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Organic food purchase behavior: The complex relationship between consumer's attitude and social norms

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Coordinator: Prof. Manuela Lavelli

Signature: ___________________

Tutor: Prof. Riccardo Sartori

Signature: ___________________

Ph.D. candidate: Andrea Scalco

Signature: ___________________

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Andrea Scalco
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To those over the years who dedicated their time to pass me their knowledge along with their passion and to those who taught me much more than what they were aware of. To those who loved and supported me and those I love, I loved and even those I cursed. For all of them I achieved so much.

Andrea Scalco

Abstract

During the last decade the purchase of green food within a sustainable consumption context has gained momentum. In particular, consumers' preference toward organic food represents a form of behavior that can both promote the preservation of the environment and contribute to the transition to a more sustainable society.

Certainly, the choice for a specific type of food is based on personal beliefs, but it is also influenced by the social dimension. In relation to this latter aspect, a current issue regarding the understanding and prediction of green consumer behavior is strongly related with the investigation of the effect exercised by group norms and collective consumption (Peattie, 2010). In line with this premise, the Doctoral project aimed to investigate the emergence of sustainable consumption behaviors by considering both the individual and social aspects. Specifically, the project examined the complex relationship that emerges from the dynamic interaction of individual behaviors and social norms in the specific context of organic food choice. Since systematic experimentation over time with social influence is difficult, the research employed virtual simulations: to this purpose, an interdisciplinary approach between psychological methods and computer sciences was adopted.

The first phase of the Doctoral project examined those psychological theories able to explain and predict consumers' intention to buy organic food products. Accordingly, the work by Scalco, Noventa, Sartori and Ceschi (2017) showed by means of a meta-analytical structural equation model the robustness of the theory of planned behavior (TPB; Ajzen, 1991) in this specific context. Therefore, the TPB was assumed as the main theoretical framework of the project.

The second phase addressed the potential conjunctions between psychological notions and computer simulations. Particularly, agent-based modeling represents a method of investigation of social phenomena that blends the knowledge of social sciences with the advantages of virtual simulations. Within this context, the development of algorithms able to emulate a realistic reasoning process for autonomous virtual agents is one of the most fragile aspects. The paper by Scalco, Ceschi, and Sartori (2017) specifically dealt with the translation of the theory of planned behavior into a computational form: several issues are discussed and some solutions are offered when

available with the hope to shorten the distance between psychological research and the methods provided by computer sciences.

Finally, starting from the findings provided by the first work and the theoretical examination conducted in the second paper, an agent-based model was built to investigate how social interactions in relation to organic food products can foster/hinder individual buying behavior among customers of grocery stores with different food arrangements. Virtual consumers in the simulation replicate a decision-making process grounded on the theory of planned behavior: each agent decides to buy conventional/green food on the base of its individual preferences and the social influence exercised by others. The agent-based model showed the effects of social influence on individual behavior: a part of the agents would like to buy green products following their individual preferences, however, the common norm hampers this intention. Consequently, these agents decide to buy regular food instead of green one triggering in this way a locked-in vicious cycle. More interesting, the simulation demonstrated that different arrangements of products can significantly affect the sales of organic food: nonetheless, the increase of sales of organic food also depends on the throng of customers inside the store.

In the end, the research improves the understanding regarding the effects of social norms on individual intention to purchase green food. In addition, it attempts to suggest how to foster organic food purchase starting from the results obtained from the simulation. As a further consideration, the Doctoral thesis tried to demonstrate the advantages of the introduction of agent-based modeling as a valuable method for psychological research in relation to the investigation of social phenomena and consumer behavior.

Content

Now the trees are almost green,
but will they still be seen
when time and tide have been.
Boy into your passing hands,
please, don't destroy these lands,
don't make them desert sands.

Soon I hope that I will find
a seed within my mind
that won't disgrace my kind.

The Yardbirds, *The Shapes of Things* (1966)

1 Introduction

Environmental sustainability represents a crucial factor to achieve a society able to minimize its impact on the ecosystem where it is inserted, lives and grows. This goal is currently ranked at the highest levels by the European Union (Boggia, Paolotti, & Castellini, 2010). As reported by Peattie (2010), the majority of environmental impact (70-80%) of domestic consumption is related to three main categories: food and drink, housing (e.g. domestic energy use), and transport (included commuting and leisure). In particular, in relation to the first category, Tobler, Visschers, and Siegrist (2011) pointed out the fact that food represents a considerable environmental issue. This is firstly due to its production (e.g. land and energy request, chemicals, greenhouse gas emissions) and transportation. However, also its consumption negatively impacts on the environment: in fact, as reported by Tukker and Jansen (2006), in Western countries food consumption accounts for about 20-30% of the overall environmental impact. Within this context, at the beginning of the current Century, the work by Jungbluth, Tietje, and Scholz (2000) suggested three strategies from a consumer perspective in order to reduce environmental impact: the avoidance of air-transported products, a preference toward organic food, and a reduction of meat consumption. After ten years, Thogersen (2010) and Tobler et al. (2011) indicated once more these options as the most effective ways to promote sustainability in the context of food consumption.

It is obvious that food represents a basic need that cannot be disregarded. Hence, consumers with their daily purchase decisions can significantly impact on current environmental issues. Nowadays, the majority of EU citizens (80%) recognizes the impact on the environment as an important issue in relation to purchase choices (European Commission, 2009). However, the large-scale survey conducted by Tobler et al. (2011) showed that they are not fully aware of the environmental impact of food consumption. For instance, they tend to overestimate the negative environmental impact of product packaging, while they largely underestimate organic food benefits. Hence, currently there is an asymmetry between empirical results and consumers' perception of environmental impact of food choice with consumers undervaluing the importance of green food.

As reported by the Council of European Union, organic production designates a food production system aimed to combine best environmental practices with the preservation of natural resources and the application of animal welfare standards. In addition, it employs a production method based on natural substances and processes. The environmental advantages of organic food products have been remarked over the years in several research works. Particularly, some studies employed life-cycle assessment to compare the environmental impact caused by organic and conventional food production systems (e.g. Boggia, Paolotti, & Castellini, 2010; Litskas, Mamolos, Kalburtji, Tsatsarelis, & Kiose-kampasakali, 2010; Longo, Mistretta, Guarino, & Cellura, 2015): most of the studies in this sector supports the idea that organic systems can lower the environmental impact w.r.t. conventional methods of production.

As pointed out by Jackson (2005), it is important to understand how we can promote sustainable consumption and discourage unsustainable behaviors. Particularly, the need for research from a consumer perspective in the organic food sector has been recently acknowledged by the report of the European Commission (2016) on agricultural research and innovation. Indeed, the consumption of organic food represents a form of behavior that can both promote the preservation of environment and lead the transition toward a more sustainable society. Therefore, it becomes crucial to investigate such phenomena in order to develop policies aimed to encourage consumers to make greener choice daily.

1.1 Brief overview of organic food market

The current importance of organic food sector is also proved by its recent worldwide economic growth. Today, the largest organic market is represented by the United States, followed by Europe with the 38% of the global retail sales. The recent report by Willer and Lernoud (2016) indicates an overall increment of the European organic market from 2014 by approximately 7.6%: the estimated value of this market is appraised to over 26 billion euros (Heinze, 2016). Particularly, in the European territory, Germany represents the major organic market (30%), followed by France (18%), United Kingdom (9%) and Italy (8%) (ISMEA). These four countries account for the two-thirds of European sales (Willer & Lernoud, 2016).

On the one hand, Italy represents one of the countries most interested by organic production system. Within the Italian territory, recent statistics report that the trend for organic farming increased by the 5.4% from 2013 to 2014. In addition, with respect to the worldwide organic food production Italy represents the sixth country with the largest areas of organic agricultural land thanks to the over 10% of agricultural land devoted to organic farming. The current value of Italian organic market is estimated at about 2.1

billion euros (ISMEA). Not surprisingly, the major channel for organic food products (39.90%) is represented by the large-scale retail trade with a turnover of about 855 billion euros.

On the other hand, the Italian estimated per capita consumption is about 42.60 euro. Even with a constant positive growth over the years (11% from 2010 to 2015), this value still set Italy out from the ten countries with the highest per capita consumption of organic products (Willer & Lernoud, 2016). Hence, it is clear that organic food sector has room to grow over the next years: psychological research should aim to support this growth with suggestions based on empirical evidences.

1.2 Understanding sustainable food consumption

Undeniably, people can own several different motivations with respect to food choice. As reported by Tobler et al. (2011), price, healthiness, sensory appeal, and convenience tend to be the most influential factors taken into account in the decision process. However, our consumption behavior is not a merely reflection of our preferences or circumstances: it also stems from our social relationships. That is to say, besides personal beliefs, the choice for a particular type of food can be strongly affected by the influence exercised by the social dimension.

As stated by Wanke (2008), after years of debates it is nowadays recognized the effect of social norms on people's daily behavior. Also Jackson (2005) highlighted that our actions are deeply embedded in social contexts: our behaviors are leaded by our personal motivations, beliefs and preferences as much as by other people around us say and do. In other words, even in the consumption context we do not behave as isolated human beings but as members of groups (e.g. families, households, communities). In addition, the effects of social influence in the consumption context become stronger in novel or uncertain situations: this can be especially true in the case of consumers' pro-environmental behaviors (Peattie, 2010).

Interestingly, the interaction between individual preferences and social factors can result in non-trivial situations. Particularly, due to social pressure people might find themselves locked in to perform unsustainable behaviors even if contrary to their personal beliefs. Accordingly, as argued by Peattie (2010), an emerging issue is related to the understanding of green consumer behavior in relation to the influence of group norms and collective consumption. In line with this premise, the Doctoral project aimed to investigate the emergence of sustainable consumption behaviors. Specifically, the project examined the dynamic interaction between individual preferences and social norms in the specific context of organic food choice.

However, generally our understanding of green behaviors stems from a reductionist tradition (Peattie, 2010). Most of the time, within this context research attempted to de-construct complex social realities in smaller pieces in order to study potential cause-effect relationships. Thus, despite the fact that from a sustainability perspective collective impact is more significant than the individual one, the emphasis has been largely placed on consumers as individuals. As a consequence, we are currently dealing with "a lot of individual jigsaw puzzle pieces" (*ibid*, p. 218) that are not capable to provide a clear picture of consumption as social phenomenon.

As stated by Liao (in Gilbert, 2008), social behavior can be studied through two different approaches. The first one matches the reductionist tradition of research and it relies on collecting several observations, arranging data and analyzing them: the final and hoped outcome is represented by a model that fits such data. The second approach asks researchers to have some prior knowledge about a certain social mechanism and then build a virtual model of it. With this latter, scientists can simulate dynamics, test several hypotheses and, in the end, gain a better understanding of complex social systems as a whole. Specifically, the term *complex* is employed to refer to those (physical or social) phenomena and systems endowed with peculiar characteristics such as non-linear dynamics, emergent behavior, self-organization, and feedback mechanisms (or, closed-loops) that can limit the overall predictability of the outcome. Railsback and Grimm (2011) highlighted how systems that we face from the reality are too complex, or they develop themselves too slowly, to be appreciated by means of the traditional approach: indeed, this is true for most of the social processes encountered in market situations.

For instance, as argued by Rand and Rust (2011) marketing phenomena are complex due to the emergent result of many individual agents (such as consumers and sellers): when their motivations and actions are combined, even simple behavioral rules can grow into sophisticated and unexpected patterns. A further challenge is represented by the feedback exercised by the aggregate social pattern on individual choices which consequently generates over time a closed-loop between the individual and social dimensions. Moreover, consumption represents a complex process due to the heterogeneity of consumers, what they consume, and the dynamic context where they are inserted (Armitage & Conner, 1999; Peattie, 2010).

Established on a reductionist perspective, most of psychological methods of investigation fail to capture the emergence of phenomena derived by the dynamic interaction of the individual and social dimension as they are unable to deal with a bottom-up approach (Kozlowski, Chao, Grand, Braun, & Kuljanin, 2013). In addition, they are commonly unable to account for feedback mechanisms and they struggle to capture heterogeneity (i.e. individual differences). Hence, psychological research should go beyond its own boundaries to find a more suitable method of investigation of complex social phenomena such as consumption behavior. Accordingly, the present research adopted agent-based modeling, a research method originated by the developments of computer sciences.

1.2.1 Computational models for the investigation of social phenomena

New research methods based on the recent developments of the computer sciences have arisen during the last decades. Indeed, one modern area of interest is represented by computational social science, which has been recently defined by Cioffi-Revilla (2014, p.29) as "the interdisciplinary investigation of the social universe on many scales, ranging from individual actors to the largest groupings, through the medium of computation". As an interdisciplinary field, it demands to several disciplines (such as social psychology, sociology, economics and computer science) to share their efforts to unearth the complexity of social reality. Several methods of analysis and topics are finding their common ground on this field. In accordance with Cioffi-Revilla (*ibid*), currently there are five main methods classified within computational social science: automated information extraction; social network analysis; geospatial analysis; complexity modeling; social simulation modeling. Each one comes with several specializations and, specifically, social simulation models include two main approaches to describe complex systems: system dynamics and agent-based modeling. The first represents the earliest kind of simulation models inside computational social science. This method has been quite popular in organizational sciences and economics departments during the last decades thanks to the fact that it is a useful instrument, for instance, to describe and forecast economic processes (Gilbert, 2008). However, psychological research might hardly find benefits from it due to the fact that system dynamic models follow a strong deterministic approach based on equation modeling. Moreover, it works only by taking into account aggregated variables (i.e. populations). Agent-based models overcome this issue by looking at the single actor.

In fact, agent-based modeling aims to reproduce the individual behavior of social actors thanks to dedicated applications and programing languages (e.g. Logo or Java). Agent-based models (ABMs) are tools especially useful to understand and analyze complex system dynamics (Epstein, 2008; Gilbert, 2004; Gilbert & Troitzsch, 2005; Jager & Janssen, 1994; Miller & Page, 2007) and their application has increased quickly over the years in various disciplines (Bozanta & Nasır, 2014). In particular, its application found a large interest in the field of environmental sciences (e.g. Ge, Polhill, Craig, Liu, & Roberts, 2016; Sánchez-Maroño et al., 2012) and marketing or consumer behavior (e.g. Delre, Broekhuizen, & Bijmolt, 2016; Delre, Jager, Bijmolt, & Janssen, 2007; Jager, 2006 & 2007; Kaufmann, Stagl, & Franks, 2009).

Inside an ABM, researchers define the rules of behavior of individual agents (representing, for instance, consumers or employees): by running the simulation over time, it is possible to study the emergence of complex patterns and/or systems that stem from the actions and combination of many individual agents. Each agent can be programmed to achieve a goal, to own a certain degree of autonomy about its decisions, to learn through experience or communication, to perform an action from a range of options, and to react to the virtual environment as well as to the other agents of the simulation (Gilbert, 2004). In addition, virtual agents can be representative of physical entities (such as stores or banks) and endowed with particular features.

ABMs are useful to investigate aggregate patterns originated by the dynamic interactions among many actors (Delre et al., 2016). As noted by Hughes, Clegg, Robinson, and Crowder (2012), the major value of agent-based models lies in their ability to investigate how the macro-behavior of a system (e.g. innovation diffusion) emerges as a consequence from the micro-behavior of many individuals (i.e. the actions of single actors). That is to say, it is possible to model the emergence of social phenomena from the bottom-up. Starting from this, ABMs allow investigating the feedback mechanisms between macro- and micro-behavior as well as the consequent closed-loop between these dimensions. In addition, they are able to overcome the common difficulty for psychological methods of investigation to treat heterogeneity. In fact, individual differences (e.g. opinions, attitudes, beliefs), as well as ways of social interactions and decision-making processes, can be modeled explicitly (Kiesling, Günther, Stummer, & Wakolbinger, 2012).

Hence, the use of computer simulations as a methodology of investigation of social mechanisms is rather a new idea, but it comes with great potential thanks to the fact that is "an excellent way of modelling and understanding social processes" (Gilbert and Troitzsch. 2005, p.1). As suggested by Cioffi-Revilla (2010), similarly to the microscope, which granted the access to physics to an incredible micro-universe made up of earlier unnoticed elements, laws and processes, computational simulations are the instrument that can drive to new theories and applications by means of unprecedented replication and virtual experimentation of social processes. Nonetheless, agent-based model should not represent a detached method from more common psychological investigation techniques. Instead, research should aim to achieve the integration between psychological methods of investigation and agent-based modeling.

In line with this premise, the next section intends to pose the framework of the project and the main research question. With more details, the work was divided into three specific questions. Then, each of the methods employed by the research project to achieve the related objective is briefly illustrated: full details are provided within the successive three papers. In the end, section 5 offers a summary of the results obtained by the overall project.

1.3 Research questions and related aims

Since sustainable consumption encompasses a wide range of behaviors (see for a comprehensive list Jackson, 2005, p.3), the framework of investigation was restricted to one of the key issue to sustainability (i.e. food consumption) and subsequently the research was narrowed to one of the current major trending sector: organic food.

The main research question addressed green food consumption with the hope to contribute to its explanation and promotion: *how do social norms among consumers and individual preferences work over time to shape buying behavior in the context of organic food choice?* Hence, the main purpose was the investigation of the dynamic interaction between the individual and social dimensions of organic food purchase behavior.

However, as argued, the research question is framed inside a complex social phenomenon endowed by peculiar characteristics (e.g. non-linearity, emergent behavior, and closed-loops). As noted, in this situation, standard psychological methods of investigation might appear to limit our capability of understanding: thus, the integration with research methods from different disciplines seemed a reasonable path. Particularly, agent-based modeling was selected as the proper method to provide an answer to the main research question.

1.3.1 Work phases

In order to make possible the investigation, the research project was divided into three phases leaded by a specific question. In addition, an objective was assigned to each phase.

1. *Is there in literature a psychological theory able to account for consumer behavior in relation to both individual and social dimensions?*

   The first objective was to identify a psychological theory able to account for consumer behavior both from an individual and social dimension. Moreover, such framework had to be tested for its validity in the specific context of organic food choice.

2. *Is it possible to convert the psychological framework previously identified into a straightforward algorithm to simulate consumers' behavior?*

   Psychological theories are mostly presented in literature as informal theories rather than formal and strict models. As a consequence, it was reasonable to expect issues or potential gaps in the theory when converted into computational algorithms. Accordingly, the objective of this phase was to critically review the psychological framework from a computational approach in order to highlight (and attempt to resolve) potential issues in the process of its application inside an agent-based model.

3. *Is the psychological framework previously identified and reviewed a sufficient condition to virtually replicate the emergence of lock-in consumption patterns?*

   The third objective was to build a computational model (i.e. an agent-based model) able to emulate consumers' decision-making process on the base of the main psychological framework previously identified and reviewed.

The final agent-based model was expected to replicate the dynamic interaction between the individual and social level of consumers' food choice. In the end, from the analysis of different scenarios, the simulation was expected to offer new insights in consumers' behaviors and to suggest potential interventions to foster the consumption of organic food products.

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2 Predicting Organic Food Consumption: A Meta-Analytic Structural Equation Model based on the Theory of Planned Behavior

Authors

A. Scalco, S. Noventa, R. Sartori, & A. Ceschi

Abstract

During the last decade, the purchase of organic food within a sustainable consumption context has gained momentum. Consequently, the amount of research in the field has increased, leading in some cases to discrepancies regarding both methods and results. The present review examines those works that applied the theory of planned behavior (TPB; Ajzen, 1991) as a theoretical framework in order to understand and predict consumers' motivation to buy organic food. A meta-analysis has been conducted to assess the strength of the relationships between attitude, subjective norms, perceived behavioral control, and intention, as well as between intention and behavior. Results confirm the major role played by individual attitude in shaping buying intention, followed by subjective norms and perceived behavioral control. Intention-behavior shows a large effect size, few studies however explicitly reported such an association. Furthermore, starting from a pooled correlation matrix, a meta-analytic structural equation model has been applied to jointly evaluate the strength of the relationships among the factors of the original model. Results suggest the robustness of the TPB model. In addition, mediation analysis indicates a potential direct effect from subjective norms to individual attitude in the present context. Finally, some issues regarding methodological aspects of the application of the TPB within the context of organic food are discussed for further research developments.

2.1 Introduction

Pro-environmental behaviors have been related to house-hold management, consumer activism with respect to environmental safety, as well as to purchase choice and usage of products (Peattie, 2010). A report by the European Commission (2009) highlighted that nowadays eight out of ten EU citizens recognize impact on environment as a central aspect when deciding which product/good they will buy. Moreover, if queried about what kind of actions has the greatest impact on solving environmental issues, a fifth of the interviewees put at second place the purchase of products produced by means of environmental-friendly methods. In particular, the United Nations have marked sustainable consumption as one of the main objectives to achieve environmental sustainability (Yadav & Pathak, 2016) and food sustainability has been indeed on UK's policy agenda since before the turn of the last century (Honkanen & Young, 2015). Within this context, the work by Jungbluth, Tietje, and Scholz (2000) highlighted the most effective ways to reduce the environmental impact of food consumption. Based on life cycle assessment[1] (LCA) analysis, the first option from a consumer perspective, in order to reduce environmental impact, is the refusal of air-transported food, followed by the preference for organic products and the reduction of meat consumption. In fact, animal products determine higher greenhouse gas emissions than products based on plants since vegetables, cereals and legumes – if not transported by plane – have the lowest gas emissions (Carlsson-Kanyama & González, 2009).

More recently, the value of these three options has been acknowledged also by Thogersen (2010) and Tobler, Visschers, and Siegrist (2011). In the latter study, a survey was carried out to investigate consumers' beliefs and motivations behind environmental-friendly consumption behaviors: in contrast to LCA results, consumers appear to rate the purchase of organic food and the reduction of meat consumption as the least environmentally beneficial options. Moreover, although avoiding air-transported food was rated as more beneficial than the previous behaviors, still it came after the avoidance of excessive product packaging and the purchase of regional food. Hence, an asymmetry

[1] As reported by Finnveden et al. (2009, p.1), life-cycle assessment represents "a tool to assess the potential environmental impacts and resources used throughout a product's life cycle". Detailed procedures for the application of LCA analysis are illustrated within ISO 2016 and its successive modifications.

between empirical results derived from LCA and consumers' perception of environmental impact of food consumption appears to exist with consumers underestimating the importance of green food consumption despite of its acknowledged environmental relevance.

Consumers' preferences toward organic food indeed represent a form of behavior that can both promote the preservation of environment and lead the transition toward a more sustainable society. Organic food represents a form of sustainable consumption due to the fact that it is produced by employing natural processes, by means of sustainable energy, and by taking into account the protection of the soil, as well as the animal welfare (European Commission, 2014). The environmental benefits of organic food w.r.t conventional one have been remarked by several LCA studies. For instance, Boggia, Paolotti, and Castellini (2000) assessed the environmental impact of different poultry production systems concluding that the organic one owns the lowest environmental impact in all crucial impact categories. A similar work was carried out by Litskas, Mamolos, Kalburtji, Tsatsarelis, and Kiose-kampasakali (2010) that evaluated the energy flow and the effects of different farming systems on gas emissions in sweet cherry orchards. Results suggested that an organic system can reduce the employment of non-renewable energy as well as gas emissions against the conventional one. More recently, Longo, Mistretta, Guarino and Cellura (2015) examined energetic and environmental impact of apple cultivation in the North of Italy. Once again, a comparison between organic and conventional production systems by means of LCA yielded that, despite a lowered productivity, an organic production system reduces the environmental impact for the majority of the analyzed impact categories.

A recent report by the European Commission (2016) about agricultural research and innovation has acknowledged the need for further research by those types of farming systems that implement ecological approaches such as the organic sector. In addition, the report highlighted the importance of taking into account the role of consumers. Indeed, choices made by consumers can have a backward influence on the food production chain, to the extent that the development of organic farming appears to be governed by market rules (Padel, Lampkin & Foster, 2011). Within the context of green consumption, however, two main types of studies can be differentiated: those coming from marketing that are mainly focused on understanding the motivations of consumers, and those coming from industrial or economical ecology that are mostly interested in the impact of consumer's behaviors (Peattie, 2010). While the second approach measures the outcome of a behavior, the first one investigates the motivations behind it. Thus, in line with the first approach, a wide range of studies within the environmental literature has assumed the theory of planned behavior (TPB; Ajzen, 1991) as the foundational backbone for investigating the psychological factors that drive consumers' behaviors toward sustainable consumption. With the words by Schultz and Kaiser, these studies addressed "the degree to which the person wants to produce a positive environmental outcome" (2012, p.4). Indeed, TPB represents a solid psychological framework that, more than others, has been able to unearth the main motivations behind food choices in relation to sustainable consumption (Peattie, 2010). In particular, given the increased importance assigned to organic food products as part of a sustainable development and the predictive power of Ajzen's theory, the amount of research aimed at understanding consumers' choice through the application of TPB has grown quickly over the last decade. Some of these works have also recently argued the canonical interpretation of the basic tenets of the TPB, as well as the strength of the associations between its fundamental factors (see, e.g., Al-Swidi, Huque, Hafeez, & Shariff, 2014; Yadav and Pathak, 2016). Therefore, we believe that a meta-analysis might be useful to shed light on some of these issues and to guide both scholars interested in studying green food-related consumers' behaviors, as well as practitioners who aim at dealing efficiently with the promotion of such products.

2.2 The theory of planned behavior in relation to organic food consumption

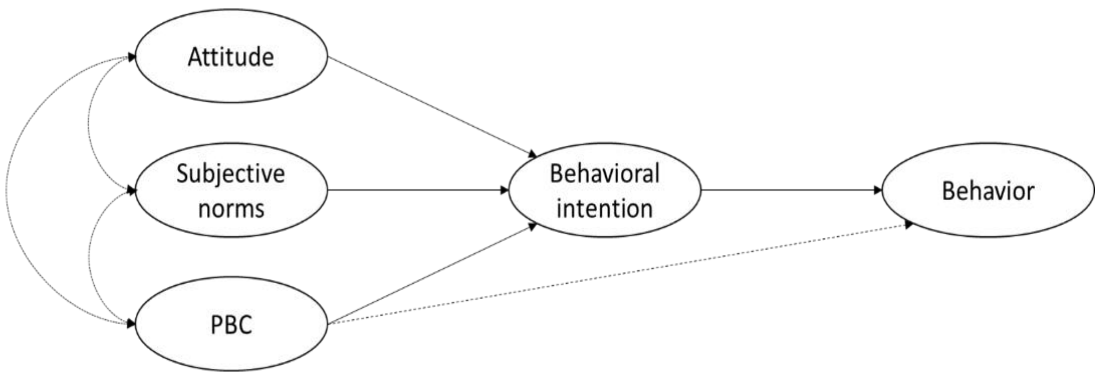
The theory of planned behavior was developed by Ajzen (1991) moving from the earlier theory of reasoned action (Fishbein & Ajzen, 1981). Both theories assume that people's behaviors rely upon deliberative bases (for instance, the contemplation of the outcomes of a certain action), but TPB also adds a component able to take into account both real and perceived difficulties that a person may experience in relation to the act of performing (or not performing) a certain behavior. Thus, TPB is a psychological model that takes into account three fundamental aspects of human behavior: personal attitude, subjective norms, and perceived behavioral control. These are the basic antecedents of the intention to engage in a certain behavior, which in turn mediates their relation with actual behavior (**Fig. 1**). Hence, intention is assumed to capture the motivational dimension and indicates the propensity to engage in a specific behavior (Honkanen & Young, 2015).

Attitude reflects individual preferences to perform or not perform a behavior. In detail, it expresses the global positive/negative evaluation of individuals about a certain behavior: the more positive the attitude, the stronger will be the intention to express such a behavior (Armitage & Conner, 2001). In the specific context of organic food consumption, Sparks and Shepherd (1992) investigated consumers' purchase of organic vegetables and argued that attitude appears to play a crucial role in shaping behavior, by directly affecting buying intention. Following Fishbein and Ajzen (1981), attitude can indeed be conceived as the sum of different beliefs that may be directly related to purchase intentions. Arvola and colleagues (2008) reported that several studies carried out in the USA and Europe showed the relevance on consumption intention of beliefs regarding organic food characteristics such as taste, healthiness, as well as the perceived benefits to/on the environment. However, the strength of the association between attitude and behavioral intention in the case of organic food consumption largely varies among studies. For instance, a recent study by Al-Swidi et al. (2014) found a strong correlation (r = 0.80) on a sample composed of University members and students from Pakistan, whereas a study carried out by Onwezen, Bartels, and Antonides (2014) on a Dutch sample showed a more modest one (r = 0.56). A study by Guido et al. (2010) also reported a small correlation (r = 0.27) using a pooled sample composed of participants from France and Italy. Thus, although most of the studies that applied the theory of planned behavior to investigate the intention to purchase and consume organic food demonstrated the crucial role of attitude in shaping buying intention, the strength of this association still remains unclear.

