prediction is included in the model.

Collectives

All consumers belong to an interconnected network created using the algorithm proposed by Watts and Strogatz (1998), which includes a parameter for the number of random links (ρ in our model) that determines the *clustering coefficient* of the network. We tested our model on more or less clustered networks. We present results for a perfectly regular lattice ($\rho = 0$, *clustering coefficient* of 0.5) and a Small World one ($\rho = 1$, with a mean observed *clustering coefficient* of 0.646).

L_c links do not change during the course of a simulation.

For purposes of illustration, Fig. 1 shows the two different network possibilities in our lattice, at $t = 0$ and $t = 1$.



Heterogeneity

Consumers are heterogeneous in their budget and intention, the latter of which are set randomly to 1 according to the proportion ι . They also belong to different networks of influence. Decision-making and the remaining aspects of the model are common to all consumers.

Goods are heterogeneous, in that no good fully resembles another. There are 2^{n_d} , each of them having or not each of the n_d dimensions considered. C_g and π determine each good's p_g , with supply for each being perfectly inelastic.

Stochasticity

Stochasticity is included in that w_i is allocated randomly (uniformly distributed across consumers), that only a given proportion is randomly preset with intention at $t = 0$, and that a consumer i for whom the proportion of adoptees in J_i reaches τ in a characteristic a will develop $I_{i,a} = 1$ with a fixed probability κ . $B_{i,a}$ is a variable subject to an

element of stochasticity also, as a consumer with a sufficiently high w_i may well buy a good with a characteristic it has no intention of purchasing.

Observation and emergence

We follow the evolution of two types of, related, indicators. The first is how *intention* is diffused throughout the network on each of the dimensions of characteristics. The second is how *purchases* of characteristics evolve on each of the dimensions.

We look at how these diffusions take place for single dimensions as well as for combined ones (the proportion of consumers with intention or purchasing more than one dimension of characteristics). It is to be expected that the diffusion curves on more than one dimension are shifted to the bottom-right with regards to single-dimension ones: as w_i constraints and I_i limits are added up, diffusion on combined characteristics should increasingly be lower than for single ones.

We term our two sets of indicators as **intention1D**, **intention2D**, **intention3D**... and **purchases1D**, **purchases2D**, **purchases3D**..., where 1D, 2D, 3D, etc. represent the number of combined characteristics on which influence and adoption are being measured. Note that 1D can include any single one of the characteristics in C_n , and thus for simulations run on $n_d > 1$ it means that *any* of them is present in the B_i or I_i sets of consumers (conversely, 2D when $n_d > 2$ includes combinations of characteristics, and so on). A consumer moving from purchasing one dimension to purchasing two will be counted both in **purchases1D** and **purchases2D**.

The question that opens up relates to the relationship between the evolution of the intention and purchase curves for different dimensions. Our interest is to study how overall adoption determines purchases, and whether its importance is indeed increased as the number of dimensions are combined. In a nutshell, **can it be expected that purchases of combined characteristics is more dependent on the diffusion process than that of single ones?** More formally, **is the impact of the evolution of adoption and intention on purchases higher as more dimensions are considered** This would be an interesting result stemming from already existing models and theories of diffusion that would validate our view on the adoption of sustainable behaviours: that these are socially constructed processes that chiefly depend on interaction, and that the more complex they become, the stronger this dependence will be.

Details

Description of the implementation details, initialisation and mathematical submodels

Implementation details

The model was implemented in NetLogo.⁵ 6.2, drawing from its library in order to adapt the Watts and Strogatz (1998) network. The results were analysed using R (R Core Team 2020).

⁵ <http://ccl.northwestern.edu/netlogo/>.

Table 5 Baseline and modified values of parameters used in the simulations

Parameter	Baseline value	Modified value(s)
n_c	100	–
ι	0.05	–
ρ	0	1
d	1	2
τ	0.1	–
κ	0.25	–
π	0.1	0.05
t^{max}	50	–

Initialisation and input data

We work on a baseline setup that we test for 4 values of n_d , as well as modified ones obtained by changing three parameters: ρ , d and π . This will permit to explore how our model responds to a greater or lesser level of network activity (through added links and a higher degree of influence), and compare it with a corresponding change in prices. With regards to actual consumption, these imply comparing the effect of price reductions on the consumption of goods with several dimensions against that of a higher level of social exchanges.