The second component refers to the common social norms (SN) that are perceived by individuals in relation to engage (or not engage) in a specific behavior (Ajzen, 1991). Adherence to norms is important as it allows group members to avoid triggering rejection responses while stimulating a sense of social approval (Cialdini, Bator, & Guadagno, 1999). In addition, Cialdini, Reno, and Kallgren (1990) distinguished between injunctive and descriptive social norms: whereas the former relate to the perception of what people generally approve or condemn, the latter are derived by the observation of how the majority of people behave in ambiguous conditions. The theory of planned behavior especially focuses on the role of injunctive norms. In particular, subjective norms are an expression of normative influence, which is related to what the most important referent individuals (w.r.t. a specific topic) consider as an acceptable or unacceptable behavior (Scalco et al., 2017). Zagata (2012) suggested that the most relevant source of social influence in relation to organic food choice comes from family and friends, whereas work colleagues have a negligible effect. Several works assessed the moderate impact of SN in relation to the consumption of organic food. Nonetheless, a recent study by Yadav and Pathak (2016) has not found any significant effect of subjective norms on the intention to buy green food. After all, Armitage and Conner (2001) had already argued that the normative component of TPB might represents the weakest amongst the constructs of the model.

Finally, perceived behavioral control (PBC) relates to the individual perception of those factors that might foster or hinder the expression of a behavior (Guido et al., 2010). According to Ajzen's model (1991), PBC influences actual behavior only if the behavior is not completely under the person's volitional control. Commonly, barriers to the purchase of organic food are associated to the higher prices and lower availability that distinguish this kind of products (Robinson and Smith, 2002). As in the attitude case, the strength of PBC on buying intention varies across studies. For instance, Dowd and Burke (2013) found an association of r = 0.51, whereas Yazdanpanah and Forouzani (2015) found a non-significant correlation. Notably, the items used within both investigations to measure the PBC focused on personal willingness and easiness to buy organic food rather than on different specific barriers (e.g. a higher price). Thus, some concerns regarding the influence of the perceived behavioral control on buying intention related with organic food still remains unresolved.

Fig. 1 - The original model proposed in the theory of planned behavior (Ajzen, 1991).



Over the years, the model proposed by Ajzen has also been extended to include several constructs aimed at increasing the variance explained by intention. For instance, in the context of organic food products, Robinson and Smith (2002) investigated perceived self-identity in relation to environmental consumerism, whereas Arvola and colleagues (2008) took into account the role of moral obligations. Nonetheless, a general review by Armitage and Conner (2001) showed that the canonical TPB model on average accounts for between the 39-50% of the variance in intention and the 27-36% of the variance in behavior[2]. More specifically, the recent work by Dowd and Burke (2013) confirmed the robustness of the original TPB model in predicting organic food consumption even above previous similar works, explaining 62% of the variation in intention. In addition, the original model proposed by Ajzen assumes that the antecedents may potentially correlates with each other (see **Fig. 1**), and several studies have so far adopted this structure obtaining significant results (e.g. Bamberg, 2002; Dean, Raats, & Shepherd, 2008; Honkanen & Young, 2015). Nevertheless, Tarkiainen and Sundqvist (2005) proposed and verified a model where subjective norms directly influenced attitude toward the purchase of organic food and no relation is present between SN and PBC. Similarly, Lodorfos and Dennis (2008) found a significant causality between social and personal spheres. More recently, Al-Swidi et al. (2014) proposed a TPB model in relation to organic food purchase where subjective norms impacted on both attitude and perceived behavioral control. Again, results appeared to show the existence of a direct relation for the SN-attitude association. Consequently, both the relationships of attitude and PBC with the social component in shaping buying decisions regarding organic food still remains rather uncertain.

As argued by Lodorfos and Dennis (2008), it seems clear that, although there is general agreement on the source of influence on the consume of organic food products, there is still the need for a clearer model based on quantitative analysis. In line with this, the present work focuses on the previous research that applied the theory of planned behavior to predict the intention to buy organic food, with the aim to shed light on the

[2] However, it should be stressed that the predictability of the model depends on the type of the examined behavior (see, for instance, Armitage and Conner in 2001, or the more recent review by McEachan, Conner, Taylor, and Lawton of 2011 regarding health behaviors).

relationships among those factors affecting consumers' choice. Notice however that, in contrast to other reviews about the TPB applied to food consumption which considered food choice in relation to healthy eating (see for instance, Riebl et al., 2015), the present work assumes a specific pro-environmental framework associated to sustainable consumption.

Therefore, the first objective of the present work is to summarize and test both the strength of the associations between attitude, subjective norms and perceived behavioral control with the behavioral intention to purchase or consume sustainable food (as well as between these factors), and the strength of the relationship between intention and actual behavior of consumers. In order to do so, a random effects meta-analysis of the correlations reported in literature has been carried out, and then the jointly contributions of the correlations among the constructs of the TPB have been examined through the application of a meta-structural equation model based on a pooled correlation matrix. In particular, we aimed to test the significance of the general model proposed by Ajzen (1991) as depicted in **Fig. 1**. The second objective is related to the assessment of some alternatives models that have been proposed in literature (e.g. Al-Swidi et al., 2014; Lodorfos & Dennis, 2008; Tarkiainen & Sundqvist, 2005), which suggest alternative formulations of the antecedents of intention by modifying the relationships between subjective norms and attitude and/or perceived behavioral control.

2.3 Method

To survey the studies, the following databases were queried during March 2016: Scopus, Web of Science, and PsychINFO. The following terms and combinations were used as research keys in titles, keywords and abstracts: ("theory of planned behav*" OR "planned behav*" OR "Ajzen") AND ("purchas*" OR "recycled" OR "nontoxic" OR "eating" OR "organic" OR "green food" OR "sustainable"). Results were extracted from the online research engines and recorded into a comprehensive database. Double entries or studies with basic missing information were excluded. Due to the broad spectrum of the used keywords, the research captured a range of 1174 publications, of which however only a selection of 108 were completely on-topic. Each record of the obtained database was indeed examined through the titles and/or the abstract and removed unless it matched the topic of interest or the general approach. In the end, to enlarge the research, some studies were added to the database by manually searching within the references provided in the selection obtained by the previous method.

2.3.1 Eligibility criteria

Studies were considered only if they were written in English language and published in peer-reviewed journals. In line with McEachan, Conner, Taylor, and Lawton (2011), unpublished material was avoided since its absence appears not to pose a threat to the validity of the analysis when dealing with the theory of planned behavior (*ibid*, see Note 2, p.33). In particular, Schulze and Whittmann (2003) showed how the levels of prediction do not significantly differ between meta-analyses of published or unpublished studies that examined the TPB. Some of the eligibility criteria already applied in the review by Hassan, Shiu, and Parry (2016) were also adopted: namely, all included studies applied a quantitative approach in dealing with Ajzen's model and followed the original operationalization proposed by Ajzen (1985, 1991) (see, for a negative example, Singh, Fassot, Zhao, and Boughton, 2006). Furthermore, all studies were required to evaluate the intention to purchase or consume (either generic or specific) organic food or food products produced in a sustainable manner.

Samples of the studies had to be composed of people older than 18 years since, as reported in Visintin et al. (2012), adolescents are still establishing their personal identity, so their moral and belief systems and their motivations behind food consumption may vary significantly compared to adults. In addition, as stated by Paul, Modi and Patel (2016), green contexts can be rather difficult to be understood and comprehended by minors.

In order to allow for the computation of summary effect sizes, each study had to report Pearson's correlations at least between (*i*) attitude and intention, (*ii*) subjective norms and intention, and (*iii*) perceived behavioral control and intention. Some studies were then excluded as they did not consider all the three basic components of the theory of planned behavior or they revised one or more of its constructs. For instance Leßmann and Masson (2015) evaluated subjective norms by asking participants: "Most people who are important to me purchase organic food". Such an item addresses descriptive norms, whereas the original TPB requests to investigate injunctive social norms (that is, what most people who are important to the participant think about the purchase and consumption of organic foods). Moreover, since some studies investigated subjective norms in relation to different comparison groups, we decided to take into consideration only one of the available correlations with the following order of relevance: (1) generic comparisons (such as: “most people who are important to me”), as proposed in Ajzen examples (2006); (2) family; (3) peers; (4) colleagues. We assumed that a generic reference comparison would be spontaneously associated by participants to the most relevant source of influence. Where generic items were not employed, friends and family members were preferred to co-workers, as the formers are common referent groups (Childers & Rao, 1992), whereas the latter are less important in the specific context of organic food (Zagata, 2012).

Studies that replaced PBC with the perception of consumer effectiveness were also accepted (e.g. Honkanen & Young, 2015). Consumer effectiveness has been indeed operationalized by Antil (1984, p. 25) as a “judgement of the ability of the individual consumer to have an effect on environmental-resource problems”. Within the context of green food consumption, we assumed that this construct could overlap with the original proposal of control behavior (Ajzen, 1991). Research that evaluated the PBC by assessing its sub-dimensions (e.g. Tarkiainen & Sundqvist, 2005, who evaluated separately price and availability of organic food) were excluded when an overall correlation with intention was not provided.

Finally, some studies were excluded as they assessed too general intentions that only partially related with green food consumption: for instance, Chatzidakis, Kastanakis, and Stathopoulou administered a questionnaire based on the TPB framework to investigate the “intention to support the fair trade movement” (2016, p. 105). Although fair trade can be related to the consumption of organic food, it can as well be related to products of different kind (e.g., apparel): thus, attitude and subjective norms may differ significantly when controlled for each fair trade product.

In conclusion, following the previous eligibility criteria, the final database used for the meta-analysis was composed of 17 contributions, which provided a total of 23 different studies and a total sample of 11349 participants. The full process of research and selection is summarized in **Fig. 2**. Among the selected contributions, only one contribution (corresponding to a single study; Vermeir & Verbeke, 2008) did not report the correlations among attitude, social norms and PBC. Thus, correlations between attitude, social norms, PBC and intention were fully provided by 22 investigations (10893 participants). Surprisingly, only 6 out of the 23 studies reported correlations between actual behavior and the other TPB constructs. In this case, as the number of measures were few, both past and prospect (only one case; Bamberg, 2002) behaviors were integrated. Although this might affect the reliability of the meta-analytic procedure with regard to these specific correlations, at the same time these six studies provided more than half of the total sample (6223 participants).

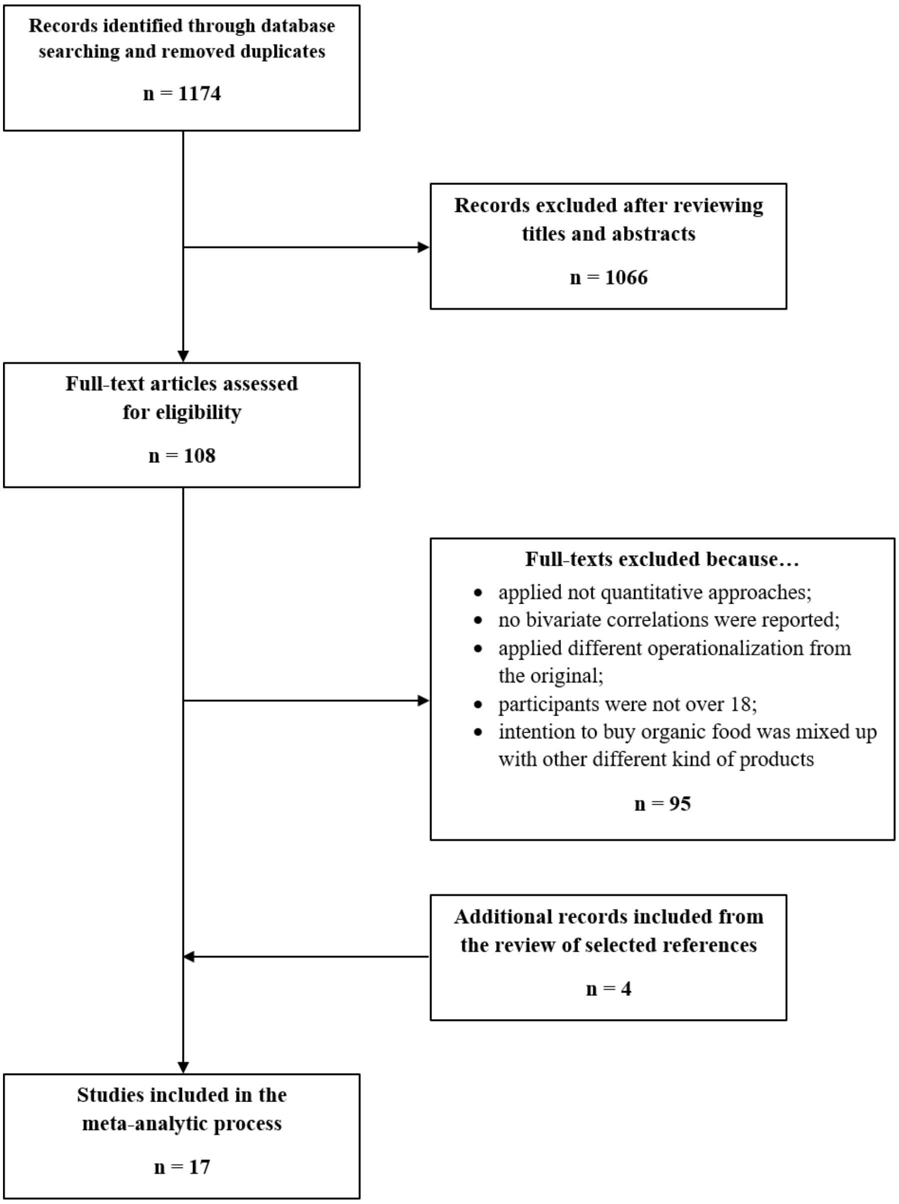
2.3.2 Coding of the studies

Selected studies were recorded into an excel database along with several information. Regarding their characteristics, we considered the year of publication, the kind of intention evaluated (i.e. generic *vs* specific; organic *vs* sustainable), the primary purpose of the study, the correlations between and among the basic components of the theory of planned behavior, and, when available, the correlations between the actual behavior and the other TPB constructs. As for the sample, we recorded the mean age, the gender distribution (as percentage of female) and its size. The full list of studies that have been taken into account by the current review and the related classification based upon the aforementioned variables can be consulted in **Table 1**. Data extracted from the studies are reported in **Table 2**.

2.3.3 Data analysis

Effect sizes are standardized values that express the magnitude of an observed phenomenon with the aim to make direct comparisons across studies (Field & Gillett, 2010). Typically, in a meta-analysis, a summary effect is provided that describes the general trend. A key issue is then the choice between fixed or random effects models. Fixed-effects models (FE) assume that the true effect size is shared by all the studies, whereas random-effects models (RE) assume that the effect size varies between studies (usually following a normal distribution). As noticed by Field and Gillett (2010), researchers should choose the appropriate model beforehand according to the involved studies and the desired inferences. In particular, RE models are more appropriate when studies are carried out by different researchers in different settings so that effect sizes can vary randomly (Bamberg & Moser, 2007; McEachan et al., 2011; Cheung, 2015).

Fig. 2 - The flowchart describes the process of research and selection and provides information about the number of studies for each phase.



In the present study, a random-effects model was then applied since most of the selected studies were carried out independently, with several samples drawn from different populations. A RE model appears also to be more in line with the two-fold purpose of the present meta-analysis: on one hand, we aimed at obtaining summary effects of the correlations between attitude, subjective norms, perceived behavioral control, intention, and actual behavior to buy or consume organic food; on the other, we aimed to test the relations amongst these constructs by means of a meta analytical structural equation model (MASEM; Topa & Moriano, 2010).

Summary effects for correlations

There are several methods to estimate summary effects using RE models. The most common ones are those provided by Hunter and Schmidt, Hedges and colleagues and Der Simonian and Laird. A brief discussion is provided in Field and Gillett (2010), whereas a more exhaustive comparison is given in Field (2005). Based on their analyses, we decided to apply the method provided by Hedges (1983), which takes into account the variance within the studies, as well as the variance between them. In order to conduct the meta-analysis on correlations, we used the open source software *R* (v. 3.3.1; R Development Core Team, 2016) and the *metafor* package (Viechtbauer, 2010). In particular, a summary effect was provided as a weighted mean of the examined effect sizes, in which higher weights were assigned to those studies employing large samples, whereas less importance was given to those using smaller ones[3]. As suggested by Bamberg and Moser (2007) and Schwenk and Möser (2009), correlations were initially transformed in the Fisher's *z* scale. Jointly with the *z* metric, the variance and standard errors of the *z* values were calculated by considering the sample size of each study. However, in line with the suggestion provided by Field and Gillett (2010), in order to remove a slight positive bias due to the *r*-to-*z* transformation, we used the adjustment method provided by the same authors. After the analysis, Fisher's *z* values were converted back into correlations. In addition, as Field and Gillett (2010) also suggest to tabulate the original effect sizes when reporting a meta-analysis along with relevant information (e.g., related sample size), we summarized the original correlations in **Table 2** for each study considering each couple of variables and provided in **Table 3** the stem-and-leaf plots about the main correlations between attitude, subjective norms and PBC with intention, which offers a more concise perspective on data.

In order to interpret the results of the meta-analytic process, Topa and Moriano (2010) recommend to employ the rule of thumb proposed by Cohen's guidelines (1992) that classify correlation coefficients as small, medium or large, for values of about, $r = 0.10$, 0.30, and 0.50. A small effect size suggests that the variables may be independent, a

[3] As pointed out by Borenstein, Hedges, Higgins, and Rothstein (2009), the way weights are assigned comes from the assumptions made about the distribution of the effect sizes in the studies (and it is strictly related to the application of fixed- or random-effects models).

medium one that the covariance is only partially established, and a large one that the covariance between the considered variables is (nearly) perfect.

After the application of the RE model, two indexes were considered to evaluate the heterogeneity among studies: I^2 and the Q-test. As stated in Godin, Vézina-Im, Bélanger-Gravel, and Amireault (2012), the former represents the percentage of total variation in the estimated effects that comes from heterogeneity rather than by chance: high heterogeneity is given for values of I^2 above 75%, whereas low heterogeneity is assumed for values below 25%. The null-hypothesis of the Q-test assumes perfect homogeneity (Cheung, 2015): thus, if the *p*-value falls below the threshold of .05, we can conclude that the studies are heterogeneous.

Finally, as suggested by Cheung (2015), residuals were tested in order to detect the presence of possible outliers for each summary effect. As proposed by Viechtbauer and Cheung (2010), externally standardized residuals (also known as externally studentized residuals) were considered. If the application of the Shapiro-Wilk test did not indicate a normal distribution of residuals, we proceeded to detect outliers by means of the observation of the *z*-scores and by visually inspecting the normal probability plot.

MASEM analysis

A meta-analytical structural equation model was applied to test the strengths of the correlations between the components of the theory of planned behavior regarding the purchase and consumption of organic food products. This was done through the application of meta-analytical procedures that firstly pooled the multiple correlation matrices available in the studies and then analyzed the result using structural equation models. Analyses were carried out by using the *metaSEM R*-package (Cheung, 2015).

Overall, the analyses intended to test several models. Models 1 and 2 (see **Fig. 3**) tested the original TPB model proposed by Ajzen (1991); the former employed all included studies, whereas the latter used only the subset of those 6 studies that provided all additional correlations between antecedents and behavior. Model 3 (see **Fig. 4**) was tested to assess a direct effect of perceived behavioral control on actual behavior. The application was suggested by the work of Shin, Hancer, and Song (2016) in the close context of local growth food.

In addition, some alternative models of the relationships between attitude, subjective norms and PBC were tested. These models have been suggested in literature to theoretically describe a direct effect of social norms on attitude which might be relevant in the case of green food consumption. Firstly, as suggested by the work of Al-Swidi et al. (2014), we assumed a direct effect of subjective norms on attitude while allowing only for a covariation between subjective norms and behavioral control (Models 4 and 5, depending on the absence or presence of actual behavior as a variable). Secondly, as suggested by the works by Lodorfos and Dennis (2008) and by Tarkiainen and Sundqvist (2005), the covariation between subjective norms and perceived behavioral control was removed (Models 6 and 7, depending on the absence or presence of actual behavior as a variable). Notice that these models come in pairs, since their original studies did not consider actual behavior; hence, at a first step, the analyses were performed only on a pooled 4x4 matrix including the correlations between attitude, PBC, SN and intention so that the tested models included 3 exogenous variables and 1 endogenous one. As a second step, the relationships of the previous constructs with behavior was also included into the model so that a further endogenous variable was added leading to the complete pooled 5x5 correlation matrix. The results section reports the indexes typically used to evaluate the goodness of a SEM. As indicators of a good fit to the data, it is usually assumed RMSEA ≤ 0.05, CFI ≥ 0.90 (if not 0.95), SRMR ≤ 0.08, and TLI ≥ 0.90.

2.4 Results

Most of the examined studies were published starting from 2011 (10 out of 17), 6 were published during the 2000s, and one in the 90s. Publication distribution is scattered among 13 journals active on several domains (e.g. economics, environmental studies, social psychology), with a third of the papers published on two journals: *Appetite* (4 studies) and *British Food Journal* (2). Only eleven studies provided data regarding sex distribution: the samples were composed of females for a slight majority ($M = 52.05$). Most of the studies started with specific hypotheses (12) rather than being explorative research (5). Moreover, about half of the studies (9 out of 17) tried to extend the application of the original model proposed by the TPB with the addition of supplemental antecedents of intention. The most frequently added factors are related to the perceived self-identity of customers and to the moral concern associated with the fairness of purchasing sustainably grown food.

Table 1 - Summary of the studies considered for the meta-analysis.

Author(s)	Year	Primary purpose	Intention to consume	Sample country	Mean age	%Female
1. Al-Swidi et al.	2014	Measuring the direct and moderating effects of subjective norms on attitude, PBC and purchase intention of organic food	generic organic food	Pakistan	33.89[a]	25.50
2. Arvola et al. (study a, first sample)	2008	Evaluation of the integration of measures of affective and moral attitude into the original TPB in order to predict buying intention of organic foods	organic apples	Italy	39.16[a]	28.00
3. Arvola et al. (study a, second sample)	2008		organic apples	Finland	39.16[a]	50.00
4. Arvola et al. (study a, third sample)	2008		organic apples	U.K.	39.16[a]	30.00
5. Arvola et al. (study b, first sample)	2008		organic pizza	Italy	39.16[a]	28.00

6. Arvola et al. (study b, second sample)	2008		organic pizza	Finland	39.16[a]	50.00
7. Arvola et al. (study b, third sample)	2008		organic pizza	U.K.	39.16[a]	30.00
8. Bamberg	2002	Investigation of the effects of three different interventions to increase the likelihood to purchase organic food in a local bio-shop	generic organic food	Germany	n.r	n.r
9. Dean, Raats, & Shepherd (study a)	2012	Impact of moral norms, self-identity and past behavior in relation to the intention to purchase specific organic food products	organic tomatoes	U.K.	39.16[a]	76.35
10. Dean, Raats, & Shepherd (study b)	2012		organic tomato sauce	U.K.	39.16[a]	76.35
11. Dowd & Burke	2013	Evaluation of the TPB in predicting sustainably sourced food with the addition of ethical factors (i.e. moral attitude and ethical self-identity).	generic sustainably sourced food	Australia	40.37	79.56

12. Guido et al.	2010	Investigation of the role of ethical factor and product personality in relation to the intention to buy organic food	generic organic food	France and Italy	n.r	n.r
13. Honkanen & Young	2015	Application of the TPB to investigate the intention to purchase and consume sustainable seafood	sustainably produced seafood	U.K.	47.00	61.00
14. Lee, Bonn, & Cho	2015	Investigation of the motivation behind the purchase of organic coffee by means of the TPB	organic coffee	South Korea	24.50[a]	65.60
15. Lodorfos & Dennis	2008	Application of the original model proposed by the TPB to investigate the intention to purchase organic food products	generic organic food	U.K.	40.04[a]	n.r
16. Onwezen, Bartels, & Antonides (study a)	2014	Evaluation of the intention to buy organic food using the original model of the TPB with a special consideration on descriptive norms and on the pride and guilt feelings	generic organic food	Netherlands	44.90	50.20
17. Robinson & Smith	2002	Application of the original model of the TPB with the addition of self-identity as antecedent of the behavioral intention	generic sustainably sourced food	U.S.A.	36.00[a]	65.00

18. Sparks & Shepherd	1992	Investigation of intention to purchase and consume organic food products considering the attitude, social norms, PBC, self-identity and past behavior	generic organic food	U.K.	n.r	n.r
19. Vassallo et al.	2016	Application of an extended model of the TPB to investigate the intention to buy sustainable food products with a focus on social pressure	generic sustainably sourced food	Italy	42.43[a]	60.00
20. Vermeir & Verbeke	2008	Use of the original model of TPB to predict the intention to buy organic dairy products with the addition of individual characteristics (i.e. confidence and personal values)	sustainable dairy products	Belgium	20.50[a]	n.r
21. Yadav & Pathak	2016	Investigation of the intention to buy organic food products in a developing nation by means of the original model of the TPB	generic organic food	India	25.59[a]	45.00
22. Yazdanpanah & Forouzani	2015	Application of the TPB model to predict the intention to buy organic foods among Iranian students with emphasis on moral norms and self-identity	generic organic food	Iran	20.98	64.30
23. Zagata	2012	Investigation of the intention to buy organic food products in the context of a country with an emerging organic food market	generic organic food	Czech Republic	n.r	25.50

[a] Mean age was indirectly elaborated on the base of the information provided within the paper.

Table 2 - Raw correlations considered for the meta-analytic procedures.

Research ID	Sample size (*N*)	ATT-SN	ATT-PBC	SN-PBC	ATT-INT	SN-INT	PBC-INT	ATT-BEH	SN-BEH	PBC-BEH	INT-BEH
1. Al-Swidi et al., 2014	184	0.562	0.180	0.314	0.798	0.696	0.216	n.r	n.r	n.r	n.r
2. Arvola et al., 2008 (study a/sample from IT)	202	0.690	0.440	0.460	0.730	0.620	0.410	n.r	n.r	n.r	n.r
3. Arvola et al., 2008 (study a/sample from UK)	270	0.520	0.220	0.280	0.600	0.560	0.310	n. r	n.r	n.r	n.r
4. Arvola et al., 2008 (study a/sample from FI)	200	0.570	0.400	0.340	0.670	0.550	0.360	n.r	n.r	n.r	n.r
5. Arvola et al., 2008 (study b/sample from IT)	202	0.760	0.350	0.360	0.710	0.640	0.240	n.r	n.r	n.r	n.r
6. Arvola et al., 2008 (study b/sample from UK)	270	0.460	0.030	0.150	0.550	0.580	0.100	n.r	n.r	n.r	n.r
7. Arvola et al., 2008 (study b/sample from FI)	200	0.510	0.260	0.210	0.510	0.380	0.160	n.r	n.r	n.r	n.r
8. Bamberg, 2002	320	0.410***	0.450***	0.320***	0.480***	0.400***	0.550***	0.480***	0.170***	0.310***	0.340**
9. Dean, Raats, & Shepherd, 2012 (study a)	501	0.660***	0.530***	0.360***	0.740***	0.720***	0.450***	0.550***	0.550***	0.310***	0.640**
10. Dean, Raats, & Shephedr, 2012 (study b)	499	0.640***	0.480***	0.430***	0.710***	0.710***	0.430***	0.350***	0.340***	0.300***	0.490**
11. Dowd & Burke, 2013	137	0.440**	0.300**	0.300**	0.680**	0.550**	0.510**	n.r	n.r	n.r	n.r

12. Guido et al., 2010	207	0.040	0.110	0.220***	0.270***	0.460***	0.420***	n.r	n.r	n.r	n. r
13. Honkanen & Young, 2015	755	0.371**	0.228**	0.130**	0.574**	0.561**	0.319**	n.r	n.r	n.r	n.r
14. Lee, Bonn, & Cho, 2015	482	0.266**	0.183**	0.136**	0.303**	0.491**	0.270**	n.r	n.r	n.r	n.r
15. Lodorfos & Dennis, 2008	144	0.281**	0.120	0.114	0.820**	0.534**	0.486**	n.r	n.r	n.r	n.r
16. Onwezen, Bartels, & Antonides, 2014 (study a)	944	0.344***	0.171***	0.228***	0.561***	0.524***	0.185***	0.420***	0.421***	0.185***	0.657**
17. Robinson & Smith, 2002	547	0.476**	0.259**	0.299**	0.459**	0.382**	0.332**	n.r	n.r	n.r	n.r
18. Sparks & Shepherd, 1992	261	0.370***	0.060	0.050	0.380***	0.300***	0.270**	n.r	n.r	n.r	n.r
19. Vassallo et al., 2016	2905	0.320***	0.670***[1]	0.250***[1]	0.780***	0.630***	0.430***[1]	0.550***	0.470***	0.600***	0.730**
20. Vermeir & Verbeke, 2008	456	n.r	n.r	n.r	0.666***	0.371***	0.389***	n.r	n.r	n.r	n.r
21. Yadav & Pathak, 2016	220	0.020	-0.030	-0.090	0.550*	- 0.020	0.150	n.r	n.r	n.r	n.r
22. Yazdanpanah & Forouzani, 2015	389	- 0.025	0.003	0.075	0.650***	0.049	- 0.021	n.r	n.r	n.r	n.r
23. Zagata, 2012	1054	0.391**	0.388**	0.222**	0.518**	0.497**	0.388**	0.239**	0.272**	0.204**	0.338**
	N. of studies	22	22	22	23	23	23	6	6	6	6

Notes. Studies with multiple samples or different research are indicated in parentheses. Raw correlations that were not reported by the original papers are marked with “n.r.”. Significance levels are reported from the original analyses (significance levels are not indicated if original papers did not report them).
Abbreviations. ATT = attitude; SN = subjective norms; PBC = perceived behavioral control; INT = behavioral intention; BEH = actual behavior.
[1] PBC correlation coefficients are reported with a negative sign in the original research: the sign has been reversed to match the operationalization performed by the majority of studies.
* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 3 - Stem-and-leaf plots of the original correlations between attitude and intention (3.a), subjective norms and intention (3.b), perceived behavioral control and intention (3.c), and intention and behavior (3.d).

Table 3.a – Att-Int

Stem	Leaf
.2	70
.3	03, 80
.4	59, 80
.5	10, 18, 55, 55, 61, 74
.6	00, 50, 66, 70, 80
.7	10,10, 30, 40, 80, 98
.8	20

Table 3.b – SN-Int

Stem	Leaf
- .0	20
.0	49
.1	
.2	
.3	00, 71, 80, 82
.4	00, 60, 91, 97
.5	24, 34, 50, 50, 60, 61, 80
.6	20, 30, 40, 96
.7	10, 20

Table 3.c – PBC-Int

Stem	Leaf
- .0	21
.1	00, 50, 60, 85
.2	16, 40, 70, 70
.3	10, 19, 32, 60, 88, 89
.4	10, 20, 30, 30, 50, 86
.5	10, 50

Table 3.d – Int-Beh

Stem	Leaf
.3	38, 40
.4	90
.6	40, 57
.7	30

Overall, the studies involved sampled participants from 14 different countries. The majority of them included European samples (17 out of 23), three studies employed samples from Asia, one from Australia, one from Middle-East and one from USA. It should be noted that the European sample included a majority of Italian participants (*n* = 3265), followed by English (*n* = 1859) and Czech (*n* = 1054). Generally speaking, the number of participants was satisfactory for all the examined studies, with a minimum of 137 participants (Dowd & Burke, 2013). Some studies (9 cases) applied sophisticated statistical analyses, such as structural equations modeling: within these cases, for some of these studies (Al-Swidi et al., 2014; Arvola et al., 2008) the number of subjects were however below the minimum acceptable threshold of 10 subjects for parameter suggested by Kline (2011).

Most of the time the questionnaire administered by the researchers investigated the intention to purchase or consume general food products: thus, items used to measure the TPB constructs were phrased in relation to "organic food" (*n* = 9) or "sustainably sourced food" (*n* = 4). Instead, specific organic products investigated by the included studies were: apples, pizza, tomatoes, tomato sauce, coffee, or dairy products. Correctly, most of the studies (14 out of 17) reported all the original items employed to assess the constructs of the TPB.

Generally, the correlations retrieved from the examined studies showed large discrepancies, ranging from small to great effects for all the relationships between the antecedents and the behavioral intention. The widest variation among correlations was found however for the association between subjective norms and intention, which showed a maximum value of $r_{max} = 0.72$ (Dean, Raats, & Shepherd, 2012), and a minimum value close to the null one ($r_{min} = -0.02$; Yadav & Pathak, 2016).

2.4.1 *Summary effects*

As mentioned in the data analysis section, the application of a fixed-effects model is considered appropriate only when there is a very low variation among studies; vice-versa, a pool of studies with high heterogeneity should be examined with a random-effects model. We therefore applied the latter to all examined correlations. However, in order to assess the goodness of our assumptions, we evaluated the I^2 and Q-test values: I^2 values ranged among the examined correlations from a minimum of 86.48% to a maximum of 98.05% thus indicating an overall very high heterogeneity among studies (see **Table 4**).

Similarly, the Q-test constantly reported values associated with a *p*-value < 0.001, thus confirming the discrepancy among the studies. Therefore, the applied RE model confirmed to be the appropriate solution for the current cases.

Residuals appeared normally distributed in all cases with the exception of the correlations between perceived behavioral control and actual behavior. In this case, one extreme outlier appeared (i.e., Vassallo, Scalvedi, & Saba, 2016, $r = 0.60$). A further meta-analytic process where the outlier was removed was performed. Again, the Shapiro-Wilk test did not indicate a normal distribution and two minor outliers were identified (Onwezen, Bartels, & Antonides, 2014; Zagata, 2012). We consider this an issue that might be due to the different measures employed during the evaluation of the PBC: further considerations regarding this point are given in the conclusion.

Results obtained from the meta-analyses are presented in **Table 4**. Each summary effect is supplied with its relative lower and upper limits for the 95% confidence interval. The strongest summary effect is given by the association between attitude and intention ($SE_{\text{att-int}} = 0.61$). Similarly, a lower but still large correlation resulted between subjective norms and behavioral intention ($SE_{\text{sn-int}} = 0.50$). Conversely, the third antecedent shows a medium effect size in relation to intention ($SE_{\text{pbc-int}} = 0.32$). A similar pattern was found in relation to the associations between the antecedents of intention and actual behavior. Particularly, the strongest correlation was found between attitude and behavior ($SE_{\text{att-pbc}} = 0.44$), followed by subjective norms-behavior ($SE_{\text{sn-beh}} = 0.38$) and PBC-behavior ($SE_{\text{pbc-beh}} = 0.33$). Moreover, the correlation between the behavioral intention and actual behavior was moderate to large ($SE_{\text{int-beh}} = 0.55$).

Interestingly, the correlations among the antecedents of intention also show different magnitudes. On one hand, the perceived behavioral control shows a small association with both attitude ($SE_{\text{att-pbc}} = 0.28$) and subjective norms ($SE_{\text{sn-pbc}} = 0.24$). On the other hand, a medium effect size was obtained for the association between attitude and subjective norms ($SE_{\text{att-sn}} = 0.43$). The latter results appear to be of particular interest since, as it will be shown in the following, it might suggest an indirect relation between social norms and intention mediated by attitude.

2.4.2 Test of the original model

In order to evaluate the combined strengths of the relationships among attitude, subjective norms, PBC, behavioral intention, and behavior, the meta-analytic structural equation framework provided by Cheung (2015) was used. Ajzen's model was tested in order to achieve a comprehensive description of previous findings in literature. Results and fit indexes are summarized in **Table 5**.

Firstly, the model was tested by taking into account all 23 studies (Model 1; $\chi^2(3)$ = 8.618, p = 0.0348, RMSEA = 0.0128, SRMR = 0.0509, TLI = 0.9836, CFI = 0.9951). Secondly, the same model (**Fig. 3**) was tested considering only the six studies that provided all the correlations between antecedents, intention, and behavior (Model 2; $\chi^2(3)$ = 4.02, p = 0.2590, RMSEA = 0.0074, SRMR = 0.0344, TLI = 0.9960, CFI = 0.9988). In particular, the goodness-of-fit indexes of the latter are far above the acceptable thresholds. Therefore, the TPB appears to be confirmed as an adequate theoretical framework to predict the intention to purchase and consume organic food products. Regarding the estimated parameters, the major influence on consumers' buying intention is confirmed to be played by the individual attitude (β = 0.44, 95% CI=[0.31,0.56]), followed by the subjective norms (β = 0.35, 95% CI=[0.24,0.46]) and finally by the perceived barriers to the purchase of food products (β = 0.12, 95% CI=[-0.01,0.24]). Additionally, a strong effect from intention to behavior emerges (β = 0.62, 95% CI=[0.54,0.70]). Nonetheless, several medium correlational effects are present among the antecedents of intention. Interestingly, the estimated association between social norms and attitude confirmed to be the strongest as it was already previously noticed in the summary effects.

In addition, the full TPB model (Model 2) underwent a further investigation. In particular, we tried to assess the invariance of the model by distinguishing between those studies that framed the questionnaire items w.r.t. the kind of food products (i.e., "organic food") and those that rather focused on the production method (such as, "sustainable produced food"). This analysis was run to check the validity of the theoretical *a-priori* integration into the previous analyses. Results obtained in the first condition showed no substantive differences, neither in the fitness of the model nor in the strength of the paths with respect to the original models. Unfortunately, we were unable to obtain reliable estimates in the second condition for the full model due to the fact that studies that included the correlation between intention and behavior were too few. However, given the fact that the results obtained in the first condition were not different from the one where studies were integrated, and that the results obtained for both groups in those models (see next section) tested in absence of the association intention-behavior did not differ, it is reasonable to presume that even the second condition would lead to a similar output.

Finally, a further model (Model 3; **Fig. 4**) based on an extension of the TPB model was investigated. This test was suggested by the unusually skewed distribution of the correlation between PBC and actual behavior (with respect to the other here presented) obtained during the computation of the summary effects. Moreover, the same model has been recently validated by Shin, Hancer, and Song (2016) in the context of local food purchase. In detail, the structure is the same of Model 2 but a direct effect from PBC to behavior is added. The indexes of fit were comparable if not superior to the previously discussed models: $\chi^2(2) = 4.27$, $p = 0.1184$, RMSEA = 0.0100, SRMR = 0.0337, TLI = 0.9901, CFI = 0.9980. The same model that takes into account only the aforementioned six studies shows even better increments of the goodness-of-fits. It should be stressed, however, that such a model might be affected by the presence of outliers associated to high samples, in particular Vassallo et al. (2016) found a correlation of 0.60 between PBC and actual behavior. If the same analysis is carried out on the remaining five studies, the fit indexes are still very good $\chi^2(2) = 3.028$, $p = 0.2201$, RMSEA = 0.0124, SRMR = 0.0277, TLI = 0.9931, CFI = 0.9988, but the estimated effect for the PBC-behavior coefficient is very low, 0.04, with a 95% confidence interval containing the zero and ranging from -0.05 to 0.11. This suggests the importance to explore this connection in further research.

2.4.3 Alternative models

In addition to the original Ajzen's formulation of the TPB, some alternative models were tested that postulate a direct relation between subjective norms and attitude. A first alternative assumes, in addition to such a direct effect, only a correlation between subjective norms and PBC (Models 4 and 5). This test was suggested by the study of Al-Swidi et al. (2014). A second alternative also drops this last association (Models 6 and 7). The test of this model was suggested by work by Tarkiainen and Sundqvist (2005) and Lodorfos and Dennis (2008). Since the aforementioned works did not employ a measure of actual behavior, Models 4 and 6 were run by excluding the construct, whereas Models 5 and 7 tried to include the association between intention and behavior.

Results suggest that both Models 4 and 5, in spite of a significant chi-square, might be considered acceptable, with slightly better indexes of fit for the model which includes the effect of intention on actual behavior (Model 5; $\chi^2(4) = 27.345$, $p < 0.001$, RMSEA = 0.0227, SRMR = 0.0710, TLI = 0.9486, CFI = 0.9795). On the contrary, results for Model 6 indicate that this model is unable to fit the original data (Model 6; $\chi^2(2) = 136.45$, $p < 0.001$, RMSEA = 0.0770, SRMR = 0.1467, TLI = 0.5593, CFI = 0.8531). Remarkably, the same assumption tested with the addition of actual behavior does not lead to any improvement in the fit (Model 7; $\chi^2(5) = 145.97$, $p < 0.001$, RMSEA = 0.0498, SRMR = 0.1262, TLI = 0.7528, CFI = 0.8764). It then appears that the suggestion to exclude the correlation between subjective norms and perceived behavioral control is empirically falsified.

Since however Model 5 is equivalent to Model 1 (minus the correlation between PBC and Attitude), it should not be surprising that the tested models seem to fit well using both correlation or a direct effect between SN and attitude. In order to test whether the substantive different implications associated to a direct affect rather than a correlation might be supported, a mediation analysis was performed to determine if an indirect effect of social norms on attention might be detected. Mediation analysis was carried out by using the method provided by Selig and Preacher (2008) which allows to generate R code to determine confidence intervals for indirect effects based on a montecarlo method. The test was conducted on the mediations SN-*attitude*-intention and SN-*PBC*-intention. Results confirm attitude as a potential mediator between subjective norms and intention (95% CI = [0.12,0.19]), thus suggesting that a direct effect of social norms to attitude might be plausible. On the contrary, the test conducted with PBC as mediator shows results strongly close to zero (95% CI = [0.02,0.05]) meaning that, although a mediation effect of PBC might exists, it can be considered negligible so that a simple correlation between SN and PBC suffices.

2.5 Discussion and conclusions

The present work reviewed the relationships among attitude, subjective norms and perceived behavioral control in relation to the intention to and the actual purchase and consumption of organic food products. Remarkably, the majority of the identified studies have been conducted in the last six years: this demonstrates that the concern for the consumption of sustainable food is spreading together with the interest in understanding the psychological motivations behind consumers' intention to purchase food produced in a sustainable manner.

Table 4 - Summary of the results obtained from the application of the meta-analysis procedures.

TPB Construct association	*k*	Total sample	Weighted *r*	CI 95% Ll	CI 95% Ul	Q-test	I^2 (Ll – Ul)
Attitude-SN	22	10893	0.432	0.340	0.517	443.96***	96.75 (94.38 - 98.42)
Attitude-PBC	22	10893	0.277	0.194	0.357	833.06***	94.94 (91.64 - 97.59)
SN-PBC	22	10893	0.238	0.182	0.292	123.06***	86.48 (73.25 - 93.85)
Attitude-Intention	23	11349	0.614	0.550	0.671	626.23***	96.08 (93.25 - 98.06)
SN-Intention	23	11349	0.504	0.429	0.571	457.21***	95.94 (93.11 - 98.00)
PBC-Intention	23	11349	0.325	0.266	0.382	210.41***	90.89 (84.06 - 95.55)
Attitude-Behavior	6	6223	0.437	0.337	0.528	128.30***	94.73 (86.71 - 99.14)
SN-Behavior	6	6223	0.379	0.263	0.484	83.87***	95.61 (87.76 - 99.28)
PBC-Behavior	6	6223	0.328	0.192	0.452	322.09***	96.58 (91.72 - 99.44)
Intention-Behavior	6	6223	0.552	0.403	0.672	331.87***	98.05 (95.00 - 99.68)

Notes. *k* = number of raw correlations; CI = confidence interval; Ll = Lower limit; Ul = Upper limit; SN = subjective norms; PBC = perceived behavioral control.
*** $p < 0.001$

Table 5 - Summary of the indexes of the goodness-of-fit obtained for each tested MASEM.

Model	χ^2 (df)	*p*-value	RMSEA	RMSEA 95% Li	RMSEA 95% Ui	SRMR	TLI	CFI	AIC	BIC
Model 1 Original TPB model	8.618 (3)	0.035	0.013	0.003	0.023	0.051	0.984	0.995	2.618	-19.393
Model 2 Original TPB model	4.023 (3)	0.259	0.007	0.000	0.024	0.034	0.996	0.999	-1.977	-22.185
Model 3 Original TPB model PBC → BEH	4.268 (2)	0.118	0.010	0.000	0.023	0.034	0.990	0.998	.268	-14.406

Notes. Models 1 and 3 include 23 studies with an overall sample composed by 11349 participants, while Model 2 employed 6 studies (6223 participants).
→ denotes direct effect.

Fig. 3 - Original model of the TBP elaborated on the bases of the pooled correlation matrix. Parameters are those obtained by fitting Model 2.

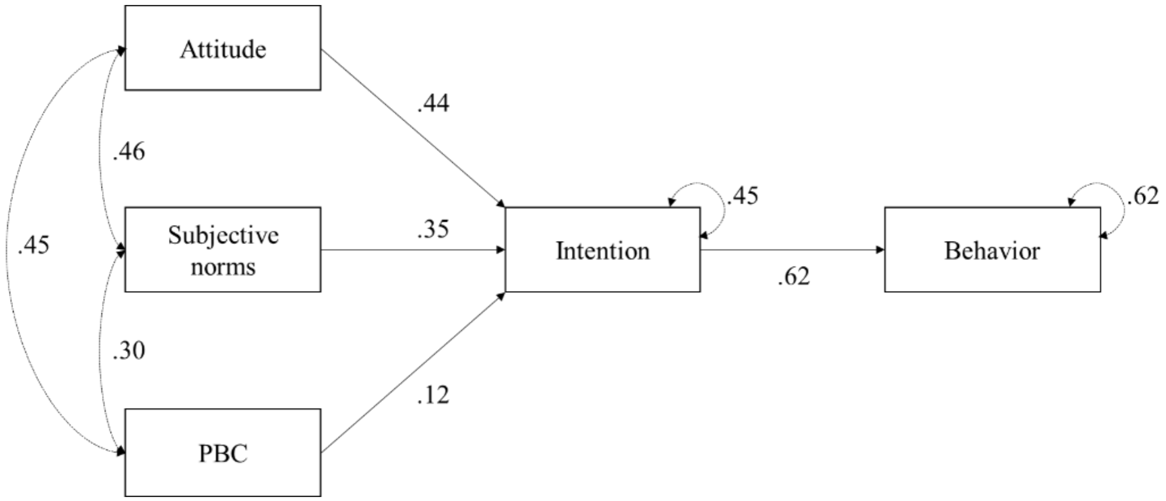
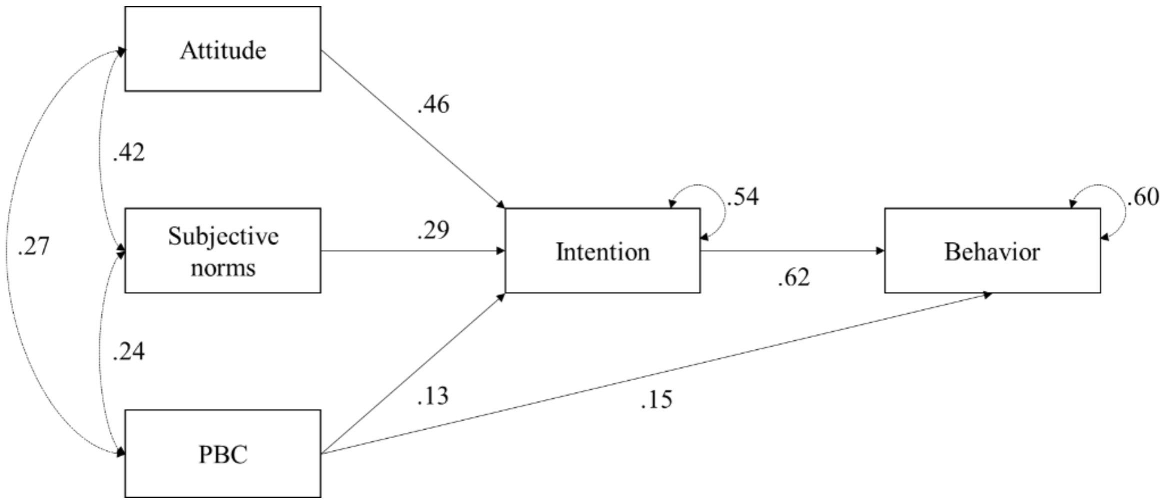


Fig. 4 - Model based on the TPB with the inclusion of a direct effect from PBC to actual behavior. Parameters are obtained by fitting Model 3.



Interestingly, contributions to this topic are scattered among journals of different fields. This reflects the interdisciplinary nature of the research and the broad interested demonstrated, for instance, by economists, nutritionists and social psychologists. Moreover, although the majority of the included studies were comprised of a European sample, their variety reflects rather well the idea exposed by Peattie (2010) about the geographical expansion of green consumption, which in its turn highlights the globalization of the concerns regarding environment.

In spite of this growing attention, it appears that the research in this field has more frequently focused on the intention to purchase and consume generic sustainable food products, rather than focusing on the actual behavior and/or on specific categories of products (such as organic coffee or tomatoes). Most of all, we would like to highlight a potentially misleading error that emerged from the review: very few of the examined studies paid attention to differentiate between the act of purchasing from the actual consumption of organic food. Hence, future research should investigate the actual behavior while distinguishing between these actions: as an example, participants enquired at the grocery store might just be responsible to shop for the whole family, and thus they might not be really concerned about the purchase of sustainable product for their own interest but under the requests of others family members. As to the results of the meta-analysis, they showed the magnitude of the single relationships among the constructs of the TPB. As one may expect, individual attitude owns the major potential to affect consumers' buying intention. This particular correlation is close to the reasonable limit of predictive utility suggested by Ajzen (2011; r = 0.60). In addition, a significant correlation emerged between attitude and actual behavior. However, results also demonstrated the significant support of subjective norms in shaping the intention to buy organic food products. In fact, in contrast with the idea that social norms might represent the weakest part of the TPB (Armitage & Conner, 2001), the summary effects show a moderate influence of the social sphere on the intention to buy organic food in the context of sustainable environment. Most of all, the importance of social norms appears to be also supported by mediation analysis which emphasize how attitude might mediate between social norms and intentions in the present context. As already indicated by Lodorfos and Dennis (2008), it is rather important to promote this kind of product through the social medium of consumers. Thus, marketers interested to promote organic food should identify important/relevant people (i.e. opinion leaders) and invest on their endorsement in order to quickly influence consumers' behavior. A consequent implication concerns the promotional campaigns employed to support organic farming or consumption. Several members of the EU already support events such as "Organic Action Days" (European Commission, 2014). In light of this finding, this kind of activity might play a crucial role to promote the diffusion of green food in a twofold manner: firstly, it may affect consumers' beliefs regarding organic food, shaping individual attitude; secondly, campaign days might foster the spreading of a shared positive social norm toward the consumption of organic food products.

In contrast, perceived behavioral control seemed to play a minor role with respect to behavioral intention. However, it must be noted that the items assessing this factor show several incongruences among the studies. In particular, during the review, an important issue emerged in relation to PBC and attitude: the same product characteristics in different investigations are conceived, and consequently measured, sometimes as part of the attitude component and sometimes as part of the behavioral control. This appears to be particularly evident with respect to price and availability of organic food. As an example, Guido et al., (2010) and Al-Swidi et al. (2014) presented an item related with the product price as a behavioral belief measured within the individual attitude whereas Zagata (2012) presented the price as a potential barrier during the evaluation of PBC. Conversely, the first authors assessed the perceived availability of organic food products as part of the individual attitude, whereas the second and the third ones proposed the same element as a potential barrier to the purchase. It appears that these kinds of incongruences among studies might pose a threat to the reliability and generalizability of the results. We recommend to consider price and availability within the measurement of the PBC, as they are strictly related to the individual perception that a consumer has the capacity to purchase organic food products: this is coherent with the explanation provided by Ajzen (2005) of perceived behavioral control. In addition, items related to price and availability were also included by Armitage and Conner (1999) within the measurement of PBC, in order to predict the intention to adhere to low-fat diets.

Analyses also showed a large summary effect for the relationship between behavioral intention and actual behavior. The magnitude of such a correlation was stronger than the other direct associations with behavior thus supporting, on one hand, that intention is the best predictor of actual behavior, but also on the other hand the notion of intention-behavior gap, meaning that even the strongest intention might not be transformed into a consequential action (see for instance, Sniehotta, Scholz, and Schwarzer, 2005). Nonetheless, there were very few studies that reported correlations among intentions and actual behavior, thus posing a potential threat to the reliability of this result. Remarkably, this issue is not new, as it has already been encountered by Schwenk and Möser (2009) while reviewing the more general environmental behavior, where among twenty-five selected studies only eleven reported the actual correlation intention-behavior. Consequently, a major concern regards the data collection: only 30% of the examined studies reported the correlation between the intention and the past or the prospect behavior. This might pose a further threat to the validation of the theory of planned behavior in relation to the purchase and consumption of organic food as its investigation appears to be often interrupted at the stage of consumers' behavioral intention. We strongly suggest that further studies take into consideration the evaluation of actual behavior of participants with respect to the purchase and consumption of organic food in addition with the other components of the TPB. Research aimed to investigate consumers' behavior should invest to include measures of actual marketplace behavior. Since a measure of prospect behavior may pose some difficulties as it requires the observation of consumer's behavior, we recommend to devote at least two items inside the questionnaire to investigate past behavior of consumers.

The final part of the analyses employed meta-analytical structural equation modeling to test several TPB models and investigate the multiple relationships among its constructs. As shown by means of the MASEMs, within the domain of organic food choice the original framework proposed by Ajzen (1991) might be considered a robust description of the ongoing processes. However, it is interesting to notice that a potential direct effect might occur between subjective norms and attitude. This result, which firstly emerged in studies that did not considered actual behavior in their analysis, appears also to hold in presence of actual behavior. Mediation analyses allowed to deepen this point by showing that individual attitude seems to play the role of mediator between subjective norms and behavioral intention. That is to say, the social sphere might be able to affect individual attitude besides behavioral intention. This was already noted by Tarkiainen and Sundqvist (2005, p.816) who affirmed that "it seems that positive (or negative) attitudes toward buying organic food «pass on» among people”. In other words, people who see organic food in a positive way might be able to influence the attitude formation of other consumers. Indeed, this means that investing in the diffusion of a positive norm toward organic food may work more efficiently than changing consumers’ attitude. On the contrary, PBC does not seem to be directly affected by subjective norms. However, it appears to affect both intention and actual behavior. This second relationship is also supported by a recent work of Shin, Hancer and Song (2016), who find a direct effect between PBC and behavior in a similar context. Nevertheless, it should be stressed that such an interesting result deserves further investigation: on one hand the associated MASEM shows extremely good fit indexes; on the other hand, however, there are at least three points that raise some concern and deserve to be deepened: firstly, as it has been previously stressed, perceived behavioral control items in the selected studies were not always methodologically sound or well-defined; secondly, there were actually only six observations of such a correlation; thirdly, the studentized residual analysis showed that their distribution might not be symmetric but highly skewed, with one outlier which is also associated to one of the studies with the larger samples. Removing such a study leads to a MASEM that shows extremely good fit indexes but also a very small value of the path coefficient between PBC and behavior. Conclusions on this specific issue appear then not to be possible and further investigations should be considered in future research.

In conclusion, it is our opinion that in spite of some limitations, like the limited availability of some quantitative measures for some of the considered effects, the decision to limit the research to published studies, and the choice of modeling with pure random-effects meta-analysis some studies which instead might have been partially correlated, the present review should provide a reliable evidence that the theory of planned behavior has a solid ground in green food consumption. In particular it is our opinion that at least three issues have emerged clearly: firstly, the need for a more methodologically robust exploration of the constructs in the future literature; secondly, the importance to establish whether the relation between perceived behavioral control and actual behavior truly holds for the present context; thirdly, the importance to explore whether the mediation role of attitude between subjective norms and behavioral intention could be suitable for other similar green products, such as locally produced food (or, local specialties), fair trade products, or even eco-friendly electronic devices. Indeed, the recent work by Paul, Modi, and Patel (2016) appears to confirm the validity of this suggestion for the broad category of green products. Thus, besides food products, future research should consider the application of structural equation modeling techniques to test either the validity of the canonical TPB model or one of the proposed alternative effects in order to deepen our understanding of the relationship between the social and the individual dimensions on consumers' purchase of green products.

2.6 References[4]

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3 Application of Psychological Theories in Agent-Based Modeling: The Case of the Theory of Planned Behavior

Authors

A. Scalco, A. Ceschi, & R. Sartori

Abstract

It is likely that computer simulations will assume a greater role in the next future to investigate and understand reality (Rand & Rust, 2011). Particularly, agent-based models (ABMs) represent a method of investigation of social phenomena that blend the knowledge of social sciences with the advantages of virtual simulations. Within this context, the development of algorithms able to recreate the reasoning engine of autonomous virtual agents represents one of the most fragile aspects and it is indeed crucial to establish such models on well-supported psychological theoretical frameworks. For this reason, the present work discusses the application case of the theory of planned behavior (TPB; Ajzen, 1991) in the context of agent-based modeling: it is argued that this framework might be helpful more than others to develop a valid representation of human behavior in computer simulations. Accordingly, the current contribution considers issues related with the application of the model proposed by the TPB inside computer simulations and suggests potential solutions with the hope to contribute to shorten the distance between the fields of psychology and computer science.

3.1 Introduction

In 1952 (p.169) K. Lewin wrote: "*there is nothing more practical than a good theory*". Vansteenkiste and Sheldon (2006) clarified this assertion affirming that theorists should work to develop theories that can be applied to solve real problems, whereas researchers in applied psychology should take advantage of available scientific theory to solve problems. Indeed, a good theory can lead to develop specific interventions aimed to drastically change people behaviors. However, if we look closer, Lewin's idea hides an intriguing paradox. In fact, if we would like to apply Lewin's teaching, we were immediately arrested by its fuzziness: how is it possible to mark as *good* a theory? An attempt to answer to this question was provided by Eysenck (1987), whereas more recently Cramer (2013) suggested six criteria. Particularly, in order to assess the quality of scientific theories Cramer proposed to consider:

i. *Comprehensiveness*: a valid psychological theory should be able to "describe, explain, predict, and control phenomena and behaviors" (*ibid,* p. 9).
ii. *Applied value*: applicability concerns the ability to presents "effective solutions to life's problems" (*ibid,* p. 11).
iii. *Precision and testability*: constructs should be clearly defined and strictly interrelated. Furthermore, constructs should be testable by valid measurements and through falsifiable hypotheses.
iv. *Parsimony*: a psychological theory should not be too complex to allow its testing[1].
v. *Empirical validity*: a good theory should be able to provide an explanation to potential disconfirming evidences.
vi. *Heuristic value*: this criterion suggests that a valuable scientific theory should be able to open new perspectives and directions in other fields.