The baseline values were chosen arbitrarily in order to produce stylised S-shaped curves, and do not correspond to precise data, which is otherwise unavailable for the type of dimensions conceived in the model (there's no exhaustive database of price differences between goods containing or not a variety of possible dimensions of characteristics). Moreover, we do not look at this stage to do parameter calibration, and so the values chosen should not necessarily be taken as having a one-to-one correspondence with the reality actual consumers face. The different parameters' values chosen are listed in Table 5.

n_d is set for both baseline and modified values at $n_d = 1, 2, 3$ and 4.

Budgets and prices are configured as follows:

$w_i \sim U(\$1, \$2)$. Each consumer is randomly endowed with a budget that can go from one to two dollars.

$p_0 = \$1$. The price of a good containing no characteristics is of 1 dollar, and is therefore accessible to all consumers. Taking the baseline value of π into account, this means that a good containing 1 extra characteristic will be priced at \$1.1 (1.05 for the modified values), a good containing two of them will be priced at \$1.2 (1.1) and so on.

No input data is used to feed the model.

Submodels

There are two main submodels present, pertaining to how consumers' intention and purchases evolve, as described in the algorithms in "Process" section. For any given characteristic, the submodels can be written as:

$$Pr(I_i^t = 1 \mid I_i^{t-1} = 0) = \begin{cases} \kappa & \text{if } \sum_{j=1}^{j_m} A_j^{t-1}/M_i > \tau \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

$$A_i^t = \begin{cases} 1 & \text{if } I_i^t = 1 \wedge w_i > p_1 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

$$Pr(B_i^t = 1) = \begin{cases} 1 & \text{if } A_i^t = 1 \\ 0.5 & \text{if } A_i^t = 0 \wedge W_i > p_1 \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

Where p_1 the price of a good containing one extra characteristic.

Given our model description and the uniform distribution of w_i , the $Pr(w_i > p_1)$ implicit in Eqs. 2 and 3 can be generalised to be written as

$$Pr(w_i > p_g) = (1 - g \times \pi) \quad (4)$$

Where p_g is the price of a good containing g of the n_d characteristics.⁶

In the following section, we analyse our results.

Results

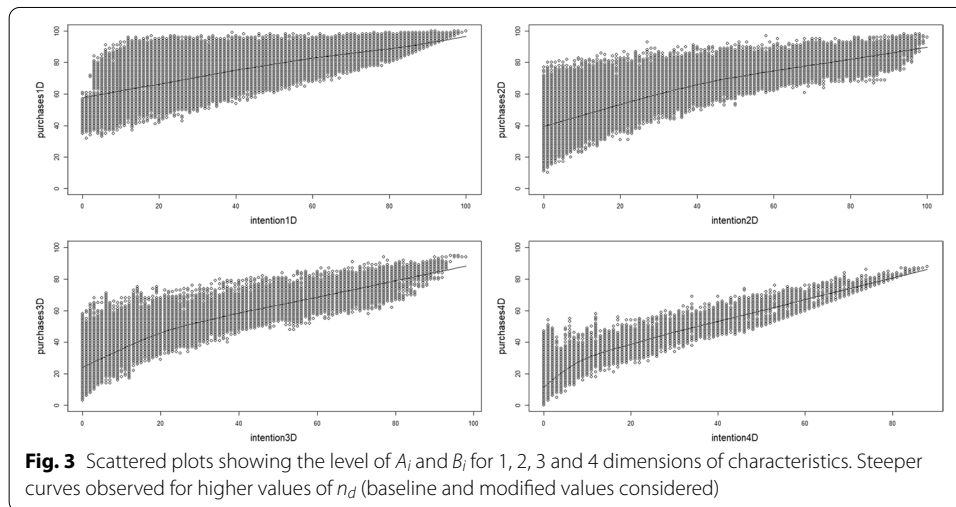
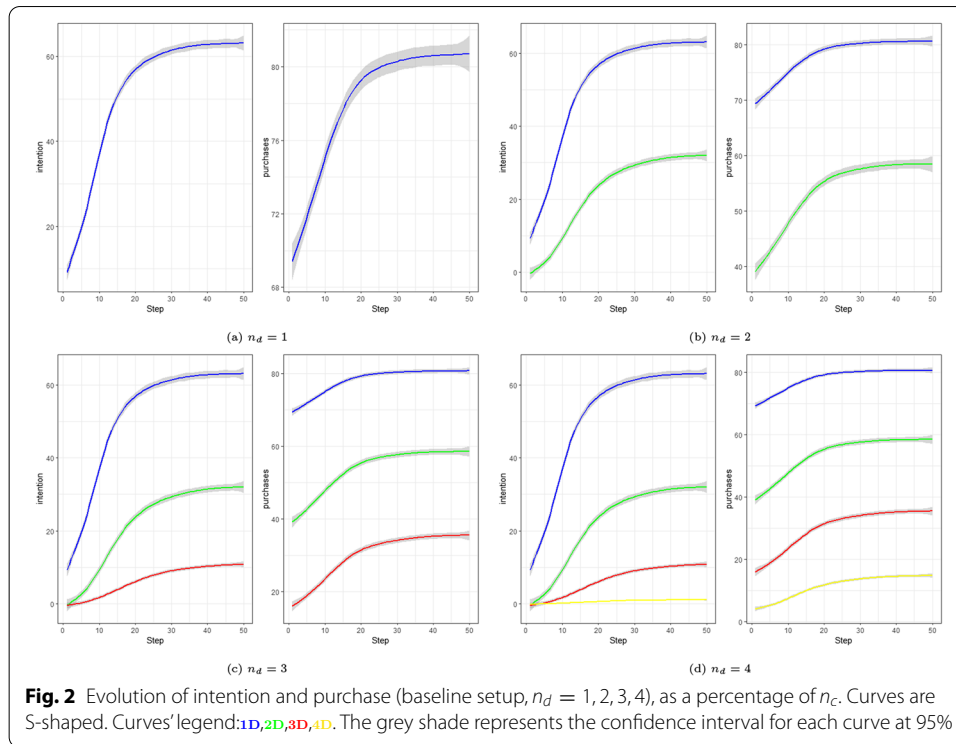
We run the model 50 times over 50 time-steps for each of the configurations proposed on Table 5 (1600 simulations and a total of 80,000 time-step observations). After this, we further checked the model running it on the same configurations but with $n_c = 50, 200, 300$, so as to verify the extent to which there are finite-size effects to it (Toral and Tessone 2007).

We propose two different approaches to study how intention and purchases evolve, in particular with respect to different values of n_d . The question we keep in mind is the one raised in “[Observation and emergence](#)” section, as to whether purchases depend increasingly on intention as the number of dimensions considered increases. We first use the global results of our simulations to find trends that can further inform our discussion, both graphically and by means of linear regressions. Then, we look at how variations in our parameters change the evolution of each of our indicators, to further explore the effect of social interaction on them. Lastly, we sketch out an analytical study of our model to shed light on how the model’s conception relates to the results we find.

Figure 2 below shows the S-shaped curves for our two indicators, obtained for the different values of n_d on the baseline setup, and for single (1D) or combined (2D, 3D, 4D) characteristics. The smoothed curves have been obtained using the loess method (Cleveland and Devlin 1988), and the grey area shows their confidence interval at 95%.

What can be seen from the figure is that, for $n_d > 1$, intention curves show increasingly lesser evolutions as dimensions are combined, something that does not seem to occur with regards to purchases. This gives already a visual hint to the hypothesis

⁶ Note that current specifications make any number of characteristics for which $n \times \pi > 1$ impossible to purchase. This, which under our baseline setup corresponds to $n_d = 10$ is an assumption that could be relaxed by using a π function that is asymptotic on 1.



presented above, as the relationship between intention and purchase is stronger for a higher number of dimensions.

Global results

Figure 3 below shows the result of plotting all observations of purchases against intention (baseline *and* modified values), separating them on 1D, 2D, 3D and 4D. Our hypothesis seems again to be corroborated, since the slope of the best-fit curve (loess method) gets steeper as the number of dimensions is increased.