The present contribution briefly discusses the goodness the theory of planned behavior (TPB; Ajzen, 1991) in light of these criteria[2]. On the one hand, it is argued that

[1] A negative example to understand the concept of parsimony is given in Jackson (2005) in relation to the theory of buyer behavior by Howard and Sheth.

[2] However, due to the limited amount of space we decided to focus the discussion to issues and solutions. Hence, references in section 3.2 are limited to major works and reviews related with Ajzen's framework.

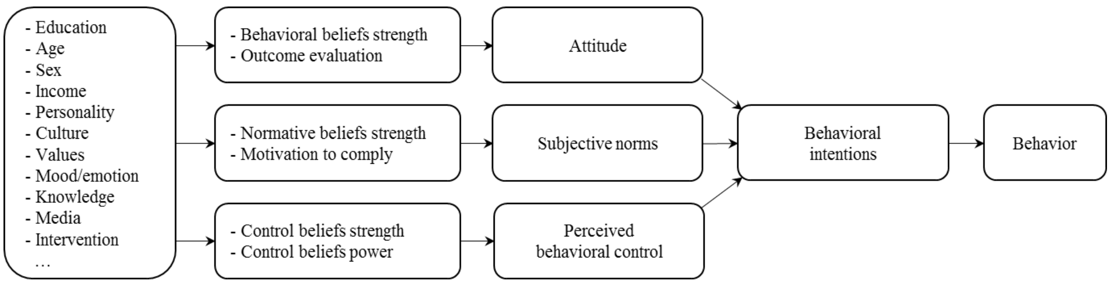
Ajzen's proposal has proven itself as a remarkable good theory over the years. On the other hand, the contribution applies a novel approach in order to highlight some gaps that should be consider in relation to the application of the TPB inside interdisciplinary works. The hope is to contribute to shorten the distance between psychology and computer science providing support to a specific theory that more than others may be helpful to establish a common ground for interdisciplinary works.

3.2 Ajzen's theoretical framework

Theory of planned behavior assumes that people behave considering the implications of their actions (Ajzen, 2011a). Beliefs play a central role in the model: they represent the information used to evaluate a certain behavior and they are supposed to determine the three basic antecedents of intention to act. Background factors (such as age or income) are generally not considered by the model: however, these factors can exert an indirect influence on intention by affecting beliefs (*ibid*). TPB does not propose a strict rational model of decision making: in fact, recently Ajzen (2014, p. 3) emphasized that "people's attitudes, subjective norms and perceptions of control follow reasonably and consistently from their beliefs, no matter how the beliefs were formed". Accordingly, TPB does not make any assumptions regarding the objectivity or truthfulness of individual beliefs: they can be unproved or even irrational. In addition, TPB does not propose that people engage constantly in the full process of evaluation: once formed, intentions and its antecedents are readily available to drive behaviors (Ajzen & Fishbein, 2005).

TPB is a psychological model that takes into account three fundamental aspects of human behavior: personal attitude, subjective norms and perception of control **(Fig. 1)**. These are the antecedents of the intention to perform a specific behavior, whereas intention mediates the relationship between the previous constructs and actual behavior.

Fig. 1 - The framework proposed by the TPB (original source: Ajzen & Fishbein, 2005).



Attitude reflects individual preferences to perform (or not perform) a certain behavior (Ajzen, 1991). Following Fishbein and Ajzen (1981), attitude can be conceived as the results of the interaction between behavioral beliefs and expected outcomes. The former indicate the perceived likelihood that a behavior will produce a certain effect, whereas the latter measure the desirability of that particular outcome.

The concept of subjective norms refers to those decision maker’s beliefs about people’s approval of a certain behavior (Ajzen, 1991). This component is constituted by the joint evaluation of individual normative beliefs (i.e. the perceived likelihood that the most important people to the person approve such behavior) and the motivation to comply to those norms.

The last factor pertains to the individual perception of those environmental factors that can facilitate or inhibit the expression of behavior (Ajzen, 2011a). In other words, the perceived behavioral control (PBC) aims to capture people’s confidence that they are capable of performing the behavior under investigation (Ajzen, 2006). PBC is comprised by the likelihood to perform an action due to perceived/physical barriers (e.g. the availability of products in stores) and the perception of control of these factor.

Finally, behavioral intention is assumed to capture the force of the individual motivation to try performing a specific behavior (Ajzen, 1985). Generally, intention has been demonstrated to be the best predictor of actual behavior, over and behind attitude, social pressure, or habit (Ajzen, 2014). In accordance with Ajzen (1991), the final value of intention can be computed as a linear function of the three basic antecedents weighted for their relevance: the weight of each component is indeed highly dependent on the investigated behavior and population (Ajzen, 2011a; Ajzen & Fishbein, 2005; Fife-Schaw, Sheeran, & Norman, 2007). However, some works in the nonlinear dynamics field argued that the application of a linear approach in the specific case of the TPB can result in a simplified description of the interaction between individual attitude and social dimension compared to nonlinear models (Smerz & Guastello, 2008; Guastello, Aruka, Doyle, & Smerz, 2008; Jacobsen & Guastello, 2007). For instance, the cusp catastrophe model applied by Smerz and Guastello (2008) on binge drinking behavior was able to account for 2.6 times more than a linear model. Finally, the theory suggests that the probability of expression of a certain behavior is proportional to the value of intention (Ajzen, 1991).

Several reviews and meta-analyses proved the suitability of the model to efficiently describe, explain and predict a wide range of human behaviors (see for instance, Aertsens, Verbeke, Modelaers, & Huylenbroeck, 2009; Ajzen & Fishbein, 2005; Armitage & Conner, 2001; Conner & Armitage, 1998; Fife-Schaw et al. 2007; Guillaumie, Godin, & Vézina-Im, 2010; Han & Stoel, 2016; McEachan, Conner, Taylor, & Lawton, 2011; Riebl et al., 2015; Topa & Moriano, 2010). In this sense, the TPB is certainly able to account for the first criteria suggested by Cramer (i.e. *comprehensiveness*).

Furthermore, despite some limitations, as reported in Ajzen (2011a, 2014) since its introduction the TPB has been successfully applied to drive behavior change interventions. Interestingly, the usefulness has been noteworthy in the field of consumer studies for the promotion of pro-environmental and healthy behaviors (e.g. Ajzen, 2011a; Bamberg & Moser, 2007; Jackson, 2005; McEachan et al., 2011; Riebl et al. 2015; Topa & Moriano, 2010). Practical applications of Ajzen's framework can be traced numerous times in literature: consequently, it is possible to assert that the TPB meets Cramer's second criterion.

In addition, over the years, numerous studies aimed to investigate decision-making processes assumed the theory of planned behavior as main research background: in 2010, Ajzen's paper achieved over 4550 citations (Ajzen, 2011b). Thus, with respect to the third criterion proposed by Cramer (i.e. *precision and testability*), the model proposed by the TPB can be endorsed with an enviable amount of evidences. Moreover, Armitage and Conner (2001) demonstrated that the original model of the TPB can account on average for 27% of the variance of intention and 39% of behavior while at the same time the model remains parsimonious as it considers only three basic components of human behavior (i.e. the individual, social and contextual factors). Therefore, also the fourth criterion (i.e. *parsimony*) requested by Cramer is covered. Nonetheless, the model is declared opened to the addition of further constructs.

Cramer also asks to a good scientific theory to answer to those potential disconfirming evidences that may arise from its application: above all, the recent discussion between Sniehotta, Presseau, and Araújo-Soares (2014) and Ajzen (2014) is able to demonstrate how this scientific theory is far from its disconfirmation or retirement.

Finally, the sixth criteria (i.e. *heuristic value*) suggests that a good theory should be able to generate new perspectives and to inspire novel directions in other fields.

Regarding this point, we believe that this theoretical framework might be able to bridge the gap between psychological research and computer science more than other competing theories.

On the one hand, Zhang and Nuttall (2011) already supported the application of the TPB inside computer simulations affirming that this particular theoretical framework allows a relatively easy translation into the form of computational algorithm and at the same time it is able to account for the individual, social and contextual elements into a single comprehensive theory. Similarly, Elsenbroich and Gilbert (2014) endorsed Ajzen's theoretical model as a suitable framework to model social norms in computer simulations. Again, also Jager, Janssen, De Vries, De Greef, and Vlek (2000) and Schlüter et al. (2017) claimed their support to the application of the theory of planned behavior as basic model of decision-making for autonomous virtual agents.

On the other hand, as pointed out by Sun (2008), informal theories[c] are useful to create explanations of complex behaviors, but they are far from precise predictions, whereas computational models can be intellectually enlightening about the theories that they aim to capture. Accordingly, we support the idea that psychological research can indeed benefit from the approach proposed by computational modeling since the development of virtual simulations such as agent-based models (ABMs) require a thorough analysis and comprehension of the most practical aspects of psychological knowledge. Starting from this, we argue that agent-based model approach can aid social scientists to consider in a unique manner the practical implications of psychological theories. In addition, Sun argued that "all branches of science progress from informal theory to formal model" (*ibid,* p.269): agent-based modeling might lead the transition in the specific field of social and organizational psychology as well as related subfields (such as consumer behavior and environmental psychology).

However, as pointed out by Schlüter et al. (2017), the merely process of formalization of a theory into a computational model often leads to recognize obstacles, gaps, and shortcomings. Hence, in the next section we briefly introduce agent-based modeling approach and successively discuss issues and potential solutions related with the introduction of the TPB into a computational model. In relation to this approach, the recent work by Schlüter and colleagues discussed in a comprehensive way the challenges that agent-based modelers might face when confronted with the development of virtual agents grounded on psychological theories. The authors reviewed and discussed several theories from social sciences offering a wide perspective on the argument and in relation to several virtual agents' cognitive abilities (e.g. perception, reasoning and learning). In contrast, the present work intends to focus its attention on the specific application case of the theory of planned behavior: hence, the discussion is limited to the design of psychological decision-making models for virtual agents.

3.3 Agent-based models

Agent-based modeling is a method of investigation of social phenomena that blends the knowledge of social sciences with the advantages of virtual simulations. Its roots can be traced to the work by Schelling (1971) who demonstrated how spatial segregation can result over time by the constant application of few simply rules by many independent agents. Besides, the works by Wolfram (2002) were able to demonstrate the emergence of complex properties at the system level with a small number of rules that define the interaction among agents. In the 80s, following an evolutionary approach, Axelrod (1986) employed simulations in order to show how cooperative behavior can result by the evolution over time of social norms (and meta-norms) within strategic situations. Later, Latané and Nowak (1994) employed simulations to illustrate the emergence of group processes and to investigate attitude distribution and change over time.

So far, this approach has been fruitfully applied in several fields, such as market dynamics, innovation diffusion, environmental psychology, consumer behavior (e.g. Jager, 2006; Jager et al., 2000; Roozmand et al., 2011) and more recently on organizational psychology (e.g. Dal Forno & Merlone, 2004; Hughes, Clegg, Robinson, & Crowder, 2012; Sartori, Ceschi, & Scalco, 2014; Secchi, 2015).

Computer simulations are able to reproduce individual and social behavior thanks to dedicated software (Scalco, Ceschi, Sartori, & Rubaltelli, 2015). As noted by Gilbert and Troitzsch, the use of computer simulations as a methodology of investigation of social mechanisms is rather a new idea, but it comes with great potential thanks to the fact that is "an excellent way of modelling and understanding social processes" (2005, p.1). Often ABMs are employed for the investigation of nonlinear dynamic systems: they are indeed able to show how the behaviors of many single agents acting for their own interest can produce self-organized systems due to their constant interaction over time (Guastello, 2008). Indeed, as noted by Guastello (2001), most of psychological and social phenomena follow nonlinear dynamics, starting from the relationship between strength and perception of physical stimuli observed by Weber and Fechner. Guastello also noticed that nowadays the knowledge originated in the field of nonlinear dynamic systems can successfully address the investigation of those phenomena already observed in the past, but for which the proper methods and concepts were missing, such as the dynamic interaction between individual preferences and social norms. Nonlinear dynamic systems intend to describe the complexity of phenomena as a whole (rather than reduce the investigation to the single parts of the system) with a particular attention to the temporal dimensions (Guastello, & Liebovitch, 2009). It is worthy to note, that, even if the temporal dimension is undoubtedly a pervasive element in every social and psychological phenomena, its inclusion in mainstream social psychology has been yet not fully recognized (Vallacher et al., 2013).

Accordingly, as pointed-out by Hughes and colleagues (2012), the major value of agent-based models lies in their ability to investigate how macro-behavior emerges as a result of micro-behavior: that is to say, contrarily to most of the methods of investigation in the social sciences, agent-based models are able to replicate the emergence of social phenomena. For example, ABMs are well suited to investigate how individual preference toward a broad category of products may result in the creation of a shared norm that in its turn influences individual buying behavior within a constant dynamic process (see for instance the work by Janssen and Jager, 1999). As stated by Guastello (2007), emergence remained “a black box” until nonlinear dynamic systems offered the suitable concepts and methods for its investigation. Generally, the term emergence refers to those observed phenomena (in biology as well as in social systems) where the higher-order properties of behavior of the system which result from the interaction of the single parts cannot be reduced nor explained recurring to only the proprieties of the elements (Vallacher et al., 2013). Computer simulations are a privileged method for the investigation of emergence phenomena as they allow specifying the elements attributes and the rules of interaction, and to observe the emergence of system behaviors that were not beforehand programmed (*ibid*).

However, we believe scholars as well as practitioners from the psychology field might be discouraged to employ ABMs due to several factors. Firstly, currently agent-based modeling owns an unclear definition due the wide interdisciplinarity (Secchi, 2015). The field is still in its early phases and common languages, as well as methods, are currently under discussion and bounded by disciplines. Currently, even the term "agent-based model" is not unanimously accepted and it can overlap with similar ones in other fields. Following Jager (2006), agent-based models require the formalization of artificial humans, called "agents", inside a virtual world where the researcher can experiment with the complexity that arise through the interactions of the individual, social and environmental layers. Inside an agent-based model, people's individual differences, ways of social interactions and decision-making processes can be modeled explicitly (Kiesling, Günther, Stummer, & Wakolbinger, 2012). Above all, agent-based model approach demands the development of algorithms where such agents are able to autonomously make decisions and interact similarly to humans (i.e. there is no central process that governs agents).

Secondly, in contrast to statistical approach, ABMs are strictly related to population heterogeneity: that is to say, each virtual agent is endowed with peculiar characteristics such as beliefs, preferences, or any individual difference (Squazzoni, Jager, & Edmonds, 2013). A recent review on agent-based models of innovation diffusion conducted by Kiesling and colleagues (2012) showed an increasing interest in agent-based modeling: as explained by the authors, this shift mainly occurred due to the ability of ABMs to take into account consumers heterogeneity in contrast to mathematical models. Interestingly, among these models, agents' decision-making process is commonly designed starting from the theory of planned behavior.

Nonetheless, the development of an algorithm able to recreate the reasoning engine of independent agents represents one of the most fragile aspects of this kind of works (Ceschi, Scalco, Dickert, & Sartori, 2015). Indeed, the support of psychological theories to develop realistic decision-making processes for virtual agents is needed in order to increase the validity of simulated behaviors (Jager, 2006; Jager & Janssen, 2003). Roozmand et al. (2011, p.1030) even claimed: "what is important in agent modeling is presenting an architecture which functions like the human mind".

Though, the transformation of an established psychological theory into the form of a computer algorithm can arise several issues, and even a "good theory" can show gaps when confronted with agent-based model approach.

3.4 Current issues and potential solutions

As suggested by Schubring, Lorscheid, Meyer, and Ringle (2016), the clarification of how agents reason about their choices is both challenging and crucial in order to achieve a reliable virtual model of human behavior. The following subsections describe some of the problems that can be encountered when attempting to apply the theory of planned behavior as main reasoning engine for virtual agents. Where possible we tried to suggest potential solutions or workarounds based on literature or our personal experience.

3.4.1 Data and preliminary model assessment

Rand and Rust (2011) pointed out that agent-based model approach allows the concretization of many psychological theories while at the same time it is able to deal with real data. However, the integration of data starting from an established theoretical background such as the TPB is still under development. By the way, Alt and Lieberman (2010) proposed an ambitious work that attempted to connect in a straightforward way the gap between survey data method and virtual simulations. Unfortunately, in their example the authors employed second-hand data (specifically, the World Values Survey) that could not correctly match the theoretical assumptions required by the TPB. In addition, no statistical analyses were conduct to confirm the goodness of fit of selected items with the model proposed by the TPB. Indeed, statistical analyses are a necessary step in order to assess the ability of Ajzen's model to explain and predict the examined behavior (Ajzen, 2011a). This operation should be conducted before the actual application of the TPB inside an ABM. If Ajzen's model is not able to provide a sufficient explanation of the examined behavior, the factors, measures or the model itself should be reviewed. In addition, statistical procedures such as regression analyses are required to supply the weights of each antecedents of intentions (*ibid*). Thorough guidelines regarding the development of questionnaires based on the TPB and proper application of statistical analyses can be found for instance in Ajzen (2006), Francis et al. (2004), and Hankins, French and Horne (2000).

3.4.2 Dealing with a static model

As pointed-out by Schlüter et al. (2017) it is certainly a challenge to develop a model of causal relationships able to account for behaviors and interactions over time. Virtual simulations are executed over time while the original TPB was mainly developed as a predictive model rather than as a theory of behavior change (Ajzen, 2014).

As initially suggested by Ceschi, Dorofeeva, Sartori, Dickert and Scalco (2015) and further elaborated in Scalco et al. (2017), an established structural equation model (SEM) of the behavior under examination can serve as a reliable starting point to design agents' decision-making process. SEMs are a modeling technique commonly widespread among social and psychological science (Hox & Bechger, 2009) where the relationships among variables is expressed by regression coefficients: a structural equation model is in fact built within a cause-effect framework. Thus, the theory of planned behavior can be represented using a SEM: the standardized regression coefficients obtained by the statistical output will consequently suggest the relative magnitude of the effect of personal attitude, social influence and PBC on intention. Similarly, a regression coefficient is provided for the association intention-behavior.

However, SEMs are conceived as static models: that is to say, they are not able to express change over the time. Fuzzy logic and the method proposed by Schubring et al. (2016) might represent interesting workarounds to connect SEM and agents' decision-making processes.

The work by Casillas, Martínez-López, and Martínez (2004) illustrates the application of fuzzy logic as a practical solution to complement the results obtained through structural equation modelling. In fact, fuzzy logic "enables the use of uncertainty measures to quantify the ambiguity associated with the prediction of psychological parameters" (Kushwaha & Kumar, 2009, p.131): thus, it is particularly useful to formalize and reason with psychological concepts.

An additional and recent alternative is supplied by the work of Schubring et al. (2016). In this case, the authors proposed an interesting and quite straightforward method to compute probabilities starting from the regression coefficients obtained by means of a partial-least square structural equation model. By using the specific parameter related to the association intention-behavior, it is possible to obtain a value of probability which can be processed by computers. Interestingly, in their work Schubring et al. (2016) applied in a fruitful way the proposed approach to the technology acceptance model, which shares some similarities with the theory of planned behavior.

3.4.3 When does intention become behavior?

Although the TPB offers a formal way to compute behavioral intention, the theory cannot really define when individuals will actually perform an action. For example, how is it possible to establish a threshold value for intention such that agents will actually adopt innovation? The general formula associated with the theoretical framework merely suggests that the probability to express a certain behavior is proportional to intention (Ajzen, 1991). Intention-behavior gap represents an issue from an agent-based modeling perspective since a detailed and flawless algorithm is required to run simulations.

Schlüter et al. (2017) observed that options that have a higher intention are more likely to be executed. Accordingly, the TPB has been applied with success inside the agent-based model proposed by Kniveton, Smith, and Black (2012), which simulated the immigration flows in Burkina Faso. In this case, behavioral intention is calculated for each of the possibility given to virtual agents (i.e. to migrate in one of four parts of the state or abroad): the alternative with the highest intention value is chosen and the associated behavior is then performed. Similar works are presented in Schwarz and Ernst (2009) and Scalco, Jager, Bolderdijk, Ceschi and Sartori (a working paper presented in the successive chapter).

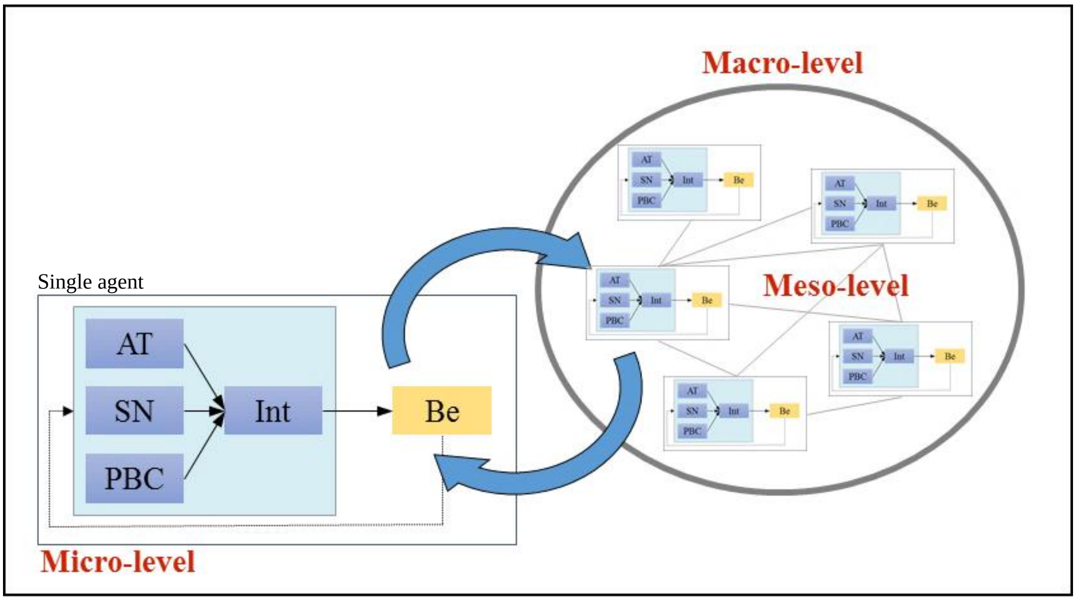
Alternatively, in order to connect intentions with actual performance of behavior, Alt and Lieberman (2010) suggested to normalize across the virtual agents the obtained valued of behavioral intention providing for each agent a relatively likelihood that should be compared with the overall population. Similarly, the model by Sogani, Muduganti, Hexmoor, and Davis (2005) asks agents to compute the behavioral intention as a probability or, alternatively, as a threshold value that can be set by the modeler.

Another method of resolution comes from the work by Schubring et al. (2016). Since this work has been already discussed in the previous section, it will not be considered further here.

3.4.4 Feedback mechanisms

Complex dynamic systems commonly studied by agent-based models are often characterized by feedback mechanisms and closed-loops. As explained by Conte et al. (2012), loop process expresses the link between micro- and macro-level: the behaviors at the individual level determine the whole system outcome, which then provides a feedback to the individuals. In other words, the choices made by virtual agents have an overall effect on the behavior of higher social structures (such as teams or the society as a whole) that in its turn affects the subsequent decisions of single agents at the next time step **(Fig. 2)**. This process endures over the time of the simulation. In this case, the social component of the TPB (i.e. subjective norms) can serve to link agents' individual behavior with the creation of a shared norm at the macro-level that can be then interiorized by virtual agents.

Fig. 2 - The picture represents the closed-loop between micro- and macro-level. Whereas the former involves single agents, the latter is interested by the emergence of social phenomena. The meso-level represents the bridge between these levels where the interaction among agents takes place. Following the theory of planned behavior, agent's intention (Int) to perform a certain behavior (Be) should be characterized by its attitude (AT), subjective norm (SN) and perceived behavioral control (PBC). In addition, individual behavior can influence backward the antecedents of intention. When an agent is inserted within a social context, the behavior expressed by other agents will exercise an influence on it, which in its turn will affect others at the next time step in a constant interaction over time.



Nonetheless, feedback mechanisms should be thought also at the individual level. In this sense, the TPB is limited due to the fact that it is not able to specify how the actual behavior will affect the basic antecedents of the intention. Researchers need to make specific assumptions about this point. However, a first suggestion comes from Ajzen (2011a): in the context of behavioral interventions, the author suggested that new information can change behavioral, normative or control beliefs. In this sense, Ajzen and Fishbein (2005) noticed that the performance of a behavior represents itself a source of new information to the individual. Similarly, Staats (2003) suggested that the TPB allows a dynamic evolution of the antecedents of the intention based on repeated behavior. Moreover, some works assumed past behavior as a predictor of behavioral intentions (e.g. on consumer behavior, Dean, Raats, and Shepherd, 2012) or actual behavior (see in particular the literature reviewed by Conner and McMillan, 1999).

In line with this, Verwaart and Valeeva (2011) proposed an agent-based model in order to investigate the adoption of animal health practices among farmers with the aim to support the development of food safety policies. The decision to adopt food safety practices was purely based on the theory of planned behavior. Farmers update their behavioral and normative beliefs in accordance with a feedback system based on, respectively, premiums or penalties for their actual performance, and the observation of other producers.

Alternatively, other works assumed the evaluation of the outcome of actual behavior as a direct affect that may change attitude. For instance, an interesting computational model has been developed by Sogani and colleagues (2005) with the intent to reproduce and predict the acceptance of computer technology. Again, agents' decision making process was characterized starting from the TPB. The authors proposed a closed-loop between the amount of technology users and subjective norms. In other words, they connected the number of adopters with the formation of an injunctive social norm.

3.4.5 Partiality of the explanation

As discussed in section 3.2, TPB represents a parsimonious model of decision-making based upon a deliberative process. Few simple rules can be sufficient to observe the emergence of complex social patterns: however, it is undeniable that several other psychological mechanisms can be related to the actual expression of a certain behavior. Particularly, we suggest that in relation to agents' modeling habit and impulsiveness should be considered as complementary explanations.

On the one hand, Verplanken and Orbell (2003) identify habit as a precise psychological construct rather than a mere frequency of observed behavior (i.e. contrary to the notion of past behavior). Also Ajzen (2001) argued that habit can directly influence behavior such that intentions can become even irrelevant when an action has been performed many times.

On the other hand, impulsiveness is related to actions performed spontaneously with poor consideration regarding the associated consequences (Beatty & Ferrell, 1987).

Churchill, Jessop, and Sparks (2008) jointly evaluated the TPB model with a measure of impulsivity to predict high-calorie snack consumption. Results showed that the additional inclusion of impulsiveness contribute to the prediction of the investigated behavior over and above the standard TPB model.

As a consequence, a realistic virtual agent should be endowed at least with the chance to perform actions starting from habit, impulsive behavior or a deliberative process. Again, starting form an established structural equation model, habit, impulsive and deliberative behavior can be modeled as probabilistic functions thanks to the contribution by Schubring et al. (2016; see section 3.4.2).

Nonetheless, we recognize that several other heuristics can be relevant: regarding this point, Jager and Janssen (2003) offered a helpful categorization based on individual cognitive effort and the use of social information.

3.5 Summary

As noticed by Rand and Rust (2011), it is likely that computer simulations such agent-based models will assume a greater role in the next future in order to help us understand reality. As discussed, it is important that such simulations could be grounded on established psychological theoretical frameworks. As pointed out by Schlüter et al. (2017), one of the major challenge of agent-based modelers relies on the identification and transformation of informal theories on decision-making into clear and straightforward causal models of relationships such that they might be processed by a computer. Given this, we briefly reviewed the goodness of the theory of planned behavior through the application of the sixth criteria proposed by Cramer (2013). We consequently recognized the theory of planned behavior as a efficient and parsimonious model of representation of virtual agents' decision-making processes. Its ability to consider individual, social and external factors in conjunction with its solid background makes it a valuable resource and a common reference for interdisciplinary works between psychological research and computer simulations. Particularly, the ability of the theory to design a framework able to take into account jointly individual preferences and social influence is consistent with the examination of potential loops between micro- and macro-behaviors of social systems usually investigated by means of ABMs. In addition, physical barriers can be virtually designed to prevent the actual agent's performance and study the consequences with respect to the simulated behavior. As a conclusion, the theory of planned behavior is certainly able to offer a valid and realistic model of deliberative decision-making process for virtual agents: the application of concepts and methods from the nonlinear dynamics field such as agent-based modeling is expected to further improve the ability to explain social phenomena. As argued by Elliott and Kiel (2004), agent-based modeling might be the method able to bring acceptance and functionality to the sciences of complexity.

Nonetheless, by reviewing the theoretical background, agent-based model approach enforced us to deduce the ultimate implications of the TPB: this process led to recognize some gaps in the specific application of this theory. These issues have been discussed in relation to computer simulations and some solutions available at our knowledge were offered when possible. Though, despite the division proposed within the current work, discussed issues can present several interconnections. For instance, feedbacks mechanisms can be thought in relation to model dynamics, as well as the integration of data can be associated with the evaluation of competing behaviors. Indeed, the interconnection among these issues represents itself a further challenge for theory and model development.