Table 6 Least squares linear regressions run for all values of I_i on B_i , baseline and modified values considered. β increases as more dimensions are considered

	Estimate	Std. error	t value	Pr(> t)
(a) purchases1D ~ intention1D				
y-intercept	61.1155	0.0642	951.45	0.0000
β	0.3504	0.0009	398.02	0.0000
(b) purchases2D ~ intention2D				
y-intercept	44.0634	0.0680	648.45	0.0000
β	0.4823	0.0011	423.06	0.0000
(c) purchases3D ~ intention3D				
y-intercept	28.4439	0.0671	423.98	0.0000
β	0.6630	0.0016	423.69	0.0000
(d) purchases4D ~ intention4D				
y-intercept	15.8966	0.0686	231.62	0.0000
β	0.8887	0.0026	346.55	0.0000

Table 7 Comparison of y-intercepts and β s for the regression of **purchases4D ~ intention4D** for several values of n_c . The p-value of the results of an Anova test comparing the different β for $n_c = 50, 200$ and 300 against that of $n_c = 100$ are shown. The hypothesis of different values of β can be rejected with 95% confidence

	$n_c = 50$	$n_c = 100$	$n_c = 200$	$n_c = 300$
y-intercept	16.6334	15.8966	16.6334	14.191
β	0.8797	0.8887	0.8797	0.891
p-value	0.0311	–	<0.0001	<0.0001

To verify these results, we test them using least squares linear regressions for intention on purchases. Table 6 shows the estimates for y-intercept and β for each of the four regressions run. This helps confirming that slope of the curves becomes steeper, with β going above 0.888 when four dimensions are considered.

Figure 3 and Table 6 thus appear to confirm our hypothesis: as the number of dimensions increases, the effect of overall intention becomes an increasing determinant of purchases. The reader may notice from Fig. 3 that the correlation between purchases and adoption is not perfect. This happens because of the random component of purchases that has been described earlier, whereby consumers with $I_{i,a} = 0$ but whose $w_i > p_g, a$ may unknowingly buy a good containing it. This observed variability is lower as dimensions are increased, a result given by the fact that the random component is a decreasing function of the number of characteristics considered: the likelihood of purchasing without intention goes down as dimensions are combined.

As mentioned above, the literature has found the presence of finite-size effects on social computational models, whereby the number of agents in a simulation run strongly affects its outcome. In order to quickly assess this in our model, we checked the β for **purchases4D ~ intention4D** under $n_c = 50, 200$ and 300 . We then compared these β s with that of $n_c = 100$, using an Anova test to assess the null hypothesis of different values of β for different n_c . Table 7 below shows the result of the exercise and indicates that no finite-size effect are present, at least within the range of values explored.