Finally, it is important to remark that the theory of planned behavior represents only a theoretical framework for the design of agents' decision-making processes: indeed, the complexity of human behavior should be captured through the support of different theories and multiple disciplines (Jager & Janssen, 2003; Schlüter et al., 2017). In light of this, much work is expected to be conducted over the next years in order to significantly mark the alliance between psychological knowledge and computer simulations of social human behavior.

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4 Green Consumer Behavior: Simulating the Diffusion of Sustainable Food inside Grocery Stores

Authors

A. Scalco, W. Jager, J. W. Bolderdijk, R. Sartori, & A. Ceschi

Abstract

Consumers' choice for standard versus green products (such as organic ones) plays a critical role in the market development of sustainable food: over the years, research devoted most of its efforts to investigate individual motivations behind green consumer behavior. Particularly, an emerging issue is strongly related with the investigation of the influence of group norms and collective consumption (Peattie, 2010). However, since systematic experimentation with social influence is difficult, we developed a virtual simulation with the purpose to study how interaction among customers of grocery stores can foster/hinder intention to buy green food and how consumers can be affected by different food arrangements. In this way, we also connected the theory of planned behavior (Ajzen, 1991) with a social phenomenon recently identified by Bolderdijk and Cornelissen (2017): undercover altruism, which states that individuals sometimes act more morally in private than in public settings if they perceive that a certain behavior is exceptional.

The simulation creates a population of virtual consumers inside a grocery store. For each product that should be purchased, the agents can decide between conventional and organic food. Two store configurations are taken into account: mixing versus separating green and conventional food. The general results showed the emergence of undercover altruism: agents would like to buy green products following their individual preferences, however, the common norms hamper this intention. Eventually, many agents decide to buy regular food instead of green one triggering in this way a locked-in vicious cycle. Finally, the simulation demonstrated that different arrangements of food products can significantly affect the sales of organic food: nonetheless, the increase of sales of organic food also depends on the throng of customers inside the store.

4.1 Introduction

In stimulating a transition toward a sustainable society, the food sector plays an important role: in this respect, consumers’ preference for green rather than conventional products represents a crucial factor for the market development of sustainable food. Generally, the terms “green food” or “sustainable food” is employed to refer to three kinds of product (Vassallo, Scalvedi, & Saba, 2016): locally grown food (including specialties), fair trade products, and organic food. The organic food market has grown considerably in the last decade along with a significant geographical expansion suggesting a growing concern regarding environmental issues (Daunfeldt & Rudholm, 2014; Peattie, 2010).

In fact, organic products derive from a farming system aimed to combine best environmental practices with the preservation of natural resources and the application of animal welfare standards (European Council, 2007). The environmental benefits of organic production system have been empirically tested over the years. Above all, life-cycle assessment analyses constantly report an overall lower environmental impact for organic production systems with respect to conventional ones (e.g. Boggia, Paolotti, & Castellini, 2010; Litskas, Mamolos, Kalburtji, Tsatsarelis, & Kiose-kampasakali, 2010; Longo, Mistretta, Guarino, & Cellura, 2015). In addition, the preference toward organic food has been recognized as the second most effective way to minimize the environmental impact of food consumption from consumer point of view (Jungbluth, Tietje, & Scholz, 2000; Thogersen, 2010; Tobler, Visschers, & Siegrist, 2011).

The research in this specific sector has gained momentum during the last decade witnessed by the positive trend of marketing research interested to understand consumers’ motivations toward organic products (Scalco, Noventa, Sartori, & Ceschi, 2017). Nevertheless, the need for further research in the organic food sector from a consumer perspective has been recently encouraged by the report of the European Commission on Agricultural Research and Innovation (2016). Particularly, as pointed out by Peattie (2010), a current issue regarding the investigation of green consumer behavior is strongly related with the investigation of the influence of group norms and collective consumption. Indeed, the collective impact of consumers’ choice can affect backward food production stimulating the growth of organic farming systems. Hence, it becomes important to investigate the social dimension behind consumers’ preference toward organic products in order to support marketers and policy-makers in encouraging people to make greener choices daily.

4.2 Social dimension of consumption

On the one hand, the choice for a particular type of food is indeed based on personal beliefs. For instance, Tobler et al. (2011) pointed out that sensory appeal, perception of healthiness, and price tend to be the most influential factors that can affect consumers' food choice. Bonti-ankomah and Yiridoe (2006) explained that the preference for organic rather than conventional food is largely based on "credence characteristics": that is to say, consumers are attracted by attributes that are difficulty (or even impossible) to notice but still play an important role in the decision process. Interestingly, in the case of organic products some characteristics are impossible to be evaluated by consumers even after the consumption (e.g. chemicals). Particularly, several studies regarding the preference toward organic products highlighted the major role played by perceived environmental-friendliness, taste, healthiness and quality (Arvola et al., 2008; Daunfeldt & Rudholm, 2014; Honkanen, Verplanken, & Olsen, 2006; Scarpa et al., 2007; Vermeir & Verbeke, 2006).

On the other hand, consumption behavior also depends on the perception of social norms. Product choices are deeply connected with social dimension to the extent that even in the consumption context we do not behave as isolated human beings but as members of groups. Following Cialdini and Trost (1998), a social norm represents a rule that is known and understood by the members of a certain group and that leads (or constrains) the choice of action without being an explicitly shared law. In other words, social norms can be seen as unwritten rules that shape our daily behavior.

It is generally accepted by literature to distinguish the reason behind conformation toward social norms between normative and informational motivations. Due to the high interrelation between these sources of influence they are difficult to untangle both from a theoretical and empirical perspective (Cialdini & Goldstein, 2004). Nonetheless, while the former is generally explained by the aim to gain social approval from the members of a referent group, the latter is connected with the need for an accurate interpretation of reality and the identification of the proper behavior (Deutsch & Gerard, 1955). In particular, the tendency to conform to social standards is higher when people find themselves in situations characterized by novelty, ambiguity or uncertainty, which can be the case of consumers who intend to engage in pro-environmental behaviors like the purchase of organic food (Cialdini, 2001; Peattie, 2010).

A possible downside of social influence is represented by lock-in situations (Janssen & Jager, 1999): if in a population of consumers many individuals prefer green products, but do not choose them because they falsely assume - on the basis of observation - that the norm is against green products, they are likely to purchase regular products, thus strengthening the norm for conventional products in a vicious cycle. As pointed out by Griskevicius, Cantú, and Van Vugt (2012), imitation of others' behavior is recognized as an unconscious process automatically triggered by our brain. This process has been underappreciated in the understanding of environmental issues: in fact, much of these problems come from a conflict between what people believe they ought to do and what they see (or believe) others do. Similarly, Jackson (2005) acknowledged that people's choices are constantly affected by social norms such that these latter can represent a powerful source of influence to hinder or to encourage pro-environmental behaviors. Therefore, a transition or tipping-point in social norms can lead the behavioral change of consumers with great benefits for the environment (Nyborg et al., 2016).

Nonetheless, recent results obtained by Bolderdijk and Cornelissen (2017) suggest that consumers who privately are inclined to purchase a green product may avoid doing so publicly out of the fear that their norm-deviating behavior may elicit negative social responses on behalf of fellow consumers who frequently choose conventional products. Interestingly, the research has been able to bring to light a social phenomenon, defined as "undercover altruism", that goes against the common idea that we give our best version of ourselves to gain social approval. On the contrary, among the techniques that people can employ to integrate themselves with a social group, they may choose to avoid showing their most virtuous tendencies. Particularly, undercover altruism specifies that individuals sometimes act more morally in private than in public settings if they perceive that a certain behavior is exceptional.

The authors conducted several studies across different settings in order to evaluate the occurrence of this phenomenon in relation to donation behaviors. Particularly, in Studies 1A and 1B the likelihood of making donations to strangers (a panhandler and a street musician) was examined in relation to two different conditions: when the donators were alone and when they were in the presence of other people who would witness the donation. The presence of observers was supposed to elicit an uncomfortable social comparison: by anticipating such situation, people may prefer to avoid donating when accompanied. As supposed, the results showed that the likelihood of donating was lower when people were accompanied by others in comparison to when they were alone.

In contrast, Study 1C examined the intentions to donate in the context of a supermarket that was supporting a 3-day Catalonian food drive. Several cues were provided suggesting a free donation of food as the common norm (e.g. volunteers were present inside the store wearing t-shirts and sponsoring the campaign). In this case, a donation was made by almost half of the observed customers (contrary to the previous studies, where donations were rare). Moreover, people were more likely to donate when accompanied rather than when alone.

Thus, when charity is not supported by a distinctive norm (like in Study 1A and 1B) the presence of others inhibits people to engage in acts of pro-social behavior. On the contrary, when pro-social behaviors are clearly supported by contextual cues people do not prevents themselves from acting morally. Indeed, in the latter case, cues promoting the donations as a common behavior overcome the chance of express donation behavior as an exhibition of moral superiority.

In addition, Study 4 examined whether vegetarians and vegans prefer to avoid positioning themselves as morally superior by concealing their dietary preferences. In particular, participants were offered with the opportunity to express their inclination by signing a petition to increase the vegetarian options in supermarket assortments. Each participant was inserted in a group discussion with other three people: in reality, these latter were instructed confederates who, before the participant receive it, read the petition and openly decided to refuse to sign it. Vegetarians as well as vegans were supposed to be prone to sign the petition as it was in line with their personal attitude. However, deciding to sign the petition can be interpreted as a signal of moral reproach against others. Thus, the experimental setting was specifically designed to elicit undercover altruism: in fact, it was expected that the participants might be motivated to hide their moral inclinations in order to avoid potential awkward social situations. In addition, the effect of contextual cues was examined under the supposition that a participant might be more inclined to exhibit a virtuous behavior when this does not imply a moral reproach against others (similarly to Study 1C). Thus, two conditions were created where the petition was externally endorsed or not. Results supported the hypotheses: particularly, when a public support was not present, only a slightly majority of the vegetarians and vegans signed the petition. On the contrary, when an external endorsement was present the number of participants who decided to sign the petition was significantly higher compared to the previous condition.

Therefore, without clear cues suggesting a virtuous act as a common and accepted behavior, people seem to be more prone to engage in exceptional acts of pro-social and pro-environmental behavior when they do not perceive any kind of social presence. The authors suggested that this behavior might be driven by the common ability of individuals to anticipate possible negative reactions by people who do not share the same moral concerns. Before taking a morally superior position through exceptional virtuous acts, people may prefigure the creation of an uncomfortable situation where they are implicitly affirming that all other behaviors are wrong. In addition, people are aware that such awkward social comparison might represent a threat to the members of a social group who might therefore engage in defensive responses (such as ridicule or exclude the source of the threat). For instance, Minson and Monin (2012) studied the anticipation of moral reproach felt by a majority of meat-eaters when considering the moral choices made by a potential minority of vegetarians. The results showed that meat-eating participants perceived small differences between the morality of meat-eaters, whereas they expected vegetarians to feel this gap as almost ten times larger. More interesting, the force of the defensive responses (measured as negative associations) was positively correlated with the expectancy that a vegetarian exhibits its moral superiority. Consequently, in order to integrate with groups, people sometimes avoid to behave on the base of their best tendencies preferring to conform to the norm.

Bolderdijk and Cornelissen concluded suggesting that the low diffusion of environmental-friendly products may not reflect a real selfish preference. On the contrary, the refusal of such products could be related to an adaptive response to an underlying control mechanism hided in the social dimension. As a consequence, the number of consumers motivated to engage in pro-environmental consumption might be underestimated due to those consumers trapped inside a lock-in vicious cycle driven by the tendency to “undercover altruism”.

In line with this premise, the presented model attempted to investigate the dynamic interactions between the individual and social dimension in shaping buying behavior in the specific context of organic food. Particularly, the research employed agent-based modeling to recreate the consumption context of numerous consumers inside a grocery store. This methodology of investigation of social phenomena has grown quickly in the field of marketing and consumer behavior (Jager, 2007; Delre, Broekhuizen, & Bijmolt, 2016; Rand & Rust, 2011) due to its advantages compared to the experimental or analytical approach. Above all, it allows the chance to investigate the interaction over time among the individual, social and environmental dimensions, to avoid difficulties and costs associated with real experiment settings, and to testing different scenarios following a “what-if” approach.

Thus, the research aim is twofold: firstly, the model attempts to virtually recreate the phenomenon of consumers’ social influence in order to understand how it can foster/hinder the adoption of green products prevailing individual preferences. In this way we also aim to connect the theory of planned behavior with a specific social phenomenon (i.e. undercover altruism) through a computational approach able to show the lock-in of sustainable products inside a dynamic model. Accordingly, in the present simulation each virtual agent is able to choose independently between conventional or green products based on its own personal beliefs: however, their choices are also affected by the choices made by surrounding agents.

Secondly, we aim to explore if this socio-psychological barrier to sustainable behaviors can be affected (and overcome) by means of different kinds of store layout. Indeed, research has already suggested that product arrangement and position can increase product sales by engaging more efficiently individual consumer (Daunfeldt & Rudholm, 2014; Santucci & Schifani, 1999; van Herpen, van Nierop, & Sloot, 2012; Van Nierop, Fok, & Franses, 2008). However, literature within this topic had little consideration about social influence due to product location inside stores. In fact, in contrast to specialized organic retailers which attract more habitual rather than occasional organic buyers, large-scale retail stores (such as grocery stores) can offer the chance to increase sales of green food due to the different kinds of consumers they gather together. However, undercover altruism might suggest that even an opposite effect can occur (i.e. a regression toward conventional products by regular buyers of organic food). Thus, the model intends to investigate when the physical arrangement of conventional and green food products can enhance/reduce the chance of consumers to affect each other choices toward a category of products. Ultimately, the virtual model should suggest how certain arrangement of food products inside grocery stores can promote the purchase of green food via social influence. Hence, following the distinction proposed in Kiesling, Günther, Stummer, and Wakolbinger (2012), the current model employ a high level of abstraction and generic representations rather than focusing on practical aspects (e.g. sales forecast). Indeed, only basic data were introduced since we focus the investigation on the effect over time of social norms on individual preferences.

4.3 Main theoretical framework

Consumer behavior research suggested several models in order to explain and predict organic food choice (Bonti-ankomah & Yiridoe, 2006). Among these, the theory of planned behavior (TPB; Ajzen, 1991) has been largely employed with successful results both in studies that examined food purchase behavior from an environmental and health perspective (see for instance the reviews by McEachern, Schroder, Willock, Whitelock, & Mason, 2007, Riebl et al., 2015, and Scalco, Noventa, Sartori, & Ceschi, 2017).

The theory of planned behavior explains an action as a consequence of a deliberative process based primarily on the intention to perform it. Intention to buy is then affected by three fundamentals factors: personal attitude, subjective norms, and perceived behavioral control (PBC). Particularly, following Ajzen (1991), attitude can be conceived as the product of belief strength and the evaluation of a certain outcome or attribute. For instance, in the context of green behavior, the outcome can be represented by the perceived probability to minimize the environmental impact thanks to the purchase of a certain item. The second term represents the influence exercised on a subject by the perception of others' beliefs and the observation of their behavior. Finally, PBC defines consumers' confidence to be able to carry out the purchase. Thus, it depends both from psychological (e.g. price perception) and contextual factors (e.g. the availability of products).

We acknowledge that also habit and impulsive behavior can both affect product choices: however, we choose to ground our model on a deliberative model of decision making given the fact that 74% of all purchase decisions are made inside stores (Daunfeldt & Rudholm, 2014). Besides, in contrast with potential criticisms toward the cognitive requests and rationality linked to Ajzen's decision-making model, it is important to consider that once formed, intentions and its antecedents are readily available to drive behaviors and that no assumption are made about the objectivity or truthfulness of consumers' beliefs (Ajzen, 2014; Ajzen & Fishbein, 2005; Bonti-ankomah & Yiridoe, 2006). Moreover, given the aim to investigate the dynamic interaction between individual and social dimensions the TPB offers the chance to model a psychological decision-making process able to take into account both these dimensions.

In addition, several studies during the last decades employed Ajzen's model (both in the original and extended versions) as the main framework to investigate consumers' motivations behind the purchase of organic food (Conner & Armitage, 2006; Guido, Prete, Peluso, Maloumby-Baka, & Buffa, 2010). Particularly, in order to evaluate the significance of the relationships between the model factors, a meta-analysis has been recently conducted by Scalco, Noventa, Sartori, and Ceschi (2017). The results showed the robustness of Ajzen's model to explain the purchase and consumption of green products. Specifically, attitude seems to have the major effect on intention to buy organic food (r = 0.61) followed by subjective norms (r = 0.50). In contrast, perceived behavioral control contributes more modestly (r = 0.32). Furthermore, the analyses showed also a large correlation between intention and actual behavior (r = 0.55). In addition, the authors built a structural equation model based on the TPB starting from the pooled correlation matrix of the examined studies in order to obtain an exhaustive validation of the whole framework. Once more, the results confirmed the relative magnitudes of the antecedents of intention. However, the model highlighted intention as the best predictor of buying behavior over and above attitude. Consequently, the theory of planned behavior appears to be a valid and reliable psychological model to develop virtual agents' decision-making process for organic food purchase. Nonetheless, Ajzen's theoretical framework can arise several issues in the process of implementation inside an agent-based model (Scalco, Ceschi, & Sartori, 2017; Schlüter et al., 2017): consequently, some additional work was required to obtain a flawless algorithm for the virtual model.

4.4 Model overview

The simulation is developed in Netlogo 6.0[1] (Wilensky, 1999) and it creates a population of virtual consumers inserted inside a grocery store with the goal to purchase several food products. Each agent has a shopping list with a specific number of products that must be purchased before leaving: it can choose a product within the whole store and it can move freely in order to reach it. The goal pursuit by the agents is to fulfill their personal shopping list with food products: when they are satisfied (i.e. the list is completed) they exit from the store[2]. The number of items to be purchased is randomly assigned at the beginning of the simulation, while the maximum length of the shopping list can be fixed from the interface (from 1 to 7).

Each purchased product is added to the agent's virtual shopping cart: for each item the agent can decide between a conventional or a green version. Besides their personal preferences, each agent independently chooses to buy green or conventional food on the base of the local consumption pattern it perceives. The decision-making process is implemented following the model provided by the theory of planned behavior (Ajzen, 1991). Starting from this, the basic formulation employed to determine the intention to purchase a certain product at time *t* for a random agent *i* is equal to:

$$I_{t,i} = w_1(A_{t,i}) + w_2(SN_{t,i}) + w_3(PBC_{t,i})$$

For modeling purposes and due to the fact that the agents in the simulation are "compelled" to buy, we assumed intention to buy like the direct expression of behavior. However, since TPB is not able to provide a threshold value such that intention turns into the actual performance of buying behavior, we followed similar works that computed the intention for each course of action (e.g. Kniveton, Smith, & Black, 2012). Thus, at each time step of the simulation every agent computes both the intention to buy conventional and green food: the highest intention drives the consequent purchase behavior. As shown by the previous formula, intention (I) is composed by three main factors: attitude (A), social norms (SN) and perceived behavioral control (PBC). The terms indicated by *w*s are statistical regression coefficients assumed from the structural equation model proposed

[1] The code of the simulation is available in section 6 ("Appendix").

[2] We did not take into account the post-evaluation process and allowed agents to enter a second time inside the store since our purpose for this simulation was limited to the investigation of those essential conditions that allow the spread of social norms.

by Scalco, Noventa, Sartori, and Ceschi (2017). They determine the relative importance of individual preference, social influence and contextual factors in the specific case of organic food purchase.

More specifically, within the present model attitude (A) is based on the evaluation of several food characteristics that can be manipulated by the interface to simulate different levels of product attributes. Coherently with the idea that the attitude toward a product stems from a multifaceted set of beliefs (Guido et al., 2010), the computation of agents' attitude toward regular and green products is based on multiple evaluations of food characteristics compared with agent's personal belief.

Agents' beliefs are obtained from a previous survey structured following Ajzen's guidelines (Ajzen, 2006) and gathered from a 147 student participants. Beliefs from this sample showed a normal distribution given that kurtosis and skewness did not exceed suggested conventional threshold values (Field, 2009). Examined beliefs were specifically related to the perception of (*i*) healthiness, (*ii*) safety (i.e. likelihood that organic food is free from chemicals), and (*iii*) environmental friendliness[3]. Thus, the virtual agents have been endowed with three personal beliefs regarding organic food: a value from 0 to 6 normally distributed based on the mean and standard deviation obtained from the original sample. Beliefs related to conventional food products are equally distributed but we supposed a reduction by 10% of consumers' expectations on the same three attributes. During the simulation, each agent compares its personal beliefs regarding food with the actual characteristics of the products. If the food attribute exceeds the personal beliefs of the agent, that particular food scores one point, otherwise zero. The final evaluation for both kinds of product is computed as the average value of scores: consequently, attitude to buy regular or green food ranges from 0 to 1. This allows performing a comparison with the others elements of the general formula.

The second term (SN) indicates the common kind of product purchased at a given time by the surrounding consumers. As stated by Kiesling, Günther, Stummer, and Wakolbinger (2012), social influence operates on multiple levels: particularly, the authors distinguished among micro-, meso- and macro-level to indicate, respectively, the influence exercised locally through pairwise communication (especially, word-of-

[3] Besides product price, research suggested these as the most important factors in relation to the evaluations of organic products in consumers' purchase decision process (Bonti-ankomah & Yiridoe, 2006).

mouth), the influence originated from the immediate social environment (e.g. the neighborhood), and, finally, the influence that comes from the interaction of an agent with the society as a whole. Following this categorization, the current work focused the investigation of social influence at the meso-level, where conformism and social comparison are common phenomena (*ibid*). In addition, in line with the model proposed by the work of Verwaart and Valeeva (2011), subjective norm is inferred by each agent through the observation of the choices made by other consumers walking inside the virtual store. Thus, every agent evaluates the common norm by calculating the number of adopters of regular and green food over the total number of customers considered within a limited space (i.e. the aisle). Likewise attitude, the final value of this factor ranges from 0 to 1.

The last term (PBC) represents the perceived behavioral control. In the case of organic food, price and availability of products seem to be the most relevant factors that can hinder the actual purchase of products (Al-Swidi et al., 2014). With respect to the former, we assumed a premium price for organic product equals to 35%: this value was obtained from previous research (Defrancesco & Rossetto, 2007; Santucci & Schifani, 1999). Average product price can be manipulated from the program interface from 0€ to 5€. Instead, the availability of products is explicitly defined by the program code: a time interval can be defined such that products are randomly restocked when they are out of stock.

4.5 Tested scenarios

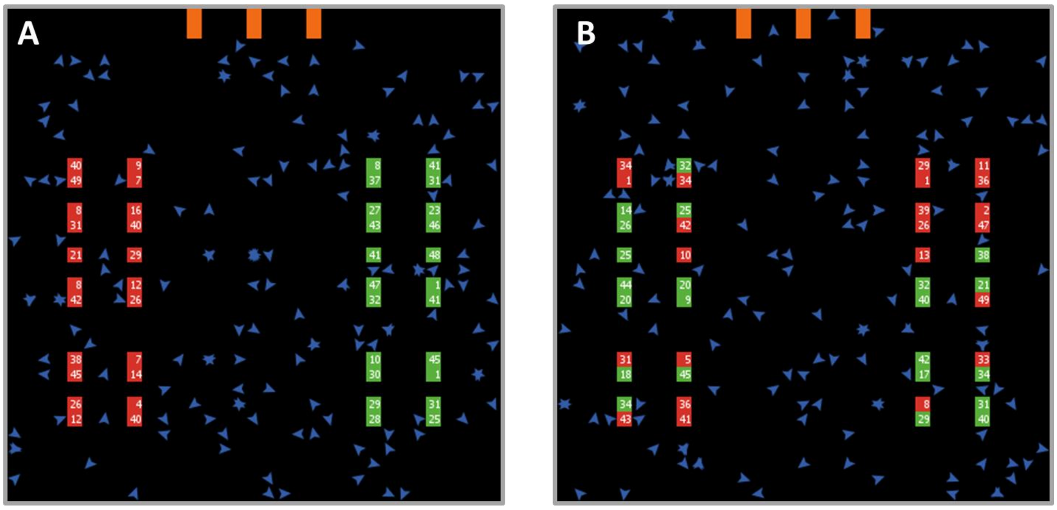
Some research already demonstrated the different effects of products arrangement in stores on consumer’s choices. For instance, Van Nierop et al. (2008) showed that shelf layout can significantly affect sales and marketing effectiveness, whereas van Herpen et al. (2012) found that the arrangement of products by brand leads to higher market share for organic products. Following the latter, when sustainable products are clustered together they enhance their chances to be purchased thanks to the fact that they are noticed more easily and quickly in comparison to when they are placed close to comparable conventional products (where they become less distinctive). Thus, sales of green food are generally higher when products are clustered rather than scattered among product categories.

Nonetheless, while product position on shelves has been extensively examined, locations issues have received much less attention in literature (*ibid*). In particular, influence among consumers and spread of norms about food consumption due to product arrangement in stores has not be taken into account yet. A further examination of product arrangement can attempt to consider the social dimension of purchase behavior. In fact, when sustainable products are clustered it is more likely that consumers having a different attitude toward food (i.e. conventional/green) do not gather together; instead, when green and conventional food are placed closely consumers might affect each other choices by the mere observation and the internalization of common norms. In the latter case social phenomena like undercover altruism (Bolderdijk & Cornelissen, 2017) might suggest that habitual organic buyers can deceive their intentions to buy green food if it is located close to regular food due to the presence of buyers less concern with environmental or health issues. Different arrangements of product within the virtual store should provide some insights regarding the circumstances of when this phenomenon can occur.

Hence, in order to study how food arrangement can affect the spread of social norms, part of the simulation code is specifically devoted to design the store. In particular, the program allows arranging conventional/green food on virtual shelves as well as their position inside the store. For the purposes of this work, we selected two basic configurations with distinct product positions. **Fig. 1** depicts an example of the virtual store with the different arrangements: the first one replicates a supermarket allocating green food in a separate area of the store, thus creating a strong differentiation between regular and organic food (condition A**:** clustered products). Conversely, the second configuration creates the opposite situation: products are allocated by mixing up green and conventional food among the aisles (condition B: mixed products).

Each configuration is tested in several scenarios. Particularly, in order to assess the agents' behavior on the base of the developed decision-making model, the first set of runs was conducted under basic control conditions (SC1). Therefore, these first simulations were performed by assigning to green and conventional products the same level regarding each one of their attributes (i.e. any difference regarding healthiness, safety and environmental-friendliness was modeled), apart from price which was lower for the latter kind of food. Thus, following a rational decision-making process we expected that every agent would prefer to buy conventional food.

Fig. 1 - The figure shows the different configurations of the virtual store. Customers are shown using blue arrows. Orange patches indicate exits. Organic food is represented by green squares, whereas conventional products are indicated by red ones. Numbers on the patches represent the amount of available products.



Successively, we varied the number of consumers inside the virtual store between the second and third scenarios (SC2 and SC3). Thus, while the former emulates a crowded grocery store, in the latter only few customers are present among the aisles. Indeed, since social phenomena such as undercover altruism are dependent on the presence of other people, we supposed that the number of agents within the virtual store can affect the spread of social norms. Particularly, in line with the results by Bolderdijk and Cornelissen (2017), we expected to observe a reduction of the sales of green products when the supermarket is crowded rather than relatively empty given that the common norm favors conventional products.

Similarly, we manipulated the maximum number of products that the agents are interested to purchase during the simulation (i.e. the length of the shopping list). We expected that a short list of products can hinder the spread of norms since the amount of products to be purchased can be positively correlated with the time spent by consumers inside the store. Once again, for this variation we distinguished between crowded/uncrowded markets (SC4 and SC5). A summary of configurations for tested scenario is reported inside **Table 1**. Products attributes are reported as the difference between characteristics of green food compared to conventional one. In this case, we hypothesized a constant difference equals to 50% (except in SC1). In the same way, following the results reported by previous works, premium price of organic food was fixed at 35% (Defrancesco & Rossetto, 2007; Santucci & Schifani, 1999).

Table 1 - Configurations associated to tested scenarios.

Scenario	No. agents	Max items	ΔEF	ΔHL	ΔSE
SC1	50	7	0%	0%	0%
SC2	350	7	+50%	+50%	+50%
SC3	50	7	+50%	+50%	+50%
SC4	350	2	+50%	+50%	+50%
SC5	50	2	+50%	+50%	+50%

Notes. Each scenario is replicated 250 times under conditions A (clustered products) and B (mixed products). No. agents = the number of agents generated at the beginning of each run of the simulation; Max items = maximum number of products to purchase; ΔEF, ΔHL, ΔSE = difference between regular and organic products in relation to environmental-friendliness, healthiness, safety.