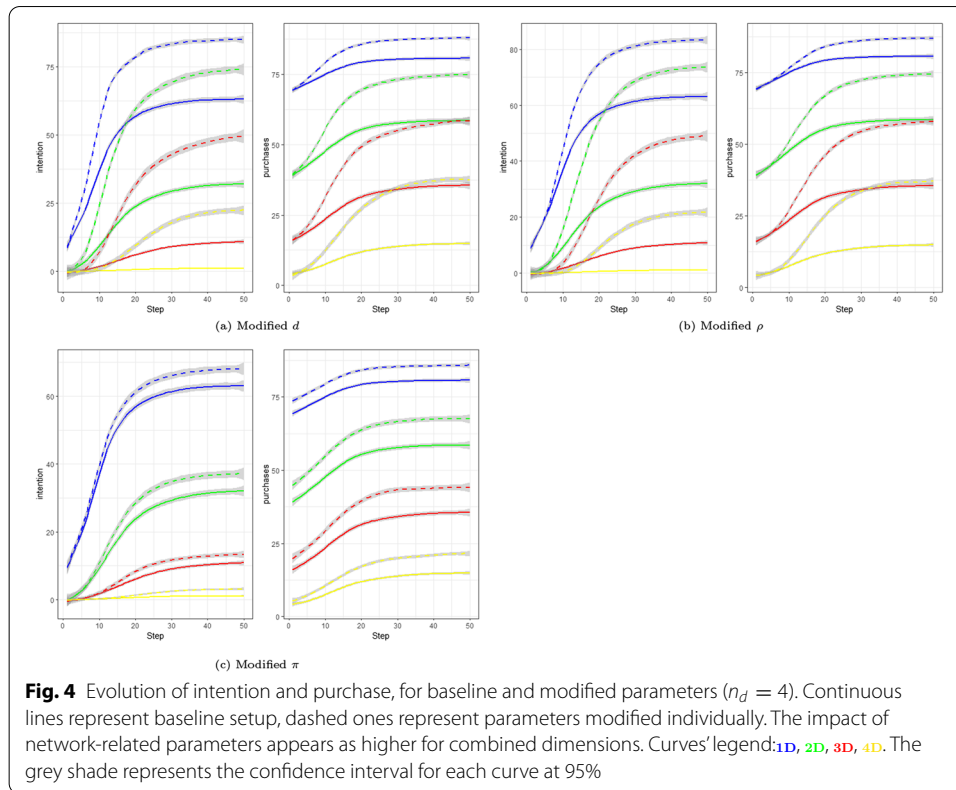


Table 8 Observed indicators at $t = 50$ for baseline and modified setups, parameters modified individually. In brackets, difference with baseline values (as indicators are normalised to represent percentages of the population, this difference represent the increase in the respective proportions). The effects of intention gains on purchases when *network-related* parameters are modified is strictly higher as more dimensions are considered. Conversely, the effects when the π parameter is modified do not appear to be dependent on the number of dimensions considered

Indicator	Baseline setup	distance-influence = 2	random-consumer-links = 1	price-premium = 0.05
intention1D	79.88	90.42 (10.54)	89.48 (9.6)	85.18 (5.3)
purchases1D	89.24	90.44 (1.2)	89.80 (0.56)	94.22 (4.98)
intention2D	51.18	87.90 (36.72)	84.84 (33.66)	55.94 (4.76)
purchases2D	73.26	80.04 (6.78)	79.34 (6.08)	83.56 (10.3)
intention3D	16.58	64.24 (47.66)	61.86 (45.28)	19.82 (3.24)
purchases3D	46.20	66.10 (19.9)	64.52 (18.32)	57.00 (10.8)
intention4D	1.10	22.36 (21.26)	21.72 (20.62)	3.12 (2.02)
purchases4D	14.82	36.96 (22.14)	37.22 (22.4)	20.86 (6.04)

Parameter results

To better grasp this, and in order to understand its practical implications, we have chosen to modify three of the parameters. Two of them (d and ρ) are network-related: the first changes the average number of nodes in an agent's network of influence, and the second affects the topology of the network by introducing a small world element to it,

through the inclusion of random links between consumers (see Fig. 1). The last parameter (π) is modified so as to compare against a non-network one.

Our framework and the results above imply that increasing the activity of the network should have a stronger effect on purchases as a higher number of dimensions is considered, when compared to a non-network intervention such as a price reduction.

Figure 4 and Table 8 below provide with confirmations of this. When d or ρ are modified (to 2 and 1, respectively) the effect on purchases is stronger as more dimensions are considered, which is not strictly the case for intention. Conversely, when π is halved (to 0.05), the results on the two variables do not appear as strongly dependent on the number of dimensions considered.

To fully understand this, it is useful to keep in mind the maximum *theoretical* percentage of purchases for n_d combined characteristics, which can be deduced from Eq. 4 to be $(1 - n \times \pi)\%$. Under the baseline setup, a maximum of 90% of consumers should be able to purchase one dimension of characteristics, 80% two dimensions, and so forth. What happens when the *network-relevant* parameters are modified (which corresponds to a higher level of social interaction), is that purchases come much closer to these levels than when π is modified. The impact of the latter is stronger in our simulations for 1 and 2 dimensions of characteristics, but lower for 3 and 4.

Analytical results

As stated in the introduction, agent-based modelling has helped overcome some of the limitations that aggregate and analytical models have, as sources of heterogeneity and randomness can be added without loosing the possibilities of comprehension. Nonetheless, once the above results have been obtained, it is worthy to explore what can be deduced from the model's formalisation in terms of theoretical and analytical conclusions. This subsection is an initial effort in this direction.