4.6 Results

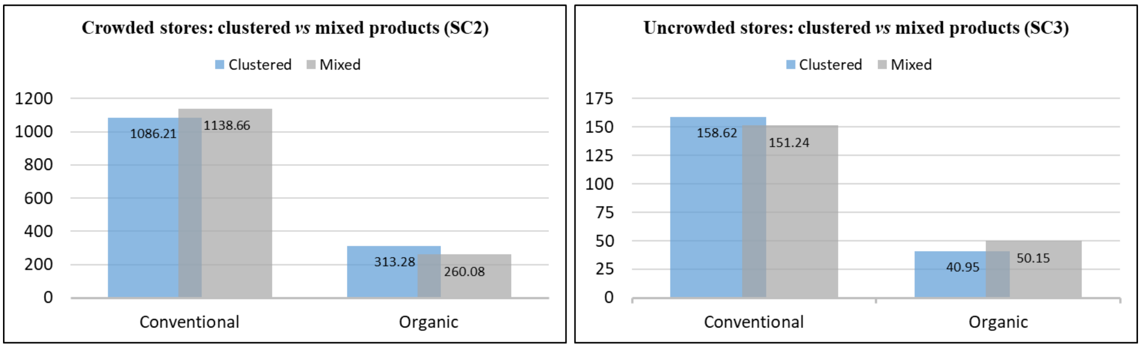
The first set of runs (SC1) was conducted in order to observe the behavior of the applied model of decision-making under neutral conditions: in fact, when product attributes present no difference, except a lower price for conventional food, it is reasonable to expect that agents overlook green products. As supposed, results confirmed that the agents disregarded in every run green products preferring conventional ones (**Table 2**). Different arrangements of products have no effect on buying behavior. Base on this result, we did not proceed to test SC1 with a higher number of agents as it is realistic to expect the same result regarding the amount of green product sold.

Scenario 2 and 3 tested the model with a different number of customers inside the store. Despite the higher values assigned to the attributes related to green products, due to the higher price and the force exercised by the common norm the amount of organic food sold was lower compared to conventional ones both in the clustered and mixed configuration of each scenario.

Interestingly, the reduction of sales for organic product differed from the expectations (**Table 2 and 3**). T-tests performed on the distribution of green product sales among the repetitions of the simulation confirmed the significant differences between the clustered and mixed configurations of green products in both Scenario 2 and 3. However, the arrangements of products seem to have a different effect depending on the number of agents inside the store. In fact, in SC2 the amount of green products sold in the clustered condition (M = 313.28, SD = 43.76) appears significantly higher ($t(498) = 13.401$, $p < 0.001$) compared to the mixed condition (M = 260.08, SD = 45.01). On the contrary, in

SC3 the volume of organic food purchased by the agents in the clustered condition (M = 40.95, SD = 9.58) is significantly lower ($t(498) = -10.999$, $p < 0.001$) when compared to the mixed condition (M = 50.15, SD = 9.11).

Fig. 3 - The charts show the amount of conventional and organic food sold (distinguished on the base of condition) in the crowded stores (SC2) and in those sparsely populated (SC3).



Finally, in SC4 and SC5 the maximum amount of product to be purchase was reduced in order to observe potential differences in the spread of social norms due to the time spent by the agents inside the store. Once again, the scenarios differ for the number of agents (higher in SC4). In this case, the different arrangements of food inside the store did not lead to a significant increase of products in neither tested scenario. Nonetheless, it is interesting to note that the results emerged in the previous scenarios appear to be replicated also in this case. In fact, on the one hand in SC4 the average number of organic products sold appears higher (though not significant; $t(498) = 1.054$, $p = 0.293$) in the clustered condition (M = 129.92, SD = 13.32) rather than the mixed one (M = 128.60, SD = 14.75). On the other hand, in SC5 the amount of green products sold in the cluster condition was lower (M = 18.62, SD = 4.15) compared to the second one (M = 19.13, SD = 4.23). Again, also in this case the difference has not been proved to be significant ($t(498) = -1.346$, $p = 0.179$).

Table 2 - Amount of conventional and green product sold in each scenario and associated ratio distinguished on the base of condition: clustered products (A) *versus* mixed products (B).

Scenario	SC1		SC2		SC3		SC4		SC5	
Condition	A	B	A	B	A	B	A	B	A	B
Conven. products sold	199.81	199.18	1086.21	1138.66	158.62	151.24	395.89	396.31	56.38	55.68
Green products sold	0	0	313.28	260.08	40.95	50.15	129.92	128.60	18.62	19.13
Ratio	0	0	0.29	0.23	0.26	0.34	0.33	0.33	0.34	0.35

Notes. The results report the average value obtained by the repetition of 250 runs of the simulation for each condition.

Table 3 - t-Tests performed on the distribution of green product sold between conditions A and B.

Scenario	SC1*	SC2	SC3	SC4	SC5
t(df)	0.487(498)	13.401(498)	-10.999(498)	1.054(498)	-1.346(498)
p-value	0.627	< 0.001	< 0.001	0.293	0.179

* Since in SC1 no green product was sold, t-test was performed on the distribution of conventional products sold.

4.7 Discussion and conclusions

As discussed, consumers play an important role in shaping environmental issues through their daily purchase behaviors. Indeed, the choice for organic products appears to be a valuable answer from a consumer point of view in order to reduce the environmental impact of food consumption. Particularly, the preference for green food products in contrast to conventional ones can contribute the growth of an environmental-friendly production systems and thus support a transition toward a sustainable society. However, food choice represents a complex behavior difficult to understand and investigate: individual factors play a critical role in consumers' decision process, while the social dimension constantly affects and reshapes personal preferences and, eventually, buying intentions.

Interestingly, individual and social dimensions are able to create a closed-loop thanks to their constant interaction such that consumers might find themselves trapped in a locked-in vicious cycle where, even when green food is generally preferred, conventional products are more likely to be purchased. In addition, the insights provided by the work by Bolderdijk and Cornelissen (2017) suggest that behaviors that are seen as exceptional (such as the purchase of green food in large-retail stores) might not be performed in order to avoid creating uncomfortable social situations.

Therefore, the present research aimed to test the dynamic interaction between the individual and social dimension of organic food purchase. An agent-based model was built in an attempt to connect an established theoretical framework (i.e. the theory of planned behavior) with social phenomena such as normative influence and undercover altruism. Accordingly, the simulation has been able to replicate the effect of social influence among consumers inside the virtual stores. Despite personal preferences, several agents show the tendency to rely on the phenomenon of undercover altruism highlighted by Bolderdijk and Cornelissen (2017). That is to say, they prefer to add to their virtual shopping cart conventional products due to the presence of other agents within the surrounding area even when their attitude was higher for organic products. Thus, the behavior of these particular agents reinforces the norms toward conventional products which in turn affects the choices of the following agents.

However, the presence of this phenomenon seems to be stressed or reduced both on the base of the products arrangement and the crowd present inside the store. In fact, while the crowded store (SC2) showed a higher volume of green products sale in the clustered condition, the opposite effect was observed in a relatively empty supermarket (SC3), where organic products obtained a larger preference when mixed with conventional products rather than clustered.

Thus, the results obtained especially from scenarios SC2 and SC3 provides some additional insights in relation to the arrangement of food and the promotion of a positive norm toward organic products. In fact, van Herpen et al. (2012) already suggested that by clustering organic products their sales increase thanks to the fact that their visibility is enhanced (i.e. they are noticed quickly) rather than when mixed with other conventional products: however, the present model showed that this result is more easily obtained in crowded stores rather than empty ones. This effect may be due to the fact that a clustered arrangement of green food together with a distinct location prevents a regression of those consumers due to undercover altruism phenomenon: indeed, the effects of social dimension are limited since consumers who frequently choose conventional products are separated in a distinct area and cannot exercise a strong influence on green consumers as in the mixed condition. Conversely, the likelihood to sell organic products in relatively empty grocery stores appears higher when green food is mixed with conventional one. This effect may be explained by the minor influence that green consumers perceive by other people and the slow spread of a positive norm toward organic products. In this case, a potential solution to foster the spread of sustainable food might be represented by bundles of different organic products (rather than the more common offer “2 for 1”) in order to nudge green consumers to move along the aisles of the stores. In this way, a consistent minority (Moscovici & Zavalloni, 1969) might work as a cue signaling the preference for organic products as a common behavior rather than appears as an exceptional act. In contrast, the results suggest that the same solution might be counterproductive in the case of a crowded store with mixed products.

In addition, it can be suggested that large-retail stores characterized by consistent flows of customers prefer the arrangement of green food on separate and distinctive area of the store (as suggested by the results of van Herpen et al., 2012). Conversely, stores aware of a sporadic flow of consumers should prefer to mix green with conventional products. Particularly, the effects generated by a cluster and a mix configuration of products on green food sales should be especially considered to those supermarkets highly affected by seasonality of consumers (e.g. store located in tourism destinations).

Nonetheless, the current model presents several limitations. Firstly, the work focused on a single fragment of the common evaluation process of market products. As suggested by Kotler, Armstrong, Saunders, and Wong (1996) choices made by consumers represent a process comprised by several distinct phases (i.e. need recognition; information search; evaluation of alternative; purchase; and post-purchase experience). Indeed, the simulation focused purely on a deliberative evaluation of the proposed alternatives (i.e. conventional/green food).

Secondly, we acknowledge that the work focused on a sole psychological theory (i.e. the theory of planned behavior). Indeed, as pointed out by Schlüter et al. (2017) several theories from different disciplines (particularly, economics and psychology) should be reviewed and integrated inside a social simulation in order to obtain a far more comprehensive description of the reality via agent-based models. Moreover, within the current model we employed the original version of the theory of planned behavior where three antecedents determine agents' intention to buy green products. Future developments of the simulation should take into account also further constructs: indeed, additional variables can help to improve the explanation and power of prediction of virtual decision-making processes related to organic food consumption. For instance, values and trust in food producers have been identified as significant factors that can affect intention to buy organic products (Aertsens, Verbeke, Mondelaers, & Huylenbroeck, 2009; Suh, Eves, & Lumbers, 2015).

Thirdly, the proposed work focused its attention on spatial distribution of green and conventional products and the differences among products attributes were not extensively explored but constrain to reasonable assumptions. Actually, the model attempted to explore the phenomenon of undercover altruism, which represents a hindrance to the adoption of pro-environmental behaviors, in relation to the spread of social norms from an abstract level. Hence, additional work is expected in order to improve the accuracy of the predictions of the current model.

Finally, it seems interesting to focus the investigation on innovators' motivations rather than undercover altruists, as well as their connection with the social dimension of food consumption. That is to say, future developments of the model should aim to shed a light on those conditions that favor the emergence of those individuals with a positive attitude toward conventional product but who prefer to goes against the common norm and purchases green food products.

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5 Conclusions

As argued, food consumption has a crucial impact on current environmental issues. Particularly, consumers' preference toward organic food plays a crucial role in order to achieve the goal of a sustainable society. Besides country governments, the need for research in this sector from a consumer point of view has been promoted by the report by the European Commission (2016). Accordingly, the present project aimed to investigate food consumption from a social perspective with the purpose to aid marketers as well as policy makers to encourage pro-environmental behaviors. Particularly, the present research project has been divided into three main questions addressed each one by a specific scientific paper: the next sections provide a brief overview of the results obtained by each work.

5.1 Validation of the psychological framework

As pointed out by Kalafatis, Pollard, East, and Tsogas (1999), several explanatory theories have been developed over the years in order to explain driver mechanisms of people purchase decisions. As discussed, in the field of consumer behavior the theory of planned behavior (Ajzen, 1991) remarkably demonstrated its power of explanation. In addition, this theoretical framework has been successfully employed in the field of food consumption, environmental studies, and agent-based modeling. Due to the vast amount of literature available, the ability of explanation and prediction, and the chance to jointly consider individual and social factors, it was hypothesized that the TPB might be a valid answer to the first question proposed by the current research project.

Over the years several studies employed the TPB in order to explain and predict consumer behaviors in the specific context of organic food choice: however, contrasting findings emerged. Thus, it was important to appraise the validity of Ajzen's model in this specific context. To achieve this objective, the first work (Scalco, Noventa, Sartori & Ceschi, 2017) reviewed those studies that employed this theoretical framework to predict consumers' intention to purchase and consume organic food. The purpose was to test the significance of the original model proposed by the TPB in comparison to more recent alternative models. Hence, a meta-analytical procedure was applied to test the strength of each relationship among model constructs. The results showed the robustness of this psychological model to explain the purchase and consumption of organic products.

Specifically, attitude seems to have the greatest impact on intention to buy organic food (r = 0.61), followed by subjective norms (r = 0.50). Instead, perceived behavioral control contributes more modestly (r = 0.32). Furthermore, the analyses also showed a large summary effect between intention and actual behavior (r = 0.55).

In addition, the research employed a meta-analytical structural equation model in order to synthesize multiple correlation matrices into a comprehensive structural equation model. Once more, the results confirmed the significance of the theoretical framework and the relative magnitudes of the antecedents of intention (however, the statistical model highlighted intention as the best predictor of buying behavior over and above attitude). Thus, the theory of planned behavior appeared to be a valid and reliable psychological framework to explain and predict organic food purchase. Starting from this, the TPB was adopted as the primary framework for the development of a realistic virtual agent's decision making process.

5.2 Approaching an informal theory from a computational point of view

As suggested by Zhang and Nuttall (2011), Ajzen's theory offers a theoretical framework (relatively) easy to be converted into the form of an algorithm. However, a critical review of the theory from a computational point of view was required in order to highlight potential issues or gaps that might result in the successive phase of application. Accordingly, the second contribution of the project (Scalco, Ceschi, & Sartori, 2017) attempted to critically review the theory of planned behavior in light of the computational approach proposed by agent-based modeling. This work addressed the potential conjunctions between the psychological knowledge and virtual simulations in the specific application case of the theory of planned behavior. On the one hand, the work is based on an in-depth examination of the major works by the original proposer of the theory (i.e. Isaac Ajzen). On the other hand, the contribution benefits from a previous experience of modeling this particular theoretical framework inside a virtual model of recycling behavior (see Scalco et al., 2017, provided as annex of the current work).

The paper illustrated how the theory of planned behavior has been proved over the years as a consistent and remarkable good theory, which is supported by numerous research scattered among different fields. However, as expected, when the computational approach was applied to the theoretical framework, this latter showed the presence of potential gaps. Particularly, the major issue lies in the addition of the temporal dimension (see section 3.4.2). Nonetheless, some works drawn from the computational sciences have been able to provide interesting solutions useful to overcome this limitation. In addition, the theory of planned behavior does not offer clear information regarding the potential feedback mechanisms derived by the performance (and appraisal) of the performed behavior. Modelers should pose specific assumptions in relation to this point. Finally, it is crucial to assess the validity of the model proposed by the TPB for the behavior under examination: in this case, methods from psychological research (e.g. structural equation models) can serve to this purpose and to drive the development of the computational model algorithms.

5.3 Emulate consumers' behavior and promote organic food purchase

Finally, starting from the findings from the first work and the examination conducted in the second paper, an agent-based model was built to investigate how social interactions in relation to green food products can foster/hinder buying intention among customers of grocery stores with different store layouts (Scalco, Jager, Bolderdijk, Sartori, & Ceschi, working paper). Each virtual consumer has the chance to decide to purchase conventional or organic food. The related decision-making process has been grounded on the TPB and the results obtained from the presented meta-analytical structural equation model. Particularly, we employed a computational approach in order to connect a psychological framework with a specific social phenomenon recently identified by Bolderdijk and Cornelissen (2017): undercover altruism. In the end, the simulation has shown to be able to replicate the complex relationship that stem from the dynamic interaction between consumers' preferences and the effects of social influence.

Interestingly, the final simulation provided an answer to the promotion of pro-environmental behavior. In fact, on the one hand, the tested scenarios confirmed the results provided by van Herpen et al. (2012): sales of organic products increase when these products are clustered rather than when mixed with conventional ones. Indeed, the effects of the social influence exercised by those consumers who prefer regular products is strongly reduced when green food products are clustered and set apart from conventional ones. Moreover, the presence of undercover altruists is largely reduced such that green consumers can based their purchases on personal attitudes without the interference of the social dimension. On the other hand, this result is confirmed only in the case of a crowded market. In fact, the model showed that the likelihood to sell organic products in sparcely populated stores is higher when the green and conventional products are mixed. This result might be explained by a reduced social influence effect on this kind of consumers. In addition, under this condition it is possible to hypothesizes a slow spread of a positive norm toward green products also in those consumers who were initially more inclined toward conventional products.

Starting from these findings, the computational model offered some suggestions to promote the purchase of organic food. Briefly, grocery stores should arrange their conventional and green products on the base of the average flow of consumers. This can be especially remarked for those supermarkets which are highly affected by seasonality of clients. In addition, stores with sporadic flow of consumers should consider to mix conventional and food products. Moreover, in order to support the spread of a positive norm toward sustainable food, these markets can consider the idea to promote special bundles of different organic products. In this way, consumers are encouraged to move along the aisles of the store to collect different green products: the formation (and visibility) of a consistent minority (such as suggested by the studies by Moscovici) might promote green behavior as a common behavior rather than appears as an exceptional act.