At any time-step, the total overall number of purchases of goods containing g characteristics can be deduced from Eqs. 2 to 3 to be:

$$\begin{aligned} \mathbf{B}^{g,t} &= n_c \times [Pr(\mathbf{B}_i^{g,t} | \mathbf{I}_i^{g,t} = \mathbf{1}) \times Pr(w_i > p_g) + Pr(\mathbf{B}_i^{g,t} | \mathbf{I}_i^{g,t} \neq \mathbf{1}) \times Pr(w_i > p_g)] \\ &= n_c \times Pr(w_i > p_g) \times [Pr(\mathbf{B}_i^{g,t} | \mathbf{I}_i^{g,t} = \mathbf{1}) + Pr(\mathbf{B}_i^{g,t} | \mathbf{I}_i^{g,t} \neq \mathbf{1})] \end{aligned}$$

Where the vectorial notations for \mathbf{B}^g and \mathbf{I}^g indicate the collection of g characteristics. As characteristics are independent, the probability of purchasing g of them is equal to the probability of purchasing a single one to the power of g , and so the above can be rewritten to:

$$\mathbf{B}^{g,t} = n_c \times Pr(w_i > p_g) \times \sum_{k=0}^{k=g} \binom{g}{k} Pr(B_i^t | I_i^t = 1)^k \times Pr(B_i^t | I_i^t \neq 1)^{g-k}$$

With i representing an average agent. Using Eq. 4, we can rewrite the above to:

$$\mathbf{B}^{g,t} = n_c \times (1 - g \times \pi) \times \sum_{k=0}^{k=g} Pr(I_i^t = 1)^k \times [0.5(1 - Pr(I_i^t = 1))]^{g-k}$$

Which, using the binomial theorem, can be rewritten to:

$$\mathbf{B}^{g,t} = n_c \times (1 - g \times \pi) \times [Pr(I_i^t = 1) + 0.5 \times (1 - Pr(I_i^t = 1))]^g$$

Or, equally:

$$\mathbf{B}^{g,t} = n_c \times [(1 - g \times \pi) \times 0.5 \times (1 + Pr(I_i^t = 1))]^g \quad (5)$$

Equation 5 shows that the overall level of purchases for g characteristics at time-step t is dependent on the value of π as well as on the probability of any consumer reaching the state of $I_i = 1$. What we are interested in studying is how $\mathbf{B}^{g,t}$ responds to changes in g , and how this is in turn affected by higher or lower intention to adopt. In other words:

$$\delta \frac{\Delta \% \mathbf{B}^{g,t} / \Delta g}{\delta Pr(I_i^t = 1)}$$

Our results in the previous subsections imply that there are values of the arguments in Eq. 5 for which the above is strictly positive.

We first study $\Delta \% \mathbf{B}^{g,t} / \Delta g$, which we pose as:⁷

$$\Delta \% \mathbf{B}^{g,t} / \Delta g = \frac{\mathbf{B}^{(g+1),t} - \mathbf{B}^{g,t}}{\mathbf{B}^{g,t}}$$

Replacing from Eq. 5, this is equal to

$$\begin{aligned} \Delta \% \mathbf{B}^{g,t} / \Delta g &= (n_c \times (1 - (g + 1) \times \pi) \times [0.5 \times (1 + Pr(I_i^t = 1))]^{g+1} \\ &\quad - n_c \times (1 - g \times \pi) \times [0.5 \times (1 + Pr(I_i^t = 1))]^g) \\ &\quad \times n_c \times (1 - g \times \pi) \times [0.5 \times (1 + Pr(I_i^t = 1))]^{-g} \end{aligned}$$

Which equals

$$\Delta \% \mathbf{B}^{g,t} / \Delta g = 0.5 \times \frac{(Pr(I_i^t = 1) + 1) \times (g \times \pi + \pi - 1)}{g \times \pi - 1} - 1 \quad (6)$$