5.4 References

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6 Appendix

The following section reports the original code employed to run the simulation presented inside the paper "*Green Consumer Behavior: Simulating the Diffusion of Sustainable Food inside Grocery Stores*" by Scalco, Jager, Bolderdijk, Sartori, & Ceschi (sect. 4).

```
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;; $MAIN CODE                   ;;
;; Define the main procedures   ;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;

;; includes the code employed to design the store, compute buying
intention, and customers data initialization
__includes ["Store_Layout_Design.nls" "TPB_Library_v.2.1.nls"
  "Customers_data.nls"]


globals [

  MonitorNormStd      ;; average values related to the perceived social
                         norm among the agents
  MonitorNormGrn
  MonitorAttStd       ;; average values related to the individual
                         attitude of the agents
  MonitorAttGrn
  availability        ;; compute the ratio between conventional over
                         green products
  StdFood             ;; amounts of conventional and green food
  GrnFood
  N.UA                ;; total numbers of undercover altruists
  N.CH.std            ;;   "       "       choerent toward green food
  N.CH.grn            ;;   "       "       choerent toward regular food
  N.IN                ;;   "       "       innovators
  %CH.std             ;; percentages of the previous values
  %CH.grn
  %UA
  %IN
  grnProdSold         ;; amount of green and conventional products
                         bought by the agents
  stdProdSold

]

patches-own [

  foodType            ;; kind of food (green/standard) on the patch
  isEmpty?            ;; true if products on the patch (i.e. shelve) is
                         out of stock

]

turtles-own [

  mxLngShopList       ;; number of products that the agent's must buy
                         before exit
```

```
  shopList            ;; list of products bought by an agent
  lastProdBought      ;; the last product bought by the agent (also,
                         the last item added to the shop list)
  satisfied?          ;; true if shopping list is full, false otherwise
  productTarget       ;; the product the agent is looking for inside
                         the supermarket
  decided?            ;; used to maintain the focus on an object until
                         the agent achieves it
  path                ;; employed in earlier phases of the model to
                         monitor the path of the agents in the world
  age                 ;; age of the agent
  mark                ;; to avoid count turtles more than one time in
                         plots and monitors
  out?                ;; to avoid killing turtle (otherwise plots and
                         monitors will invalidate results)

  ;; personal beliefs
  belief.chemfree     ;; min acceptable standard about chemfree
  belief.price        ;; max price for food (i.e. Willigness to Pay)
  belief.health       ;; min acceptable standard about health of food
  belief.env          ;; importance of the collective benefits

  Norm.Std            ;; evaluation of social norm adopted by
                         surrounding agents
  Norm.Grn
  Att.Std             ;; personal attitude toward std/green product
  Att.Grn
  ItB.StdFood         ;; intention to buy (ItB) std/green food
  ItB.GrnFood
  role                ;; behavior assumed by the agents
                         (UA/CH.grn/CH.std/IN)

]

;;;;;;;;;;;
;; SETUP ;;
;;;;;;;;;;;

;; Create the requested number of consumers
to generate-customers

  crt #cstmrs
  [
    ;; set the new customers on the entrance (= yellow patches)
    move-to one-of patches with [pcolor = yellow]
    set color blue
    set heading 180
    ;; initialize internal agent's variables
    initializeCustomer
    ;; generate a set of beliefs
    generatePreferences
  ]

end
;;;;;;;;;;;;
;; GO     ;;
;;;;;;;;;;;;

;; Main procedure of the simulation model
```

```
to go

  ;; update global vars each cycle
  updateGlobals

  ;; Some basics control before the begin of the simulation
  if not any? patches with [pcolor = yellow] [ user-message "Please,
  define entrances and cashiers." stop ]

  ;; Regulate customers flow inside the store
  if (cstmrs-flow != 0 and ticks != 0) and ( (remainder ticks cstmrs-
  flow) = 0) [ generate-customers ]

  ;; agents on orange patches are considered as customers that exits
  from the store
  ask turtles [if ([pycor] of patch-here = max-pycor and [pcolor] of
  patch-here = orange) [set out? true stop]]

  ;; agents that are moving around the store shop
  ask turtles with [out? = false]
  [
    ifelse ((not satisfied?))
    [ goShopping ]    ;; if shopping list is not full, agent goes on
                         looking for products
    [ goHome ]        ;; if the sopping cart is full, the agent goes
                         toward the store exits (i.e. orange patches)
  ]

  ;; Refill the shelves every fixed ticks (0 = no restock)
  if ((restock-time? != 0) and (ticks mod restock-time? = 0)) [
  restock ]

  ;; update graphs and monitors
  updateOutput
  updateDisplay

  ;; if all agents filled the shoplist the simulation can stop
  if all? turtles [satisfied? = true] [stop]

; wait 0.1 ;; active to follow agents movement on screen
  tick

end

;; Compare intentions to buy standard/green food based on TPB and
define a specific product to buy inside the store
to decide-product

  if not decided?
  [
    ;; decision can also take into account habit
    let p.habit random-float 1
    let foodChoice red ;; instantiate a temporary var
    ifelse ((p.habit < habitStrength) and (habit? = true))
    [
      set foodChoice red ;; decision made on the base of habit
    ]
    [
```

```
      ;; decision based on a deliberative process ("TPB_Library" is
      here called)
      calcTPBs  ;; evaluate the kind of product that should be bought
      ifelse ItB.StdFood >= ItB.GrnFood [ set foodChoice red ] [ set
       foodChoice green]
    ]
    set productTarget one-of patches with [pcolor = foodChoice]
    set decided? true
  ]

end

;; Update the agent's shopping list, remove product from shelves and
updates the amount of product sold
to goShopping

  ;; the agent decides what product it needs to buy at the store
  decide-product
  let choice [pcolor] of productTarget

  face productTarget ;; set the agent toward the product to buy
  if (distance productTarget < 1.5) ;; agent pick up the product
  [
    ifelse [plabel] of productTarget > 0
    [
      if choice = 15  ;; 15 = red color -> std product
      [
        set shopList fput "std" shopList
        set lastProdBought "std"
        set stdProdSold stdProdSold + 1
      ]
      if choice = 55  ;; 55 = green color -> grn product
      [
        set shopList fput "green" shopList
        set lastProdBought "green"
        set grnProdSold grnProdSold + 1
      ]
      ;; remove the chosen product from the shelve
      ask productTarget
      [
        set plabel plabel - 1
        set plabel-color white  ;; reset color of plabel
        if plabel = 0
        [
          set foodType pcolor   ;; store the kind of food that was on
                                   the shelve to restock it later
          set pcolor white
        ]
      ]
    ifelse (length shopList = mxLngShopList)
    [ set satisfied? true stop ] ;; if list is full, agent is ok

    [
      set decided? false
      generatePreferences ;; generate a new set of preference for the
                             next product to buy
      decide-product      ;; after agent bought a product,
                             productTarget is reset
    ]
```

```
  ]

    [
      set decided? false  ;; if the product target isn't available,
                             agent must choose another product
      decide-product
    ]
 ]

  ;; if the shopping list is full the agent is satisfied and (at the
  next cycle of the sim) can go to the exits
  if (length shopList = mxLngShopList) [ set satisfied? true stop ]

  ;; If the agent is not in front of the products it must go toward it
  ifelse not any? patches with [pcolor = choice]
  [ stop ]
  [
    if (one-of neighbors4 != productTarget )
    [
      movement(productTarget)
    ]
  ]

end

;; Ask agents to reach the exits when they completed the shopping list
to goHome

  ;; procedure to reach the cashier and follow the line
  ifelse [pcolor] of patch-here = orange
  [
    move-to one-of neighbors4 with [(pcolor = orange)]
  ]
  [
    let target one-of patches with [pcolor = orange and pycor = max-
     pycor]
    movement(target)
  ]

end

;;;;;;;;;;;;;;;;;
;; MOVEMENTS   ;;
;;;;;;;;;;;;;;;;;

;; Procedure to move the agents around the store and reach products
to movement [trg]

  face trg ;; face the product target to buy

  let target-xcor [pxcor] of trg
  let target-ycor [pycor] of trg
  let steps nobody

  ifelse (satisfied?)
  ;; if agent is not satisfied, it cannot move to cashiers
  [ set steps neighbors4 with [(pcolor = black) or (pcolor = yellow)
     or (pcolor = orange)]]
  ;; if shopList is full, agent can move to the cashiers
```

```
  [ set steps neighbors4 with [(pcolor = black) or (pcolor = yellow)]]

  let next-step min-one-of steps [distancexy target-xcor target-ycor]
  set path fput next-step path

  move-to next-step

end

;;;;;;;;;;;;;;;;;;;;;;;;
;; PLOTs and OUTPUT   ;;
;;;;;;;;;;;;;;;;;;;;;;;;

;; Update global vars related to norms and attitudes
to updateOutput

  if count turtles with [satisfied? = false] > 0
  [
    set MonitorNormStd mean[Norm.Std] of turtles with [satisfied? =
     false]
    set MonitorNormGrn mean[Norm.Grn] of turtles with [satisfied? =
     false]
    set MonitorAttStd mean[Att.Std] of turtles with [satisfied? =
     false]
    set MonitorAttGrn mean[Att.Grn] of turtles with [satisfied? =
     false]
  ]

end

;; Update food availability inside stores, global vars and agents'
roles
to updateGlobals

  ;; ask TPB Library to define agents' behavior on the based of
   attitude and perceived soc norm
  defineRoles

  ;; evaluate the amount of food supply inside the virtual store
  set StdFood sum [plabel] of patches with [pcolor = red]
  set GrnFood sum [plabel] of patches with [pcolor = green]
  set availability StdFood / GrnFood

  ;; update global vars to track trends related to agents' behaviors
  if count turtles with [mark = false] > 0
  [
    set N.UA count turtles with [role = "Undercover-altruist" and mark
     = false]
    set N.CH.std count turtles with [role = "Coherent STD" and mark
     = false]
    set N.CH.grn count turtles with [role = "Coherent GRN" and mark =
     false]
    set N.IN count turtles with [role = "Innovator" and mark = false]

    set %UA N.UA / (count turtles)
    set %IN N.IN / (count turtles)
    set %CH.std N.CH.std / (count turtles)
    set %CH.grn N.CH.grn / (count turtles)
  ]
```

```
  ;; mark one time those agents who bought something to avoid to count
   them at each step
  ask turtles with [(lastProdBought = "std" or lastProdBought =
   "green") and (satisfied? = true)] [set mark true]

end

;;;;;;;;;;;;;;;;
;; DISPLAY    ;;
;;;;;;;;;;;;;;;;

;; Update the visualization of the simulation
to updateDisplay

  ;; neutral color for every agent
  if color-preferences = "Neutral"
  [ ask turtles with [color != blue] [set color blue] ]

  ;; color agents on the base of individual preference
  if color-preferences = "Color ind preferences"
  [
    ask turtles
    [
      ifelse stdFood.Attitude >= grnFood.Attitude
      [ set color red -  (3 * stdFood.Attitude) ]
      [ set color green - (3 * grnFood.Attitude) ]
    ]
  ]

  ;; color agents on the base of intention to buy
  if color-preferences = "Intention to Buy"
  [
    ask turtles
    [
      ifelse ItB.StdFood >= ItB.GrnFood
      [ set color red -  (3 * stdFood.Attitude) ]
      [ set color green - (3 * grnFood.Attitude) ]
    ]
  ]

  ;; color agents on the base of the percevied social norm
  if color-preferences = "Color perceived soc norm"
  [
    ask turtles
    [
      ifelse (((Norm.Std = 0) and (Norm.Grn = 0)))
      [ set color grey ]
      [
        ifelse (Norm.Std > Norm.Grn)
        [ set color red -  (3 * Norm.Std) ]
        [ set color green - (3 * Norm.Grn) ]
      ]
    ]
  ]

  ;; show behaviors of the agents using agents' labels
  ifelse Show-roles? and any? turtles with [role != ""]
  [ ask turtles
```

```
    [
      if role = "" [set label ""]
      if role = "Coherent GRN" [set label "CH.grn" set label-color
       green]
      if role = "Coherent STD" [set label "CH.std" set label-color
       red]
      if role = "Undercover-altruist" [set label "UA" set label-color
       blue]
      if role = "Innovator" [set label "IN" set label-color magenta]
    ]
  ]
  [ ask turtles [set label ""] ]

end


;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;; $CUSTOMERS' BASIC DATA              ;;;
;; Initialize variables and beliefs    ;;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;


;; Initialize each internal agent's variable
to initializeCustomer

  set lastProdBought ""
  set productTarget one-of patches with [pcolor = red]
  ;; NB following common norm, first decision is set on std products
  set decided? false
  set path [[]]
  set age 18 + random 13
  generatePreferences

  set mark false
  set out? false
  set satisfied? false
  set mxLngShopList 1 + random maxShoppingProducts
  set shopList []

  set Norm.Std 0
  set Norm.Grn 0

  set ItB.StdFood 0
  set ItB.GrnFood 0
  set role ""

end

;; Generate a set of beliefs for a particular agent
to generatePreferences

  ;; Beliefs related with personal attitude
  set belief.env random-normal 3.90 1.54
  ifelse belief.env > 6 [set belief.env 6] [ if belief.env < 0 [set
   belief.env 0] ]
  set belief.health random-normal 4.69 1.17
  ifelse belief.health > 6 [set belief.health 6] [if belief.health < 0
   [set belief.health 0] ]
  set belief.chemfree random-normal 4.55 1.40
```

```
  ifelse belief.chemfree > 6 [set belief.chemfree 6] [ if
  belief.chemfree < 0 [set belief.chemfree 0] ]

  ;; Beliefs related to PBC
  set belief.price random-normal 4.36 1.89
  ifelse belief.price > 6 [set belief.price 6] [ if belief.price < 0
   [set belief.price 0] ]

end


;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;; $THEORY OF PLANNED BEHAVIOR                      ;;
;; Calculate intention to buy a specific product   ;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;

;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;; TPB CALCULATION        ;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;

;; Compute the intention to buy green/conventional food
to calcTPBs

  ;; weights are taken from Scalco, Noventa, Sartori, & Ceschi (2017)
  set ItB.StdFood ((0.44) * stdFood.Attitude + (0.35) *
  stdFood.SocNorm + (0.12) * stdFood.PBC)
  set ItB.GrnFood ((0.44) * grnFood.Attitude + (0.35) *
  grnFood.SocNorm + (0.12) * grnFood.PBC)

end

;; Define the behavior of each agents in the simulation based on
attitude and perc soc norm
to defineRoles

  ask turtles with [satisfied? = false]
  [
    set role ""
    ifelse ([pcolor] of productTarget = red
      and (stdFood.Attitude >= grnFood.Attitude)
      and (stdFood.SocNorm >= grnFood.SocNorm)
      and (ItB.StdFood > ItB.GrnFood) )
    [set role "Coherent STD"]
    ;; attitude and SN are coherent toward conventional products
    [
      ifelse ([pcolor] of productTarget = red
        and (stdFood.Attitude < grnFood.Attitude)
        and (stdFood.SocNorm > grnFood.SocNorm)
        and (ItB.StdFood > ItB.GrnFood) )
      [set role "Undercover-altruist"]
      ;; attitude is green, but SN goes against it and it buy std food
      [
        ifelse ([pcolor] of productTarget = green
          and (grnFood.Attitude >= stdFood.Attitude)
          and (grnFood.SocNorm >= stdFood.SocNorm)
          and (ItB.GrnFood > ItB.StdFood) )
        [set role "Coherent GRN"]
        ;; attitude and SN are coherent toward green products
        [
```

```
          if ([pcolor] of productTarget = green
            and (grnFood.Attitude < stdFood.Attitude)
            and (grnFood.SocNorm > stdFood.SocNorm)
            and (ItB.GrnFood > ItB.StdFood) )
          [set role "Innovator"]
          ;; attitude is for std food, but SN goes against it and it
             buy green food
        ]
      ]
    ]
  ]

end


;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;; STD vs GREEN EVALUATIONs   ;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;

;; Report standard food attitude
to-report stdFood.Attitude []

  let eval.chemfree 0
  let eval.health 0
  let eval.env 0
  let eval.final 0

  ;; compute lower expectations on conventional food
  let temp.low.belief.chemfree belief.chemfree - (belief.chemfree *
   lowFactor)
  let temp.low.belief.health belief.health - (belief.health *
   lowfactor)
  let temp.low.belief.env belief.env - (belief.env * lowfactor)

  ;; evaluate each factor as a comparison between the personal beliefs
   of the agent and the actual char of the food. If the belief is met
   by the characteristcs of the food, it scores 1, otherwise 0
  ifelse (stdFoodHealth < temp.low.belief.chemfree ) [set
   eval.chemfree 0] [set eval.chemfree 1]
  ifelse (stdFoodEnv < temp.low.belief.health) [set eval.health 0]
   [set eval.health 1]
  ifelse (stdFoodChem < temp.low.belief.env) [set eval.env 0] [set
   eval.env 1]

  ;; final evaluation of food is the avg score of the characteristics
  set eval.final ((eval.chemfree + eval.health + eval.env) / 3)

  set Att.Std eval.final ;; update internal variable
  report eval.final

end

;; Report green food attitude
to-report grnFood.Attitude []

  let eval.chemfree 0
  let eval.health 0
  let eval.env 0
  let eval.final 0
```

```
  ifelse (grnFoodHealth < belief.chemfree) [set eval.chemfree 0] [set
  eval.chemfree 1]
  ifelse (grnFoodEnv < belief.health) [set eval.health 0] [set
  eval.health 1]
  ifelse (grnFoodChem < belief.env) [set eval.env 0] [set eval.env 1]

  set eval.final ((eval.chemfree + eval.health + eval.env) / 3)

  set Att.Grn eval.final
  report eval.final

end


;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;; PERCEIVED SOCIAL NORM    ;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;

;; Report percevid social norm toward conventional products
to-report stdFood.SocNorm

  ;; create a group of agents represented by those customers
sorrounding the called agent
  let socialGroup nobody
  set socialGroup other turtles in-radius 1.5 with [(length shopList >
  0) and (pcolor != orange)]
  ;; NB: the instruction avoids to consider agents with no products in
  the cart or at the cashiers
  ;; NB: "in-radius" includes even the turtle who is executing
  instructions, so it must be remove from agentset using "other"

  ifelse count socialGroup = 0
  [ report 0 ] ;; If there is no-one around, or if people around did
                  not buy anything, social influence is equal to zero
  [
    let stdFoodBuyers count socialGroup with [lastProdBought = "std"]
    set Norm.Std stdFoodBuyers / (count socialGroup)
    report stdFoodBuyers / (count socialGroup)
  ]

end



;; Report percevid social norm toward green products
to-report grnFood.SocNorm

  let socialGroup nobody
  set socialGroup other turtles in-radius 1.5 with [(length shopList >
  0) and (pcolor != orange)]

  ifelse count socialGroup = 0
  [ report 0 ] ;; If there is no-one around, or if people around did
                  not buy anything, social influence is equal to zero
  [
    let grnFoodBuyers count socialGroup with [lastProdBought =
     "green"]
    set Norm.Grn grnFoodBuyers / (count socialGroup)
```

```
    report grnFoodBuyers / (count socialGroup)
  ]

end

;;;;;;;;;;;;;
;; PBC    ;;;
;;;;;;;;;;;;;

;; Report standard food PBC
to-report stdFood.PBC []
  let eval.price 0
  let eval.final 0
  let stdFoodPrice 0
  set stdFoodPrice precision(foodPrice)2

  ifelse (stdFoodPrice > belief.price) [set eval.price 0] [set
  eval.price 1]
  set eval.final ((eval.price) / 1)

  set Att.Std eval.final
  report eval.final

end


;; Report green food PBC
to-report grnFood.PBC []

  let eval.price 0
  let eval.final 0
  let grnFoodPrice 0
  set grnFoodPrice precision(foodPrice * (1 + deltaPrice))2

  ifelse (grnFoodPrice > belief.price) [set eval.price 0] [set
  eval.price 1]
  set eval.final ((eval.price) / 1)

  set Att.Grn eval.final
  report eval.final

end


;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;
;; $STORE DESIGN                            ;;
;; Design the layout of the grocery store   ;;
;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;;


;; Fill the shelves with standard food products (plabel = current
available supply)
to fillStdFood

  set pcolor red
  ifelse place-single-product? [ set plabel 1 ] [ set plabel 1 +
  random 50 ]
  set plabel-color white
  show plabel
```

```
  set isEmpty? false
  display

end

;; Fill the shelves with green food products (plabel = current
available supply)
to fillGrnFood

  set pcolor green
  ifelse place-single-product? [ set plabel 1 ] [ set plabel 1 +
   random 50 ]
  set plabel-color white
  show plabel
  set isEmpty? false
  display

end

;; User can place standard product on the shelves with a click
to place-std.food

  if mouse-down?     ;; reports true or false to indicate whether
                        mouse button is down
  [
    ask patch mouse-xcor mouse-ycor
    [ fillStdFood ]
  ]

end

;; User can place green product on the shelves with a click
to place-grn.food

  if mouse-down?
  [
    ask patch mouse-xcor mouse-ycor
    [ fillGrnFood ]
  ]

end

;; User can delete products, walls or shelves with a click of the
mouse
to delete

  if mouse-down?
  [
    ask patch mouse-xcor mouse-ycor
    [
      set pcolor black
      set plabel-color black
      set plabel ""
      display
    ]
  ]

end
```

```
;; User can place the chashiers (= exits) with a click
to define.cashiers

  if mouse-down?
  [
    ask patch mouse-xcor mouse-ycor
    [ set pcolor orange ]
  ]

end

;; User can define the entrances with a click
to define.entrances

  if mouse-down?
  [
    ask patch mouse-xcor mouse-ycor
    [ set pcolor yellow ]
  ]

end

;; Restock new supplies when called
to restock

  ask patches with [plabel = 0] [set isEmpty? true]
  ask patches with [pcolor = white and isEmpty? = true]
  [
    ifelse foodType = red
    [ fillStdFood ]
    [ fillGrnFood ]
  ]

end

;; Design a standard supermarket with no effort by the users
to simple.market

  ca
  set N.CH.grn 0

  ;; Create shelves
  ask patches with [(pxcor = 12) and (pycor > -12) and (pycor < 7)]
   [set pcolor white]
  ask patches with [(pxcor = -12) and (pycor > -12) and (pycor < 7)]
   [set pcolor white]
  ask patches with [(pxcor = 8) and (pycor > -12) and (pycor < 7)]
   [set pcolor white]
  ask patches with [(pxcor = -8) and (pycor > -12) and (pycor < 7)]
   [set pcolor white]
  ask patches with [(pycor = -5)] [ask neighbors4 [set pcolor black]]
  ask patches with [(pycor = 7) or (pycor = 4) or (pycor = 1) or
   (pycor = -1) or (pycor = -9)] [set pcolor black]

  first-food-arrangement

  set-default-elements
```

```
  ;; initialize the market at a random historical moment where
  consumers are inside the grocery store
  crt #cstmrs
  [
      move-to one-of patches with [pcolor = black]
      set color blue
      set heading random 360
      initializeCustomer
      generatePreferences
  ]

end

;; Design 1 entrance and 5 cashiers
to set-default-elements

  let i min-pxcor
  repeat 7
  [
    ;; design 2 standard entrances on the top-edges of the world
    ask patches with [(pycor = max-pycor or pycor = max-pycor - 1) and
     pxcor = i] [set pcolor yellow]
    ask patches with [(pycor = max-pycor or pycor = max-pycor - 1) and
     pxcor = i * (-1)] [set pcolor yellow]
    ;; design 3 chashiers on the centre-top of the world
    ask patches with [(pycor = max-pycor or pycor = max-pycor - 1) and
     (pxcor = -4 or pxcor = 0 or pxcor = 4) ] [set pcolor orange]
    set i i + 1
  ]

end

;; Arrange the food for the first time the store
to first-food-arrangement

  ;; If mix? is true, the procedure will mix std food with green food,
  otherwise they will be placed in separate aisles
  if not mix-products?
  [
    ask patches with [(pcolor = white) and (pxcor < 0)][ fillStdFood ]
    ask patches with [(pcolor = white) and (pxcor > 0)][ fillGrnFood ]
    set-default-elements
    stop
  ]
  let halfShelves count (patches with [pcolor = white]) / 2
  ask n-of halfShelves patches with [pcolor = white] [ fillStdFood ]
  ask n-of halfShelves patches with [(pcolor = white) and (pcolor !=
  red)]  [ fillGrnFood ]

end

;; Procedure allows switching the arragement of food during the
simulation (used to evaluate switches related to tipping-point)
to switch-food-arrangement

  if not mix-products?
  [
    ask patches with [(pcolor = red or pcolor = green)and(pxcor < 0)]
     [ fillStdFood ]
```

```
    ask patches with [(pcolor = red or pcolor = green)and(pxcor > 0)]
     [ fillGrnFood ]
    set-default-elements
    stop
  ]
  let halfShelves count (patches with [isempty? = false]) / 2
  ask patches with [isEmpty? = false] [fillStdFood]
  ask n-of halfShelves patches with [pcolor = red] [set isEmpty? true]
  ask patches with [isEmpty? = true] [fillGrnFood]

end
```

7 (ANNEX) The Implementation of the Theory of Planned Behavior in an Agent-Based Model for Waste Recycling: A Review and a Proposal[1]

Authors

A. Scalco, A. Ceschi, I. Shiboub, R. Sartori, J-M. Frayret, & S. Dickert

Abstract

In the near future, the waste management sector is expected to reduce substantially the adverse effects of garbage on the environment. However, the increasing complexity of the current waste management systems makes the optimization of the waste management strategies and policies challenging. For this reason, waste prevention is the most desirable goal to achieve. Despite this, low levels of household recycling represent the key factor that complicates the current scenario. Keeping this in mind, the present work investigates the determinants of recycling behavior through the development of an agent-based model. Particularly, we examined what would induce households to increase the probability to engage in recycling behaviors on the base of the individual attitude and sensitivity to social norms. The theory of planned behavior (TPB) has been implemented as agents' cognitive model in environmental studies with the aim to predict recycling outcomes. Furthermore, in order to increase the realism of the simulation and the adherence of the model with the theory, we followed two strategies: firstly, we used real data to model a city district (Diong, 2012). Secondly, we made use of the coefficients of the structural equation model presented in the work by Chu and Chiu (2003) to build the agents' cognitive model. As a whole, the results are in line with literature on descriptive social norms. Furthermore, the results indicate that the introduction of descriptive social norms represents a valuable strategy for public policies to improve household recycling: however, injunctive social norms are needed first.

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[1] The current study represents an extension of the work requested to the completion of the Ph.D. research project. However, it was particularly useful to deepen the connections between the theory of planned behavior proposed by Ajzen and agent-based modeling. The current chapter is based on the work appeared in A. Alonso-Betanzos, N. Sánchez-Maroño, O. F. Romero, G. Polhill, T. Craig, J. Bajo, & J. M. Corchado (Eds.), *Agent-Based Modeling of Sustainable Behaviors* (2017).

7.1 The problem with waste

Environmental protection ranks very high on the global agenda. In 1987, the World Commission on Environment and Development (the Brundtland Commission) introduced a new term known as *sustainable development* (United Nations Commission, 2004). This concept was later used to describe the international community's attitude regarding economic, social, and environmental development. So far, only some countries have taken advantage of the economic possibilities of waste management, exploiting the general need of countries to dispose of their waste and combining it with the equally widespread necessity to find sustainable means to generate energy. Currently, Sweden represents the best example: they have converted waste processes into a profitable sector, leading them, in the last few years, even to import waste from other countries (Rousta, Richards and Taherzadeh, 2016).

Most of all, the waste management sector is expected to achieve significant results in the near future, with a substantial reduction of the adverse effects of garbage on the environment. However, the increasing complexity of the current waste management systems coupled with the demanding environmental protection targets makes the optimization of the waste management strategies and policies challenging. For this reason, waste prevention is the most desirable option, followed by the preparation of waste for reuse, recycling, upcycling and other recovery, with disposal (such as landfills) as the last resort.

With respect to recycling participation, ample evidence exists that the problem with household waste will continue to grow over time. This evidence includes sociological factors pertaining to overpopulation, the increasingly faster pace of resource exploitation, as well as the over-consumption made possible by higher incomes. In 2012, the United Nation (UN) made projections that the population of the earth may reach 8.3 and 10.9 billion by 2050 (United Nations, 2014): such a population increase would speed the rate of natural resource depletion and increase the production of wastes. Thus, the problem is twofold: we would be faced with the loss of both materials and energy; likewise, the problem of treating and disposing of the waste, which itself can cause environmental damage and additional costs to society. For instance, the European Commission has estimated that the per-year costs of municipal and hazardous waste disposal in Europe already exceeds €75 billion (European Commission, 2007).

Given this annual cost, there is a great motivation to reduce expenses and, if possible, make the sector pay for itself or even turn it into a profit. For example, costs can be reduced by taking advantage of the possibilities of the waste-to-energy processes (Psomopoulos, Bourka, and Themelis, 2009).

At any rate, in order to achieve a better future management of waste, governments need the cooperation of their citizens. Nowadays, low household participation represents a key factor able to complicate the waste-recycling scenario in most countries. In Sweden, recycling compliance significantly increased from 1975 to 2012 (Rousta, Richards and Taherzadeh, 2016). In fact, during 1975, landfills received almost 1.500.000 tons (62% of municipal solid wastes; MSW), while, in 2012, this number was less than 33.000 tons (less than 1% of MSW). While the municipal recycling rates only went from 6% in 1975 to 32% in 2012, other materials have been sorted and processed in beneficial ways with energy recovery going from 30% to 52% and biological treatment going from 2% to 15% in the same period. This means that consumer compliance to the environmental program is equal to, or at least near, 99-100%, assuming that certain products may not feasibly be reprocessed into either energy or other goods.

If such a high rate of consumer compliance in recycling programs is not possible everywhere, what are the alternatives? There have been recycling programs that rely on sorting of household waste at a Material Recovery Facility (MRF) where commingled waste is processed. The problems associated with MRF waste separation is, first of all, a large investment in equipment such as “mills, cutters, screens, magnetic separators, float-sink separators, cyclones, drum separators” (Rousta and Dahlén, 2016, p.62). In addition, there are risks of contaminants for the workers. Despite these obstacles, the crucial factor for most programs simply relies on the fact that the quality of the recovered materials is often substandard. Indeed, if recycled materials should replace raw materials inside production processes, the purity of the former becomes important, even from a financial perspective, and it is critical that valuable materials have not been mixed together with foodstuff and other contaminants (Sundqvist, 2005). In line with these considerations, if commingled collection with sorting at MRFs is problematic, we are left with the difficult task of creating citizen compliance with processes of waste separation at the source.

Consequently, a refinement of waste management strategies becomes urgent in order to implement policies able to go behind both preventing waste and creating a market for recycling. In such a framework, recycling household waste becomes crucial, as it would reduce waste while saving resources. Moreover, it is critical that the public sector examines incentives that would promote recycling in households. The degree and intensity to which people conform to these behaviors depend on several technical or sociological factors, as well as the demographic and economic facts about the households (Tobias, Brügger, and Mosler, 2009). Overall, the success of a recycling programme is due to a mix of good public policy and efforts to increase public awareness and, thus, households' behavior. All of this must be take into account in order to achieve sustainable changes leading to new social norms.

Given these reasons, arising critical question is what would induce households to recycle their waste in a practicable way. One of the possible answers lies in a simple psychological phenomenon that is widely known but poorly understood: people's behavior is largely shaped by the behavior of those around them. In psychology, this phenomenon takes the name of *social norms*. These latter are in fact one of the most powerful customary rules that govern behavior in groups and societies.

However, traditional forms of market research (e.g. focus groups and surveys) are of limited use in a social norm campaign. When people are polled, they typically underestimate the effects of the campaign, because they are not usually aware that it had an effect on them. An issue that has received very little attention in the literature deals with the question of what is the most effective way to activate policy strategies in order to produce behavioral change. Therefore, to simulate possible scenarios for policy strategies, we created an agent-based model (ABM) representing a virtual society engaged in recycling behaviors. Indeed, agent-based modeling represents a promising alternative to traditional attempts to understand how social processes work over the time. Some authors even argue that "agent-based simulation (…) is the only feasible way of understanding the tangle of complex social phenomena, such as those that involve norms" (Edmonds, 2013, p.47). Indeed, modern computer simulations as a methodology of research within social sciences is a rather new idea, but it comes with great potential thanks to the fact that is «an excellent way of modelling and understanding social processes» (Gilbert, & Troitzsch, 2005, p. 1). Overall, their major value lies in the ability to investigate how the macro-behavior of a system emerges as a result of micro-behaviors (Hughes, Clegg, Robinson, & Crowder, 2012). Within the current work, the micro-behavior is represented by virtual consumers and their propensity to recycle, whereas the macro-behavior is expressed by the virtual society and leads to promote or hinder pro-environmental behavior of agents.

In our work we chose to expand on the theory of planned behavior, originally developed by I. Ajzen (1991), as a valuable cognitive model of the virtual agents populating the simulation. An agent is here defined as a computational entity that we can use as the basis for simulating social processes, as though the entity were a human agent that could perceive, act, and interact within a virtual environment in a way that we can call autonomous (Schwarz and Ernst 2008). Moreover, Ajzen's work was further developed by Chu and Chiu (2003) into an integrated model on household waste recycling. Specifically, our work presents a model scaled from their original findings in order to assign probability distributions that satisfactorily simulate recycling behavior. In models such as this, the stochastic factor is important, given the fact that we can more realistically recreate the acts of agents that might not all act according to plan. This means that there is a strong possibility that different people will act differently even when provided the same instructions and given the same situation. By accounting for this in our model, we gain realism in our simulation (Garson, 2009).

7.2 Social norms theory and recycling behaviors

As suggested by Cialdini and Trost (1998), norms are a widespread construct in social research because they indeed represent a worthwhile psychological phenomenon that can help explain human behaviors. Following their work, we chose to describe social norms as "rules and standards that are understood by members of a group, and that guide and/or constrain social behavior without the force of laws" (*ibid*, p.152). In other words, social norms can be easily conceived as unwritten rules: everyone experiences them daily, as they often guide our behavior without consciously asking or wondering about their validity. For instance, we know that it is a general rule to greet someone who we known when we hastily meet him/her on the stairs. We are not forced to do so, but we know that this can represent a violation of an accepted common rule.

Adherence to the norms of a social group allows members to avoid rejection and increase social approval (Cialdini, Bator & Guadagno, 1999). In their work, Cialdini, Bator and Guadagno (1999) reported also the interesting study conducted by Aronson and O'Leary (1983). The research started from the notion that prompts and informational campaigns are not very effective most of the time to modify the behavior of people if they are asked to adopt an innovation or to change their habits. Instead, the adoption of new behaviors can be promoted if individuals observe others actively engaging in it. Following this consideration, they started monitoring the behaviors of several subjects when showering and the resulting usage of water. To reduce the consumption of this latter, they created two conditions with the aim of improving the awareness of the importance of avoiding water losses. In the first condition, the authors applied a sign outside of the shower room. This prompt explained in four consequential instructions that water must be opened under the shower just on a first time to wet down and after being soaped to rinse off. In this way, the prompt invited to turn off the water when soaping up. In a further condition, a confederate of the researchers was introduced into the shower room. In fact, research indicates that social norms are most compelling when people are shown evidence that the behavior they are being encouraged to adopt is already practiced by people similar to them (see Social Comparison Theory; Festinger, 1954). When entered into the shower room, the confederate followed the instructions proposed by the prompt: thus, he modeled the proper behavior. Within this condition, the number of accidental participants who exhibit the right behavior increased up to 53% (against the 6% of people who followed the prompt in the previous condition). The authors concluded the study affirming that "having people model the appropriate behavior suggests to others that conserving water by turning off the shower is a reasonable and worthwhile thing to do" (*ibid*, p. 223). Therefore, the results demonstrate how powerful normative influence can be as social phenomena.

7.2.1 Understanding and investigating social norms

An important distinction is usually made among studies regarding norms. In fact, within psychological and sociological literature it is rather common to find references about *descriptive* social norms and *injunctive* social norms. The former refer to informational influence and they are related to the observation of what most others do in a particular situation. In contrast, the latter type of norms can be seen as the source of normative influence, which is related to what other people consider as acceptable or unacceptable behavior (Cialdini, Bator, and Guadagno, 1999). Therefore, descriptive social norms simply consider how others behave, without a positive or negative evaluation of the behavior and without providing evidence of what is helpful behavior from the results of their actions (Göckeritz, Schultz, Rendón, Cialdini, Goldstein, and Griskevicius, 2010). As stated by Cialdini (2007), descriptive social norms are able to transmit a simple but effective message: "If a lot of people behave in this way, this is probably the right thing that I should do". Besides, following the perspective proposed by Cialdini, Reno and Kallgren (1990), descriptive norms can represent a shortcut to make decisions in situations where there is a prevalence of ambiguity about the behavior that should be performed. Injunctive social norms, on the other hand, tend to be focused on social rewards (for instance, social approval) and punishment (in some cases, even the rejection one's own group) related to certain behaviors.

Moreover, there is an important aspect related to the psychological notion of saliency of norms. In fact, as reported in Cialdini, Reno and Kallgren (1990), norms do not have an equally powerful effect at all times and in all situations. Instead, norms must be made salient to elicit the proper response from people: that is to say, they have to be "activated" in the mind of individuals. For instance, Cialdini and Goldstein (2004) experimentally demonstrated that an injunctive normative message can increase norm accessibility, and consequently promote the recall of the right behavior, when it is linked to a functional mnemonic cue that can easily be perceived in upcoming conditions. In addition, as shown by the work by Cialdini, Reno and Kallgren (1990), anti-littering norms can become salient by pointing out that littering constitutes a blameworthy action: in this way, they are injunctive norms as they bring with them a negative connotation. As expressed by Demarque, Charalambides, Hilton, and Waroquier (2015), "persons who are contextually focused on normative considerations are most likely to act in norm-consistent ways" (p.167). Thus, it is when injunctive anti-littering norms are made salient, that people will tend to improve their pro-environmental behavior (Cialdini Reno, and Kallgren, 1990). Finally, regarding salience, the previous authors specify that when only one (descriptive or injunctive norm) is made salient to an individual's mind, that norm will exercise the stronger influence on the subsequent individual's actions. Following the previous considerations, we can consider recycling behavior as a specific form of prosocial behavior, which is in turn related with social norms (Cialdini & Goldstein, 2004; Cialdini et al., 1990). Specifically, household recycling behaviors are motivated by social norms, whereas, instead, financial incentives may even reduce these actions, as they undermine the intrinsic motivations of people reducing the proneness toward recycling (Brekke, Kverndokk, and Nyborg, 2003).

As an example, a rather interesting work about social norms has been provided by Savarimuthu, Purvis, Purvis, and Cranefield (2009). Following a bottom-up approach, they investigated the spread of a norm against littering inside a park within a virtual society. Particularly, they set up a (bi-dimensional) simulation environment with several agents that were able to interact in a social context. The agents interacted when they met on the same spot: in this situation, each agent was able to observe the behavior of the other one (littering/not littering). Furthermore, the authors developed a payoff matrix where pro-environmental behavior had a positive payoff (0.5), whereas littering had a negative payoff (-0.5). When an agent decided to pollute the park, the shared environment is ruined: this means negatively influencing the entire virtual society given that this action has an impact on the general productivity. Within the model by Savarimuthu et al., the term productivity is used to indicate the benefits that the agents receive when using the public park. Finally, the final payoffs are computed as the sum of the individual payoff and the park productivity. No central mechanism is present within the simulation; instead, each agent that considers littering as a blameworthy behavior has the ability to punish an agent engaged in an inappropriate behavior. Punished agents switch from littering to a pro-environmental behavior when the number of the received punishments exceeds their individual resistance to change. The main observable output of the simulation is constituted by the emergence of a norm (i.e. littering or not littering).

The results show that a norm against littering is established when the number of punishers is sufficiently high (at least 10% of the initial population). Otherwise, the non-littering norm spreads across the population and the productivity drops gradually. As noted by the authors, this kind of process occurs commonly inside online-based encyclopedias: a norm of collaboration is established only when there is a sufficient number of reviewers that censor, or even ban, false contributors. Furthermore, the work highlights how social norms can be successfully being established among society if the costs related with enforcements are low.

7.3 Dealing with social norms from a computational approach

Jager and Jannsen (2003) highlighted the importance to develop theoretical models of human decision processes starting from empirical research. Despite this, as pointed out by Ceschi, Scalco, Dickert, and Sartori (2015), currently there is still a lack of real integration between computational modeling and cognitive theories, both from a methodological and theoretical perspective. Indeed, cognitive psychological modeling can provide the means by which it becomes possible to identify the driving forces behind the recycling behavior and to determine the most likely successful factors for public policies. Literature indicates that environmental attitudes and situational and psychological variables are likely to be important predictors of the recycling behavior.

Interestingly, in their extensive work Elsenbroich and Gilbert discussed how to model norms (2014). Three fundamentals approaches can be useful to apply in agent-based modeling when dealing with social norms. One of these is represented by the well-known social network analysis. A social network is composed by two kind of elements: nodes (i.e. agents) and their ties (i.e. the relationships among agents). Social network analysis focuses primary on the latter. Given the fact that our model is aimed to investigating the spread of social norms without implying relationships among agents (at least, nothing more than closeness), we moved forward from this approach.