We now need to study whether $\Delta \% \mathbf{B}^{g,t} / \Delta g$ above is strictly a growing function of the probability of a consumer having $I_i^t = 1$, which itself is a function of the overall proportion of adoptees in the network. For this, Eq. 6 can be derivated on $\delta Pr(I_i^t = 1)$, which gives

$$\delta \frac{\Delta \% \mathbf{B}^{g,t} / \Delta g}{\delta Pr(I_i^t = 1)} = 0.5 \times \frac{1 - g \times \pi - \pi}{1 - g \times \pi} \quad (7)$$

Our hypothesis stands true any time

$$\delta \frac{\Delta \% \mathbf{B}^{g,t} / \Delta g}{\delta Pr(I_i^t = 1)} \geq 0$$

⁷ It is also possible to study the non-percentage change of $\mathbf{B}^{g,t}$, although it requires considerably longer space. Nonetheless, the critical points for relevant variables' values are the same.

We know from above that in our model $g \times \pi < 1$, and so the above can be rearranged to:

$$1 - g \times \pi - \pi \geq 0$$

Or

$$\pi \leq \frac{1}{1 + g}$$

This means that, under current model specifications, the main result that we find is dependent on the relationship between π and g . The price premium needs to be sufficiently low with regards to the number of characteristics considered for purchases to be increasingly dependent on intention.

Discussion and concluding remarks

Social influence is one of the central determinants of people's action, and as such has long been recognised by scholars in marketing studies (Bass 1969) and, more recently, economics (Campbell 2013; Jackson 2014). Agent-based modelling has been used to describe processes of social diffusion of innovations (Kiesling et al. 2012), including that of green products (Janssen and Jager 2002) and adoption of sustainable diets (Plohl et al. 2020).

Consumption is a complex issue. Two sources of this complexity are related to the fact that goods are multidimensional (Lancaster 1966), and that extra characteristics often have a higher price-tag attached (Aschemann-Witzel et al. 2019). Our interest is to explore how the innovation diffusion framework plays out when these two elements are taken into account, therefore contributing to understanding the adoption of multi-dimensional consumption practices. For this, we have conceived a model in which consumers' adoption of each of the characteristics is subject to a process of social diffusion, and in which intention to adopt is the result of the consumer's related nodes having reached a certain threshold of adoption.

We differentiate between purchase, intention and adoption, as a consumer may end up buying a good with characteristics he or she is not necessarily interested in adopting, as long as his or her budget allows for this possibility. The probability of such unknowingly purchases is naturally lower when several characteristics are taken into account. This opens way for social influence being a higher determinant in purchases of multidimensional goods, which we put to test using our model. We use overall intention as a proxy of social influence, as the possibility of a consumer developing intention to buy a set of characteristics is dependent on the proportion of others that have already adopted the said set. In this way, we study in different ways the relationship between overall purchases and intention.

The simulation results show that purchases are increasingly dependent on adoption as more dimensions are considered. Rising the level of social interaction in the network (by doubling the distance of influence, and by increasing the number of random links and thus lowering the clustering coefficient) confirms this property by creating an effect that is stronger on purchases than on adoption as increasing dimensions are looked

at. Conversely, the reduction of another parameter that is external to the network (the halving of price-premiums) has an effect that does not substantially change for a higher number of characteristics. In the analytical study of our model, we put the mentioned result as a hypothesis we seek to validate. We show that it is indeed valid as long as the price premium paid is sufficiently low as a function of the number of additional characteristics considered. A longer discussion on this goes beyond the scope of the present paper, although an element of response to this can be that too high a price-premium prevents a high enough proportion of consumers to adopt once they develop intention, and thus suffocates the process of diffusion on combined characteristics.

These results could have important real-life implications, as they indicate that social interaction and influence are particularly important in the development of behaviours that are attentive to multi-dimensional consumption (which can be argued is a central feature of sustainable consumption). One can thus see social interaction as being helpful in the development of a culture of consumption that is much too complex for isolated individuals to apprehend, and where price premiums limit the possibilities of individuals to spontaneously develop attentive behaviours. Although the result of our model cannot be used to give precise policy recommendations or advice on actions to follow, it is interesting to highlight that the reduction of price premiums (which can be interpreted as subsidies on goods) has lesser effects on several dimensions of characteristics than that of increasing the level of social interaction. In the context of sustainability, examples of interventions to favour this could be the organisation of local forums and activities on the topic, as well as more focus on having the voice of *early adopters* heard. Since interventions of this type are arguably less costly than mass publicity campaigns or large-scale production subsidies, their potential should not be neglected.