A second formalization invokes the social impact theory. This was firstly proposed by Latané (1981) and it was aimed to turn the influence (the "impact") of one subject on another one into a mathematical formulation. Latané suggested considering three fundamental elements for his theory: social forces, the psychological law, and the number of targets. The first one, social forces, is composed of three main parts (the number of people that can exert influence, the strength of the influence -depending on the relationships established among the subjects and their individual features-, and the immediacy of the impact). Furthermore, the fundamental law states that the social impact experienced by an agent will increase with the number of agents who are exercising social pressure. This increment follows a logarithmic function, such that a new agent will exercise less influence than the previous one. Finally, the third component refers to the number of agents influencing a subject. The estimation of the final value of the social impact is promptly given by the sum of the previous three main components. However, as stated by Elsenbroich and Gilbert (2014), even if social impact theory has the advantage to be generalizable, it is rather difficult to evaluate the social force and immediate component.

The last approach considered by the authors is the one that, more than the others, stems from a psychological background and that has been implemented inside the present work: the theory of planned behavior (TPB; Ajzen, 1991), which provides a valuable theoretical and cognitive framework to understand and explain the influence of several psychological factors, including social norms.

7.4 The psychological bases of the theory of planned behavior

Models of psychological cognitive functioning can be particularly useful to isolate the different aspects that may drive recycling behaviors, and, consequently, those successful factors of public policy that can enhance this kind of behavior. The theory of planned behavior has been developed from the previous Theory of Reasoned Action (Fishbein, and Ajzen, 1981). They both assume that people have a rational basis for their behavior in that they consider the implications of their actions. Particularly, the theory of planned behavior represents a psychological theory that, more than other cognitive models, has been extensively used within environmental studies (see for instance: Botetzagias, Dima, and Malesios, 2015; Chan and Bishop, 2013; Chen and Tung, 2009; Cheung, Chan, and Wong, 1999; Do Valle, Rebelo, Reis, and Menezes, 2005; Kaiser and Gutscher, 2003; Mannetti Pierro, and Livi, 2004; Pakpour, Zeidi, Emamjomeh, Asefzadeh, and Pearson, 2014; Ramayah, Lee, and Lim, 2012; Tonglet, Phillips, and Bates, 2004; Tonglet, Phillips, and Read, 2004; Vicente and Reis, 2008).

According to the TPB, intentions to engage in recycling behavior stem from three main factors: subjective norms, individual attitudes and the perceived personal control. The concept of *subjective norms* refers to the individual's belief that people important to the decision maker see their behavior as the appropriate way to act. Aceti (2002) argues that people are motivated to recycle by the actual pressure they receive from family and friends to do so. Furthermore, simply knowing that family, friends, and neighbors participate in recycling activities increases the likelihood of participation. In this spirit, Stern, Dietz, Kaloff, and Guagnano (1995) stressed the importance of considering the social structure within which individuals are embedded, based on the belief that social structures shape individuals' experiences and ultimately their personal values, beliefs and behaviors. Following Trafimov and Finlay (1996), it may be suggested that subjective norms are relevant only for participants with higher accessibility of a collective self. However, according to Cialdini's Theory of Normative Behavior (Cialdini, Reno, and

Kellgren 1990), it may be suggested that the actual impact of subjective social norms is underestimated when it is measured by means of anonymous questionnaires completed in private settings (Stiff and Mongeau, 1994). In fact, Cialdini, Reno, and Kallgren (1990) showed that, in experimental settings, where an injunctive anti-littering norm was made salient, participants' littering behavior was significantly reduced. As indicated by Cialdini and Trost, those institutions that want "to activate socially beneficial behavior should use procedures that activate injunctive social norms, since these norms appeared to be more general and more cross-situational effective" (1998, p.161).

The concept of attitude refers to the individual's evaluation of the action. Boldero (1995) found that intentions to recycle newspapers directly predicted actual recycling and that attitudes toward recycling predicted the recycling intentions. The expectations can reflect past experiences, anticipation of upcoming circumstances, and the cultural background. Davies, Foxall, and Pallister (2002) argued that recycling attitudes should be separated into two components: an affective and a cognitive element. The former consists of the emotional approach to the recycling imperative, whereas the latter consists of the knowledge about the outcomes and consequences of performing the recycling behavior (Tonglet, Phillips, and Read, 2004).

Finally, the concepts of *perceived control* and *moral obligation* refer to the individual's perception of their ability to perform behaviors. Taylor and Todd (1995) found that both attitudes toward recycling and perceived behavioral control were positively related to individuals' recycling and composting intentions. According to TPB, perceived behavior control will influence actual behavior only if the behavior is not completely under the person's volitional control.

7.5 Integrating an empirical model of recycling behavior

Agent simulations range from highly structured artificial worlds with few simple rules and constraints (Kohler and Gummerman, 2001) to complex models where agent interactions constrain subsequent iterations of the simulation (Sawyer, 2001) and/or multiple structural layers are considered (Stinchcombe, 2001). It is well known that the development of these algorithms is the most fragile aspect of the simulation analysis. Within the present work, in order to design a virtual society, a key activity is represented by the identification of an amount of the agent's attributes that are significant for recycling behavior. These attributes span from basic demographic attributes (i.e., age, education and income), to more specific features (i.e., environmental sensitivity, self-confidence and sense of social belonging; Ceschi, Rubaltelli, and Sartori, 2014). Most of the impact is due to these attributes and therefore it is important to consider them for the aims of the analysis. As a consequence, it is recommended to start from some empirical models, such as a structural equation model (SEM).

SEMs are a modeling technique rather widespread in social and psychological science (Hox and Bechger, 2009). They derive from the integration of three fundamental statistical techniques applied by social sciences: particularly, they combine path analysis, factor analysis, and multiple regression models. In this way, structural equation models are able to combine the methods usually applied by, respectively, sociology, psychology, and economy. Inside a structural equation model, the relationships among variables are expressed by regression coefficients: consequently, the entire model is developed following a cause-effect interpretation. The design of the model is firstly conducted following theoretical literature: that is to say, by connecting variables following findings provided by the current available research. Then, the model is tested statistically: starting from the covariance matrix of the examined variables, the fit of the model with the data is estimated by means of a maximum likelihood method. Usually, to obtain the parameters several iterations are needed until the "best fit" of the model with the data is achieved.

Among other social sciences, these models found a large usage within psychological research thanks to the fact that they are able to link latent variables to observable variables. In fact, as pointed out by Krishnakumar and Ballon (2008), a remarkable benefit of this framework is that correlations of observed indicators are clearly made as arising out of subjacent factors that are accountable for the results. That is, SEMs are able to reveal and to quantify the relationship between a behavioral expression and its underlying psychological construct. For instance, they can corroborate the existence of latent factors, such as verbal and mathematical intelligences, starting from the observed responses of a psychological test.

Nevertheless, one downside of the structural equation modeling approach is represented by the difficulty to properly capture all crucial variables regarding a specific behavior during the beginning phase of a literature review and design of the theoretical model. In addition, given the complexity of human behavior, results extracted from literature sometimes can lead to confusing or overlapping variables. The model suggested by Ajzen (1991) represents a fundamental schema of human behavior, as it is able to take into account three fundamental and distinct factors at the same time: the personal psychological attitude, the impact of the social sphere and the combination of perceived and actual factors that can hinder a certain behavior. Indeed, the schema proposed by the theory of planned behavior represents a fundamental framework to properly design a structural equation model when dealing with pro-environmental behavior. In line with this, Zhang and Nuttall already stated how the TPB can summarize psychological, sociological and environmental elements related to decision-making processes and, at the same time, it still remains relatively easy to code: the authors concluded that these characteristics make the TPB "particularly suited to modelling consumer behavior in agent-based simulation" (2011, pg. 173).

A valuable example of the application of structural equation modeling designed following the theory of planned behavior is given by the work by Chen and Tung (2014). They conducted research to develop an extension of the TPB aimed to explain and predict the consumer's intention to stay in green hotels. Following current literature, they started designing the research model, which should explain the antecedents of intention to visit green hotels, based on the individual attitude, subjective norms and perceived behavioral control. In addition, they extended the classical model of TPB by taking into account the perceived moral obligation of the studied subjects. By means of structural equation modeling, the authors were able to estimate path coefficients among the designed research model, uncovering the "force" of the causal relationships among variables. Furthermore, they were able to assess the indirect effect of consumer's environmental concern on the intention to visit green hotels. Finally, structurally equation modelling allowed revealing that the most indispensable factor of the model to predict intention to visit green hotel was the perceived behavioral control.

At any rate, as remarked by Hox and Bechger (2009), it is important to note that a structural equation model (even when corroborated by the data) does not imply the truth of the model itself. There could be several other competing models able to achieve the same fit with the data.

In addition, a current limitation of structural equation models is related to the difficulty to take into account individual differences among people. Essentially, individual differences are characterized as a set that makes individuals particular, according to their inclinations, capabilities and outcomes. This set of characteristics can affect the result of the application of general psychological laws, making their results uncertain. For instance, the studies by Tversky and Kahneman, (e.g., 1986) within the framework of prospect theory revealed a general psychological law defined as “loss aversion” (also commonly known as risk aversion). Briefly, this law tries to explain why people are more prone to weight losses substantially more than objectively commensurate gains when evaluating economic prospects. However, this sensitivity to losses may differ among people (e.g., Tversky and Kahneman, 1986; Kahneman, Knetsch, and Thaler, 1991; Mitchell, & Mickel, 1999; Ceschi, Rubaltelli and Sartori, 2014). That it is to say, people perceive losses more than their actual objective value, but individual differences modulate this perception. Starting from this, agent based modeling can help to dynamically represent, in a natural way, several scales of analysis and the importance of structures at different levels, none of which is easy to accomplish with other modeling techniques (Gilbert and Terna, 2000). In this way, the limitation of SEMs regarding the modeling of individual differences may be seen conversely related with the advantage of ABMs to represents agents’ heterogeneity (see for instance, Sartori, Ceschi, & Scalco, 2014).

7.6 Specific aim and hypotheses of the simulation

The aim of the current work is to present a model able to simulate a number of characteristics that have been scaled from the original work by Chu and Chiu (2003), modeled, and assigned with probability distributions to simulate the recycling behavior. Usually, the purpose of this stochastic effort is to endow agents with a “personality”. Contemplating the possibility of fuzzy logic implies greater simulation realism as different agents act differently in the same situation. Agents with personality lead to the modeling of more complex interactions where, for example, hypotheses may be tested more effectively by considering teams of agents with different personalities rather than single agents (Garson, 2009).

The built simulation tested two specific hypotheses related with the framework of the theory of planned behavior. On the one hand, the first hypothesis is related to injunctive social norms. Specifically, we expect that those agents that are mostly sensitive to these types of norms will also be less susceptible with respect to the impact of external conditions on their intention to recycle. Assuming scenarios with extreme values of recycling rate, the intention of the householders to recycle will be stable over time. Instead, assuming a scarce recycling rate, only those agents that are most influence by injunctive social norms will engage in recycling behavior. We presume that the simulation will end with a stable equilibrium.

On the other hand, the second hypothesis is connected with descriptive social norms. Particularly, we think that those agents that most of all are sensitive to these types of norms will be influenced negatively by the impact of external conditions, reducing the probability to recycle. In low recycling rate scenarios, the intentions to recycle will be weak. This is due to the fact descriptive social norms reduce the probability to recycle among the population. In contrast, in scenarios with a high recycling rate, the intention of householders to behave properly will be strong, thanks once again to the effects of descriptive social norms. We presume that the simulation will end with a self-reinforcing stable equilibrium.

7.7 The Planned Recycling Agent Behavior model

Our analysis is based on a simulation model of the “Planned Recycling agent Behavior” (PRB_1.1) that produces virtual neighborhoods with different agent types, waste generation and collection processes (**Fig. 1**; Ceschi, Dorofeeva, Sartori, Dickert, & Scalco, 2015). The scaling of the agents’ features is based on the coefficients relating to the TPB and taken from an SEM on motivations to recycling behavior developed by Chu and Chiu (2003), which represents an extension of Taylor and Todd’s (1995) efforts to suggest ways to influence recycling behavior. The application of scaling allows us to accelerate the simulation lowering hardware requirements to run the algorithm, leaving untouched the original ratio between agents’ variables. Particularly, the model that has been presented in Chu and Chiu (2003) included four basic coefficients expressing the recycling behavior, which include the force of subjective norms (SN_r), the individual environmental attitude (AT_r), the moral obligation perceived by the agent (PMO_r) and the perceived behavioral control (PBC_r). These factors reflect the traditional model proposed within the theory of planned behavior (Ajzen, 1991), but the inclusion of moral obligation extends the original model. Thus, the mathematical expression of the model can be represented by the subsequent formula:

$$B_r \cong BI_r[w_1(AT_r) + w_2(SN_r) + w_3(PBC_r) + w_4(PMO_r)]$$

Where the term B_r refers to the actual expression of the behavior, and BI_r expresses the intention toward that behavior. As there are no components between these elements, the theory of planned behavior (Ajzen, 1991) assumes that intention of behavior is itself a reliable measure of the probability to engage in that particular behavior. In line with the proposal by Ajzen (1985), the four terms indicated with w are empirically determined regression coefficients used to weigh each element of the formula. Moreover, the term AT_r refers to the personal attitude of a particular agent toward a certain behavior: thus, the agent computes the attitude on its expectations of the behavioral results. Boldero (1995) suggested that the personal attitude could represent a good predictor of recycling behaviors. Again, the perceived behavioral control is comprised inside the equation by the term PBC_r. This refers to the actual difficulties that an agent might experience and the perceived control that it can potentially have on them. Taylor and Todd (1995) reported how both behavioral control and attitude are positively related to the individual motivation toward recycle.

Finally, the subjective norms are included by the term SN_r. Taken together with moral obligation (PMO_r), they constitute the social determinants of the recycling behavior. While the subjective norms of the model are related with the behavior of the neighborhood, the moral obligation is connected with the injunctive norms shared by the society.

7.8 The formal model

The values of the four previous constructs contained by the structural equation model illustrated by the work by Chu and Chiu (2003) have been parameterized by a stochastics computation and used inside the simulation as probabilistic factors of behaving. In addition, in order to initialize the parameters (for instance, the number of households, trucks, waste production, etc.) we exploited the data contained inside the report about Kaohsiung City (Diong, 2012), used also by Chu and Chiu. Specifically, we referred to the values relative to the San-min district, the largest one of Kaohsiung with more than 353 thousand people and with a number of households equals to one-third of the population. All coefficients used to run the simulation are summarized inside **Table 1**.

The algorithm generates the virtual city and then, during the simulation, it manages three kind of agents: neighbored agents, garbage transporters, and landfills (see **Fig. 1**). More details about these agents are presented by the following subsections.

Table 1 - Coefficients applied to the simulation PRB_1.1. Values 1-6 are extracted from the work by Diong (2012) and they refer to San-min district. Values 7-10 are taken from the standardized and normalized regression coefficients of the structural equation model presented within the work by Chu and Chiu (2003).

Coefficient	Value
1. Population present in the virtual district	35,3451
2. Total number of neighborhood agents	1,100
3. Number of transportation systems	8
4. Landfields	2
5. Daily rubbish production for neighborhood (*R* and *Rre*)	427 kilo
6. Critical situation for a neighborhood	9 ton
7. Coefficient of the environment attitudes (*ATr*)	0.18
8. Coefficient of the subjective norms (*SNr*)	0.12
9. Coefficient of the perceived behavioral control (PBC_r)	0.33
10. Coefficient of the perceived moral obligation (PMO_r).	0.10

7.8.1 The neighborhood agent

All agents inside the simulation are able to generate recycled rubbish (*Rre*) and non-recycled rubbish (*R*). This is based on the probabilities of psychological constructs and other agent habits. Neighborhood agents recycle if they possess high levels of environment attitudes (AT_r), high subjective social norms (SN_r), and perceived behavioral control (PBC_r). This link is not mediated by other aspects (**Fig. 2**). Probabilities of these psychological constructs are normally distributed among agents.

If the level of subjective norms (SN_r) of an agent is sufficiently high, it can be socially influenced by other agents close to it. When this happens, neighbor agents close to the agent are observed and more recycled rubbish is produced if the neighbor observed is also recycling. We defined as “peer influence” (PI_r) the tendency of an agent to be influenced by others around it.

In addition, the general disposition of the agents to recycle is computed within the simulation by a decay (and an inverse decay) function aimed to resemble human psychophysical sensitivity (see, for instance, Weber, 1843). This function has been developed starting from the original model of motivation and satisfaction of needs over time proposed in the work by Jager and Janssen (2012).

Furthermore, agents’ recycling behavior is negatively influenced by the actual presence of rubbish around them. In fact, agents are endowed with the ability to observe the level of rubbish that is produced by others. When this exceeds the critical level, agents start to decrease the probability to recycle. We defined this phenomenon as “surrounding influence in recycling” (SI_r) and it is computed by means of another decay function related with the quantity of rubbish existing in the neighborhood at a certain instant of the simulation. Both peer influence and surrounding influence are determinants of the probability of an agent to recycle by being influenced by others.

Fig. 1 - Example of the PRB_1.1 simulation. The simulation presents three different types of agents. (1) Neighborhood agents turn their color from yellow to red assuming different shades. Yellow color indicates a stable situation, orange represents a state close to the critical level, red means instead that *R* achieved the critical level. Each one of the over 700 yellow square represents a household composed on the average of 1.5 agents. (2) Garbage transportation systems are represented in the model as grey and green small rectangles among neighborhoods. (3) Landfills are indicated by the green and the grey rectangle at the center of the world. They represent, respectively, the recycling and non–recycling landfills.

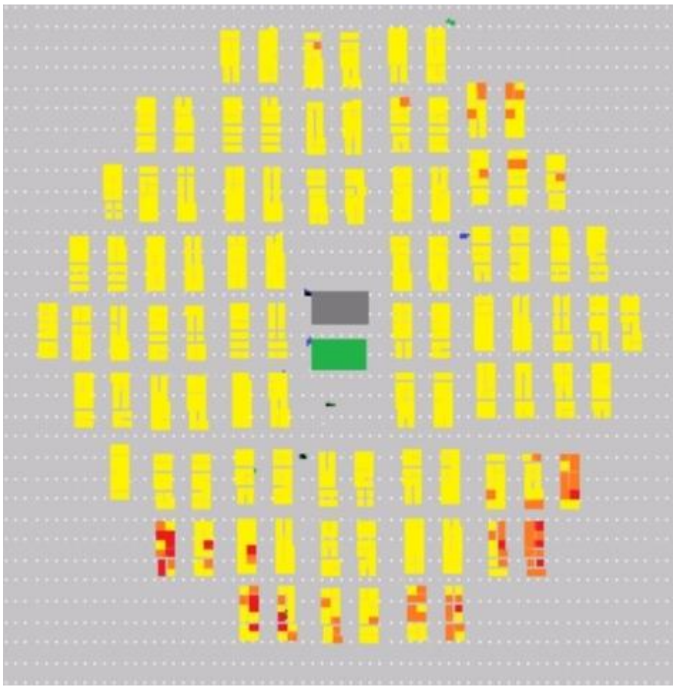
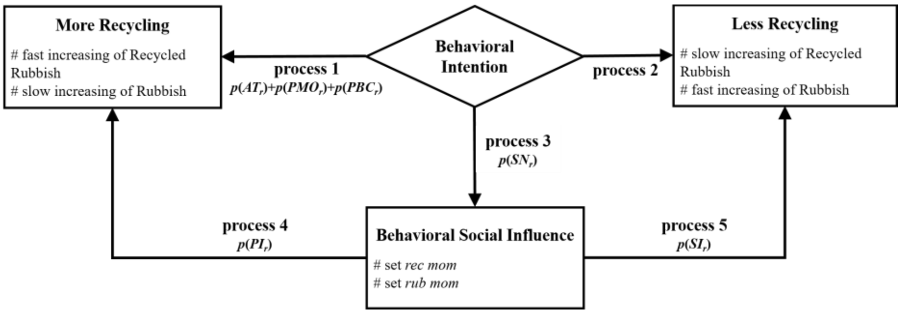


Fig. 2 – Schema of reasoning of the agents inside PRB_1.1.



The schema depicted in **Fig. 2** explains agents' behaviors inside the simulation PRB_1.1. Considering a random agent *i*, at every cycle it compares the possible actions and then it executes one of them. The comparison is performed by assessing the probability levels: the value of *p* ranges between 0 and 1 and it is considered low when lower than 0.50, otherwise it is high. The strategy followed by an agent depends on five basic processes:

- *process 1:* agent *i* computes the value of probability related with its environmental attitude $p(AT_r)$, perceived moral obligation $p(PMO_r)$, and perceived behavioral control $p(PBCr)$. If the sum of these values exceeds a probability threshold of 0.50, the agent follows this strategy and it will produce more recycled rubbish (*Rre*) than regular rubbish (*R*).
- *process 2:* if the sum of $p(AT_r)$, $p(PMO_r)$, and $p(PBC_r)$ does not reach a high level, process 1 is rejected, thus the agent applies process 2 and it recycles less. In this way, it increases the level of non-recycled rubbish (*Rre*).
- *process 3:* the agent computes the influence exercised by other agents (that is, $p(SNr)$). When it enters in this state, the agent will set the variables related with the recycle rate and not-recycle rate by observing another random agent close to it and the level of rubbish in the vicinity. Having this information, the agent estimates the peer influence (PI_r) and the surrounding influence (SI_r) in recycling and their probabilities. The PI_r level is computed by the agent each time using a specific function, which depends on whether the other agents are recycling (*1*) or not (*0*).
- *process 4:* the agent computes the level of the peer influence $p(PI_r)$: if it is high it decides to increase the probability to recycle.
- *process 5*: if the agent is scarcely influenced by the surrounding agents (*i.e.* there is a low level of $p(SI_r)$) the agent will recycle less.

7.8.2 The garbage transportation system and the landfills

The model involves a transportation system, which takes away garbage from neighborhood agents and moves it to the collecting points. The pathways adopted by pick-up trucks are optimized considering distance and time. Pick-up trucks get to the closest neighborhood agents to collect *R* and *Rre*.

Two types of trucks have been designed and implemented inside the simulation: the first one is devoted to collect only recycled rubbish (the green truck in **Fig. 1**); conversely, the second one is dedicated to gather only non-recycled rubbish. In **Fig. 1** they are indicated as, respectively, the green and grey truck. Both trucks assign priority to the neighborhood with the highest rubbish level. After a specific amount of *R* or *Rre* collected, garbage trucks move to the closest landfill.

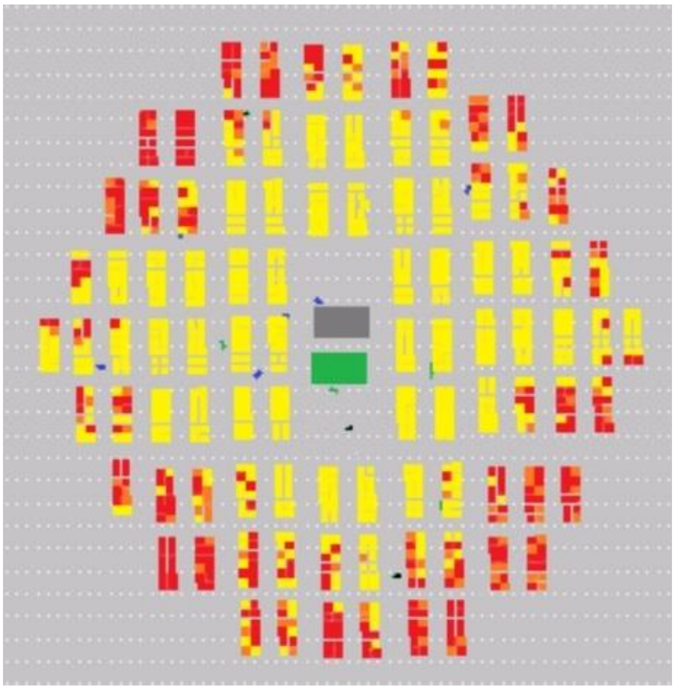
Furthermore, there are two types of collecting points (i.e. landfills) in the simulation: one for unseparated garbage *R*, the other one for recycled garbage *Rre*. The landfill removes the garbage carried by pick-up trucks over time. Besides, the virtual environment reproduces in a two-dimensional space (specifically, a torus) a district composed of 1.100 neighborhood agents. Agents are free to consume, recycle, and move within the boundaries of this virtual world.

7.9 Results and conclusions

As stated, environmental protection ranks very high on the global agenda. However, the increasing complexity of the current waste management systems makes the optimization of the waste management strategies and policies challenging. For this reason, waste prevention is the most desirable result to achieve. Despite this, low household participation to recycling represents the key factor that complicates the current scenario. Recycling household wastes becomes crucial, as it would reduce waste while saving resources. The present work investigates the determinants of recycling behavior through the development of an agent-based model. Particularly, the programed simulation tries to answer to the following question: what would households induce to increase the probability to engage in recycling behaviors? In line with this, we chose to describe here social norms as “rules and standards that are understood by members of a group, and that guide and/or constrain social behavior without the force of laws” (Cialdini and Trost, 1998). Moreover, we distinguished between the processes that lead the spreading of descriptive and injunctive social norms. While the former are related with the observation of others’ behaviors, the latter are related to what other people consider as an acceptable behavior (Cialdini, Bator, and Guadagno, 1999).

Besides the specific hypotheses and the results obtained by the research, the present contribution proposes a novel approach to agent-based modeling which includes integration of theories and quantitative methods commonly applied within psychological research. Specifically, we argue that the implementation of results obtained from statistical techniques such as structural equation models can add a significant validity with respect to the agents' behavior, due to the fact that a SEM is able to statistically express the link between a certain behavior and its psychological antecedents. In addition, due to the potential difficulties related with the design of a proper theoretical model of behavior, the scheme proposed by the theory of planned behavior represents a valuable framework. In this way, in order to build a structural equation model regarding recycling behavior (as well as similar pro-environmental behaviors) it is recommended to take into account at least the three fundamental elements proposed by Ajzen's model (1991). The validity of the model should be successively tested by applying proper statistical procedures. In the end, the results can be smoothly implemented inside an agent-based model as exemplified by the current work: in fact, the values extracted from the SEM represent the basic coefficients of the agent's reasoning engine. Moreover, we argue that the limitation of SEMs regarding individual differences is overcome by the potential ability of computer simulations of generating heterogeneous agents.

Fig. 3 - A screenshot from one run of the ABM based on the PRB_1.1 with higher *R* levels than Fig. 1. Neighborhood agents turn color because of the *R* level. When *R* is equal to the critical level they turn red, orange if they are close to the critical level, yellow when the situation is stable.



In the current work, the TPB is applied as agents' cognitive model with the aim to predict the recycling outcomes on the base of the individual attitude and sensitivity to social norms. This approach may help to identify the factors of public policy that can enhance pro-environmental behaviors. We based the parameters in the simulation on the data contained inside the report about Kaohsiung City (Diong, 2012) to model a city district. We also made use of the coefficients contained by the structural equation model presented inside the work by Chu and Chiu (2003) in order to build the agents' cognitive model. These values are parameterized by a stochastics computation and used inside the simulation as probabilistic factors of behaving. Undeniably, a potential limitation of the present study is based on using parameters and information provided by previous studies that might not fit perfectly for the proposed model: future research will have to corroborate the integration of the TPB and SEMs within an agent-based model by conducting the whole research process, from the design of the theoretical behavior model to the implementation into a virtual model. Agent-based models can simulate the efficacy of different recycling campaigns under equal conditions and, at a subsequently stage, allow the simulation of specific policies under different conditions. Moreover, agent-based models are mostly structured on algorithms that illustrate the behaviors of agents, identify their causal effects, and specify critical parameter estimates. Therefore, stochastic simulation, while retaining its versatility, is also time-effective and cost-effective. However, it is important to state that the agent behavior is stochastic. As we suggested, factors of SEMs can be implemented inside ABMs, in contrast to equations of aggregation.

The preliminary results of the model available on the site owned by OpenABM Consortium show stability and reliability in relation to the outcomes of the simulation. The visual impact creates a virtual circle where household motivation to recycle is reinforced. This circle expresses the consequences of descriptive social norms. On the contrary, the failure in recycling when the environment is full of rubbish contaminates the neighbors' behavior (**Fig. 3**). As a whole, the results are in line with literature on descriptive social norms (Cialdini, Bator, and Guadagno, 1999; Cialdini, 2007; Botetzagias, Dima, and Malesios, 2015). Findings in the literature about social norms and littering agree that in a "dirty" environment individuals are inclined to litter more than those subjected to a "clean" environment (e.g., Cialdini, Reno, and Kallgren, 1990), mainly because of the peer influence, due to the fact that agents continuously observe and mimic each other's behavior. Similarly, the surrounding has its own effect because the amount of garbage present in the system drives the trend away from its stable level. To conclude, the results obtained from several runs of the model indicate that the introduction of descriptive social norms represents a valuable strategy for public policies to improve household recycling. However, it is important to consider the sequence used to apply norms: injunctive social norms are needed in order to implement further policies based on descriptive social norms.

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