Our work opens a number of avenues for future work. In terms of modelling, there are a number of assumptions we have made that could be relaxed, as mentioned in “[Model description](#)” section. Among these, we count including interdependencies within characteristics (as individual preferences for consumption arguably play out across multiple dimensions), and the possibility of individuals being more or less capable of influencing others, in both the positive and negative sense. Issues of interdependency and heterogeneity of influence have been explored within the field of opinion diffusion (Deffuant et al. 2002, 2005; Rouchier and Tanimura 2015; Huet et al. 2019; Ye et al. 2018), and are reasonable additions to a work on the diffusion of consumption. Results from this literature have studied phenomena of polarisation, divergence of opinions and influence towards non-adoption. These are issues that need to be considered in the study of the adoption of sustainable behaviours (Xu et al. 2018), where we have argued that the issues of multidimensionality and price-premiums are present.

We tested our model using one single network setup. Further work could try and explore the results on different ones such as preferential attachment (Barabási and Bonabeau 2003). Although current knowledge makes it impossible to know with complete precision what a *real* human network of influence looks like (Manzo and van de Rijt 2020), it is a worthy effort to test the stability and sensitivity of results to different configurations Thiriot (2010).

Our model was built as a theoretical effort in order to study the emerging properties of an extension to multiple dimensions and price premiums of existing threshold

models of innovation diffusion. In this, the parameters we have used (both in the baseline and modified setup), have no real correspondence with reality, other than the fact that extra characteristics in goods tend to make them expensive. We thus do not make any claims as to the quantitative values of our results, but rather to the qualitative implications they bring about. Nonetheless, our analytical exploration shows that the results can be generalised to different parameters' values, as long as a certain relationship between them is respected. As in the case of different network configurations, further work on parameter manipulation and the study of their implications for our results would be welcome. As an example, simulations that take into account the critical point for π found in “Analytical results” section could offer interesting avenues for exploration.

From an economic point of view, our work could benefit from the inclusion of production-side effects and, more largely, the issue of economies of scale. We have assumed a perfectly elastic supply for any number of characteristics, which is hardly a realistic assumption. As demand for certain products increases, it is natural to expect that they become cheaper and more accessible to consumers. On the consumers' side, although one can argue that perfect inelasticity of demand is somewhat realistic for an essential good such as food, it is less easy to justify a similar level of importance for each of the characteristics consumers have intentions on, and thus that when consumers have to drop one they do it randomly. This is not necessarily the case in real life, as people may be more or less attentive to each of the dimensions they seek out.

All of these assumptions—which arguably reduce the *descriptive* power of our model—have been made so as to increase its *simplicity* (Le Page 2017). Modifications building on this can be tested so as to see how they affect the results we have found here.

Outside of the realm of modelling, we have found it difficult to come across data on consumption that is attentive to the multiple dimensions it encompasses, and how social influence is a determinant of it. This makes contrasting the results with actual data (most notably quantitative) difficult. Surveys, experimental and field work (particularly using participatory methods) should more directly tackle this issue, which would be an important addition to current data, and more largely to our understanding of multidimensional consumption, in particular with regards to sustainability issues.

Abbreviations

ODD: Overview, Design concepts and Details (Grimm et al. 2006, 2010; Müller et al. 2013). A standardized protocol to describe a computer model to ensure transparency and replicability.

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Authors' contributions

Pedro Lopez-Merino and Juliette Rouchier contributed equally to the conception of the model, theoretical framework, literature review and conclusions. Pedro Lopez-Merino worked on the coding and description of the model, statistical and graphical analysis, and putting together the first draft of the article.

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Availability of data and materials

The code is accessible on the CoMSSES Net/OpenABM (Janssen et al., 2008) model library <https://www.comsnes.net/codebases/9c1c2e83-86e2-4cad-8482-20529f9a9b84/>.

Declarations

Competing interests

The authors declare no competing interests.

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